The efficiency of mergers among cooperative credit banks: evidence from Italy

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ABSTRACT

In this paper we try to assess whether mergers among Italian mutual cooperative banks (Banche di Credito Cooperativo, BCCs) are efficiency-enhancing. For the purpose, we employ a two-step procedure: we first estimate bank-level cost efficiency scores for a large sample of Italian banks in the period 1993-2013 by means of a stochastic frontier approach, then we try to explain the estimated BCCs cost efficiency with a set of merger status dummy variables (never merged, before the first merger, merged once, merged twice, etc.) as well as with a vector of control variables. We find that mergers increase mutual banks' cost efficiency only after a BCC has merged at least three successive times with other BCCs, hence after reaching a remarkably large size. However, we conjecture that this growth in size could harm especially marginal borrowers (i.e. those who are likely to be served by smaller banks but neglected by bigger ones), with a strong and adverse impact on development and inequality and in contrast with the BCCs' ethics and mission.

KEYWORDS: Banking; Cooperative banks; Mergers; Efficiency

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1. Introduction

Following banking deregulation and liberalization, trends to consolidation of the banking sector have been pervasive since the 1980s in most developed countries (Amel et al., 2004; Montes, 2014). The mainstream view has been that the process of banking consolidation delivers efficiency gains and is compatible with more, not less, effective competition.

Recent literature focusing on bank business models stresses, however, that banking diversity is an asset towards achieving more resilient and functional banking systems (Ayadi and de Groen, 2016; Michie and Oughton, 2013). It is believed that, by relying on more retail and relationship banking oriented business models, savings banks and, especially, cooperative banks may favour financial inclusion of marginal customers and reduce the credit rationing of borrowers, particularly the SMEs.

Therefore there seems to be a potential trade-off between the beneficial effects of consolidation – if it helps achieve higher banking efficiency – and the unfavourable consequences of consolidation – if it dilutes banking diversity. This paper centres on one side of that potential trade-off testing whether, indeed, consolidation through M&As improves efficiency in a system of small-sized mutual cooperative banks.

Particularly, we focus on Italy, where the “Banche di Credito Cooperativo” (BCCs) are generally small credit institutions organized in a banking network that mainly operate in local areas and whose activity is grounded on mutual principles. They manage about 14% of total branches and 7% of total loans. Their typical customers are SMEs and households, with whom they generally adopt the relationship lending business model (based on long-lasting fiduciary relationships with customers) in order to cope with problems of asymmetric information.

However, in the very last years there have been pressures for a reform of the Italian credit cooperative system, as BCCs are regarded to be “too many and too little”. Particularly, a recent reform by the Italian government is intended to promote mergers in order to increase their overall efficiency, even if there are concerns that bigger BCCs might undermine network economies and make relationship lending unsustainable, thus lessening (or even offsetting) the efficiency gains from mergers.

In this paper we employ a two-step empirical framework in order to assess whether mergers among Italian BCCs can be regarded as efficiency-enhancing. For the purpose, we first estimate bank-level cost efficiency scores for a sample of 1,087 Italian credit institutions (therefore including commercial, popular, savings and cooperative banks) in the years 1993-2013 by means of a stochastic frontier approach, then we regress the estimated cost efficiency scores of 687 BCCs on a set of merger status dummy variables (never merged, before the first merger, merged once, merged twice...) as well as a vector of control variables. Our main result is that mergers are able to increase BCCs' cost efficiency only after that a cooperative bank has merged at least three successive times with other BCCs, that is to say after reaching a remarkably larger size. On the other hand, we regard this possible bigger size as a factor generating a harmful effect especially on marginal borrowers (i.e. those who are likely to be served by smaller banks but neglected by bigger ones), with a strong and adverse impact on development and inequality and in contrast with the BCCs' ethics and mission.

The paper is organized as follows. Section 2 offers some description of the credit cooperative system, as well as a picture of mutual banks' role within the Italian banking industry. The methodologies used to estimate banks' cost efficiency and to investigate the merger-efficiency link among BCCs are described in Sections 3. Section 4 illustrates data and variables, while the empirical results are presented and discussed in Section 5. Finally, Section 6 sketches some conclusions.

2. Credit cooperative banks: characteristics and consolidation trends

Cooperative banks are a key component of the cooperative movement in the credit sector, which originated in Europe in the nineteenth century as a response to the problems that small urban and rural businesses had in obtaining credit (thus facing an *ante litteram* credit rationing).

They adopt an organizational model based on democratic governance and mutualism, which evolved and differentiated in the various countries according to the needs of cooperative members as well as the specificities of national legislative frameworks. Hence, today the cooperative credit sector in Europe embraces systems that are not entirely uniform in terms of legal set-up, size and organization.

However, cooperative banks' ability to adapt and to grow in highly diverse economic and institutional environments has made them a substantial part of the banking industry in many European countries, so that the cooperative banking sector in the European Union is currently characterized by more than 4,000 local and regional banks, about 62,000 branches, and 49 million members. Although comparing international data involves some difficulty, cooperative banks' market shares (in terms of number of branches) can be put at about 60% in France, 50% in Austria, 40% in Germany, Italy and the Netherlands, 10% in Spain and Portugal.

In recent decades, competition in the banking industry increased in many countries, with Italy among them. This was largely due to relaxing of some administrative constraints and liberalization. As in most banking systems, in Italy we find both shareholder value oriented banks (SHV) and stakeholder value oriented banks (STV). The first group of banks generally has profit maximization as its sole objective, while STV banks tend to pursue a larger set of objectives, including the satisfaction of the stakeholders other than the shareholders.

Among the STV banks, cooperative banks – also known as mutual banks – occupy a prominent role (together with the Banche Popolari and a few remaining Savings Banks). They usually comprise three types of banks: Banche di Credito Cooperativo (BCCs), Casse Rurali, and Casse Raiffeisen in Alto Adige (Sud Tirol).

Their peculiar characteristics within the Italian banking industry regard: a) governance; b) organizational structure; c) size of the network.

With reference to governance, Italian BCCs are the only banks characterized by "prevailing mutualism", which consists in the following legal features:

- the "one-head one-vote" principle;
- members may own shares up to 50,000 euro;
- members must have their domicile and/or continuative business within the territory where the bank operates;
- at least 51% of risk activities must be carried out with members;
- at least 95% of the lending must be in the catchment area;
- at least 70% of profits must be put to legal reserve (with 3% devoted to Mutual Funds for the promotion and development of the cooperation), and reserves cannot be distributed to members;
- derivatives may be used only for reducing the risk of losses (hedging).

As to the organizational structure, BCCs can be defined as stand-alone banks that have joined together to become a national horizontal network with three levels: local (i.e. the individual BCCs), regional (with 15 local – regional of interregional – Federations representing, promoting, assisting and monitoring their member banks), and national (Federcasse, which upholds and protects the rights of the associated banks, and offers them legal, fiscal, and organizational assistance, also tackling overall strategy and policy guidelines). Moreover, there are 3 Central Institutions (Gruppo Bancario Iccrea, Cassa Centrale Banca of Trento, and Cassa Centrale Raiffeisen of Alto Adige) that provide wide-ranging support to the BCCs and offer services and products specifically designed for BCCs.

Finally, regarding the size of the network, after the disappearance of many local banks (incorporated into medium-large banks), today BCCs represent the greatest majority of local banks. At the end of 2014, in Italy there were 376 BCCs (56.7% of the total number of banks) with over 1.2 million members and 4,441 branches (14.4% of total branches) operating in 2,703 municipalities (46% of municipalities with at least one bank branch). Those municipalities are mostly small-medium sized urban centers (even if recently the presence of BCCs expanded also to bigger urban areas and cities). BCCs loans were 7% of total loans, and their deposits were 7.8% of total deposits.

Mutual banks have a strong expertise in the activity of traditional intermediation, which is based on the originate-to-hold model (i.e. banks provide loans to firms and individuals and hold them in their balance sheet until their maturity, bearing the related credit risk) rather than the originate-to-distribute model (where banks distribute their loans to other market participants through the securitization process, thus transferring the credit risk on other market participants). In addition, they are characterized by long-lasting fiduciary relationships with customers (largely BCCs members).

The above features favored mostly their typical customers, i.e. small enterprises and households. Actually, again at the end of 2014, 9.6% of loans granted to Italian enterprises have been issued by a BCC, a percentage that is much higher when considering enterprises with less than 20 employees, while the financing to households has reached 8.6% of the total banking industry.

Other interesting economic figures regarding Italian BCCs (which still refer to the end of 2014, values for the whole banking system in brackets; source: Bank of Italy) are the following:

- the Common Equity Tier 1 amounts to 16.1% (11.8% for the whole banking system);
- the loans-to-assets ratio is 57% (60%);
- the share of bad loans over total loans is 9.1% (10%);
- the average labour cost per employee is equal to 74.1 thousands euro (78.3 thousands euro);
- the cost-income ratio stands at 55.2% (62.1%);
- the mean of ROE of the years 2013-2014 is +1% (-4.6%).

Hence, BCCs appear less risky and more efficient than the national system as a whole.

In the very last years, requests for an update of the framework in which BCCs operate have become ever more frequent, with particular reference to more transparent and efficient governance standards and the elimination of structural weaknesses in the system.

A recent Law (49/2016) gives rise to Cooperative Banking Groups, each led by a parent company. Each BCC has to choose between joining a Group (if it aims at being authorized by the Bank of Italy to carry out banking business in the form of a BCC), or being converted into a joint stock company (when its net assets exceed 200 millions euro; however, it needs the authorization of the Bank of Italy, and must pay an extraordinary tax of 20% of its cash reserve).

The parent company of the Group is a joint stock company (with the majority of its shares held by the BCCs in the Group) that must have net assets of at least 1 billion euro, and be authorized by the Bank of Italy to carry out banking activities. It mainly directs and coordinates the BCCs in its Group, however in accordance with the principle of mutuality and in line with a cohesion contract.

Regarding BCCs, the Law now requires that the maximum share capital in a BCC that can be held by a single shareholder rises from 50,000 to 100,000 euro, and the minimum number of shareholders of a BCC increases from 200 to 500.

The above measures, especially the presence of a joint-stock company within the Group, allow for a more solid capital structure and a tighter management control. Federcasse, the National Association of the BCCs, has declared to be satisfied of the contents of the reform.

The European Central Bank expects that the Law "will accelerate consolidation among Italian cooperative banks. This process should eventually result in the cooperative banking sector as a whole having an improved capacity to absorb negative shocks, as well as providing new opportunities for rationalisation of resources and diversification of investments" (Opinion of the European Central Bank of 24 March 2016). It is now straightforward to wonder whether there would be advantages for BCCs in merging.

It is reasonable to expect that mergers facilitate a reduction of costs through the replacement of an inefficient management, the exploitation of scope economies (due to product-mix synergies), and the exploitation of scale economies (as larger organizations could get reduction of per-unit operating expenses). In addition, mergers might allow diversification of costs and risks, which derives both by broadening the scope of the consolidated bank's asset portfolio, and by expanding the geographic scope of its operations.

However, more little BCCs appear to better answer to local needs: a cooperative bank is usually characterized by a high degree of homogeneity among members, who belong to the same local community and/or social group, and are typically its borrowers. The above features enhance – through better screening and monitoring of borrowers – the efficiency/effectiveness of credit cooperatives to serve small and marginal borrowers, also succeeding in reducing financial exclusion because, as BCCs normally engage in relationship banking, they are better equipped to deal with borrowers' self selection and moral hazard.

Under this perspective, the bigger size following a merger – and the related larger business area – could prejudice BCCs' ability of effectively coping with informationally opaque markets, with adverse consequences even on the results of their activity. Or, put into different words, today BCCs are disadvantaged by their small size, specialization, and high concentration of credit risks, but are a largely not substitutable provider of loans to local borrowers.

With our empirical investigation, we aim at providing some insights on possible efficiency gains that BCCs could achieve through mergers. If they are substantial (i.e. a bigger size is a desirable outcome), there is room for an analysis and discussion on a possible future consolidation trend of the cooperative credit sector. If instead they are negligible, mergers would have the only (detrimental) result of undermining network economies and relationship lending, thus causing damage to local communities and economies.

Recent figures regarding the Italian banking industry tell us that, in the period 1993-2013, the number of Italian BCCs dropped from 671 to 385 (-42.6%), however following a trend similar to the overall banking sector (see Figure 1).

INSERT FIGURE 1 HERE

In the same period, there were several M&A operations among BCCs (including the transfers of assets and liabilities). Particularly, between 1994 and 2013 Supervisory Bulletins from the Bank of Italy report 325 M&As involving only BCCs (corresponding to about 16 a year), with a maximum of 39 in 1999 (see Figure 2).

INSERT FIGURE 2 HERE

Starting from the above framework, we are going to investigate the effects of M&As on BCCs through an empirical assessment of the changes in cost efficiency of cooperative banks from before to after the operation, comparing them to those that never merged. In order to gauge the worthiness of mergers among BCCs, we will make use of the bank-level cost efficiency scores. Actually, we regard costs as the only variable that should represent a concern for the mutual banks management (given that such banks do not pursue profit maximization).

3. The empirical strategy

Our empirical investigation first requires the estimation of BCCs' cost efficiency levels. For the purpose, considering the panel structure of our dataset, we employ the stochastic frontier model of Battese and Coelli (1992), through which we are able to get time-varying cost efficiency scores. Particularly, their approach allows for the possibility that the deviation between the observed output and the frontier output (i.e. the efficient output from a given input set) is due both to firms' own inefficiency and to stochastic shocks and measurement errors.

In the banking context, if we assume that, for bank i at time t, production costs are function of output Q, input prices W, inefficiency u and random error v, and that the last two terms are independent, the logarithmic specification of the cost function can be written as

$$\ln C_{it} = f(Q_{it}, W_{it}) + v_{it} + u_{it} \ . \tag{1}$$

The error term v_{it} has the usual characteristics – independent and identically distributed $N(0,\sigma_v^2)$ – while the non-negative inefficiency term u_{it} is assumed to be independent and identically distributed as a truncated normal distribution with mean μ and variance σ_u^2, and modelled as a function of time in the following way:

$$u_{it} = u_i \{\exp[-\gamma\,(t-T_i)]\} \ . \tag{2}$$

This means that the last period T_i contains the base level of bank i's inefficiency, which varies with time: if $\gamma > 0$, the level of inefficiency decays toward the base level (i.e. bank i improves its cost efficiency over time); if $\gamma > 0$, the bank's inefficiency increases over time up to the base level; if $\gamma = 0$, inefficiency does not change with time.

As regards the functional form of the cost frontier, in line with many latest banking studies we use a standard translog specification with three inputs and one output:[1]

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

[1] The translog function was first proposed by Christensen et al. (1971). See also Brown et al. (1979) and Caves and Christensen (1980).

$$+\sum_{h=1}^{3}\alpha_{Qh}\ln Q_{it}\ln W_{hit}+\alpha_{TQ}\ln TREND\ln Q_{it}$$
$$+\sum_{h=1}^{3}\alpha_{Th}\ln TREND\ln W_{hit}+v_{it}+u_{it}\ ,$$

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 account for technical change,[2] while v_{it} and u_{it} are the error and inefficiency terms, respectively.

In the translog cost function, by the symmetry condition it must be $\alpha_{hk} = \alpha_{kh}$. In addition, linear homogeneity in input prices requires that:

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

In order to impose the above conditions, we divide total costs and factor prices by W_{3it}, thus getting the following equation:

$$\begin{aligned}\ln(C_{it}/W_{3it}) &= a_0+a_Q\ln Q_{it}+\sum_{h=1}^{2}a_h\ln(W_{hit}/W_{3it})+a_T\ln TREND+\\ &+\frac{1}{2}\left\{a_{QQ}(\ln Q_{it})^2+\sum_{h=1}^{2}a_{hh}(\ln(W_{hit}/W_{3it}))^2+a_{TT}(\ln TREND)^2\right\}+\\ &+a_{12}\ln(W_{1it}/W_{3it})\ln(W_{2it}/W_{3it})+\sum_{h=1}^{2}a_{Qh}\ln Q_{it}\ln(W_{hit}/W_{3it})+a_{QT}\ln Q\ln TREND_{it}+\\ &+\sum_{h=1}^{2}a_{Th}\ln TREND\ln(W_{hit}/W_{3it})+v_{it}+u_{it}\ ,\end{aligned} \tag{4}$$

As it is evident from (2), the Battese and Coelli specification imposes a time path of technical inefficiency, which depends on the estimated value of parameter γ and is monotonous and common to all banks. Hence, as a robustness check, we also estimate our stochastic frontier model following the approach independently suggested by Aigner et al. (1977) and Meeusen and van den Broeck (1977).

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[2] Following Hunter and Timme (1986, p. 154), we regard *TREND* as an index of technology since, holding all other components of the cost function constant, any changes in the cost curves through time may be attributed to technological advances. This also means that the variable *TREND* does not contrast with the u_{it} term, which captures the single bank's efficiency/inefficiency (Kauko, 2009; Turk Ariss, 2010).

They were the first to provide an empirical framework for estimating production and cost functions where the specification of the error term is made up of two components – random noise and inefficiency – each with different characteristics. Particularly, the cost inefficiency component u_{it} is an asymmetric term that satisfies $u_{it} \geq 0$ but is free to vary over time without any a priori assumption. Here, following Aigner et al. (1977), we assume that u_{it} is distributed as a positive half-normal random variable $N^0(0,\sigma_u^2)$.

Regarding the cost efficiency scores *CE*, in both the Battese-Coelli (BC) and Aigner-Lovell-Schmidt (ALS) specifications they are estimated as $CE_{it} = E[\exp(-u_{it}) \mid \varepsilon_{it}]$, where ε_{it} is the overall error term.[3] Given that $u_{it} \geq 0$, the value of CE_{it} ranges between 0 and 1, with $CE_{it} = 1$ characterizing the fully efficient bank.

Once having estimated the level of cost efficiency for each bank through Equation (4), we explore the effects of mergers among Italian BCCs by regressing their efficiency scores on a set of five dummy variables that identify the sample cooperative banks by groups according to their engagement in mergers and acquisitions, as well as on a vector of control variables. Particularly, the equation is:

$$\begin{aligned} CE_{it} = {} & b_0 PREMERGE_{it} + b_1 POSTMERGE1_{it} + b_2 POSTMERGE2_{it} + \\ & + b_3 POSTMERGE3_{it} + b_4 POSTMERGE4_{it} + \\ & + b_5 \ln TOTAST_{it} + b_6 (\ln TOTAST_{it})^2 + b_7 NPL_{it} + b_8 \ln BRBUS_{it} + \\ & + b_9 EQAST_{it} + b_{10} DEPAST_{it} + b_{11} LOANAST_{it} + b_{12} POPDENS_{it} + \delta_i + \gamma_t \ , \end{aligned} \tag{5}$$

For those cooperative banks that were involved in M&As, the *PREMERGE* variable takes the value 1 for the years up to the first unification, and 0 for those following it, while the four *POSTMERGEn* variables assume the value 1 for the years after the *n*-th merger (and up to another merger, if any), and 0 otherwise. For the BCCs that were not involved in M&A activities during the sample period – i.e. our reference group – the above dummy variables are always zero. Hence, if the *PREMERGE* coefficient is positive (negative), we deduce that before the first merger the two (or more) previously independent cooperative banks were characterised by a higher (lower) level of cost efficiency with respect to the reference group. Similarly, a positive (negative) coefficient for the *POSTMERGEn* variables signals that the group of cooperative banks originating from the *n*-th merger of their story in the considered time interval achieves a significant increase (decrease) in the level of cost efficiency with respect to the reference group, meaning that this merger is efficiency-enhancing (efficiency-reducing).

[3] See Kumbhakar and Lovell (2000), ch. 4.

Regarding the control variables, total assets (*TOTAST*) are included to account for banks' size, and its quadratic term is inserted to capture possible nonlinearities in the size-efficiency relationship. Bigger BCCs need a widespread branch network, thus have to manage a more complex retail organization as well as a larger number of employees: 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. The ratio between non-performing loans and total loans (*NPL*) is a proxy for credit risk management: we expect a negative coefficient, as banks experiencing a higher proportion of bad loans are likely to be poorly managed and thus produce worse results in terms of efficiency. The variable *BRBUS* is calculated as the average sum of customer loans and customer deposits per branch, and is a proxy for the business characterizing the representative bank office; credit institutions managing more resources per office should also be more cost-efficient, and this would imply a positive sign for the estimated coefficient of this regressor. The equity to assets ratio (*EQAST*) helps to control for the level of bank capitalization: our conjecture is that, because of the agency problems between property and management, cooperative members of highly capitalized BCCs have more incentives to monitor costs and capital allocation, so managers are forced to implement cost reducing strategies that ultimately result in higher efficiency.

The variables *DEPAST* and *LOANAST* – the deposits to assets ratio and the loans to assets ratio, respectively – focus on the core activities of BCCs. Deposits are the main source of financing for cooperative banks, but they ask for a good organization in order to be gathered and well managed. Loans management is even more crucial, because lending requires specific effort and organizational capabilities by the staff, and produces significant long-term effects on both revenues and costs. Hence, their impact on cost efficiency is not a priori clear. We also include in the regression the population density (*POPDENS*), calculated as the number of inhabitants per square kilometre.[4] On the one hand, in higher-density markets 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, again the sign of this variable is not a priori predictable. Finally, δ_i is a group of regional dummy variables,[5] while γ_t is a group of yearly dummies.

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[4] As relevant geographical markets for banks, we consider the twenty Italian regions. For all cooperative banks that operate in more than one region, both population and land area have been weighted according to the distribution of branches. See also Maudos (1998) and Coccorese and Pellecchia (2009).

[5] BCCs are attributed to the region where the majority of branches is located. However, nearly 97% of the sample BCCs banks have 75% or more of their total branches in the same region.

Since by construction the variable CE_{it} lies between 0 and 1, a standard OLS regression would not be appropriate, and a double-censored tobit estimation is usually recommended.[6] However, as McDonald (2009) shows, if there are no observations for which $CE_{it} = 0$ or $CE_{it} = 1$ (which is very common in empirical applications), estimating such tobit model is the same as estimating a linear regression model, since the two likelihood functions coincide. In this case, an alternative strategy is the OLS estimation where the dependent variable is replaced by its logistic transformation, given by

$$CE_{it}' = \ln\left(\frac{CE_{it}}{1 - CE_{it}}\right), \tag{6}$$

where $CE_{it}/(1-CE_{it})$ are the odds of the efficiency scores.

In what follows, we will make use of both approaches in order to check the robustness of results. Besides, as the dependent variable CE_{it} is a predicted value coming from the first-stage regressions, it is crucial to adjust the second-stage standard errors in order to avoid a potential generated regressor problem (Pagan, 1984). For this purpose, in both specifications of Equation (5) we estimate bootstrapped standard errors with one thousand replications.

4. Data and variables

Balance sheet as well as profit and loss account data of banks come from ABI (the Italian Banking Association), and cover the time interval 1993-2013. For the estimation of the efficiency scores, we have considered all types of credit institutions (commercial, popular, savings and cooperative banks): this guarantees us a better assessment of cost performances because of the fact that we take into account the whole Italian banking industry instead of just a limited subgroup. The above data have been matched with those published yearly by the Bank of Italy, particularly the number of branches of each bank. All information on the various M&As concerning the cooperative banks have been gathered from the various Supervisory Bulletins available at the Bank of Italy.

In line with the intermediation approach to banking costs (Sealey and Lindley, 1977), the three inputs we consider in the cost function are deposits, labour, and capital. The corresponding cost figures, therefore, are interest expenses, personnel expenses, and other operating costs (net of financial expenses), whose sum equals total costs.

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[6] «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.

The price of deposits (W_1) is calculated as the ratio between interest expenses and the sum of deposits and other funding. The price of labour (W_2) has been computed by dividing personnel expenses by the number of employees. Finally, the price of capital (W_3) has been proxied by the ratio between the other operating costs and the number of branches. The output Q has been measured by total loans.

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. After this data selection process, the (unbalanced) sample comprises 12,927 observations on 1,087 banks observed over 21 years. On average, it includes about 12 observations for each bank (see Table 1).

As for the second stage estimation, the size of the sample is smaller because it is restricted to include only cooperative banks. Actually, 8,275 observations are available, and refer to 687 BCCs (see Table 1), among which we have recorded 317 M&As: particularly, during the sample period 174 cooperative banks resulted from one merger, 44 banks came out from two sequential mergers, 13 from three subsequent mergers, and 4 from four successive mergers. On the other hand, 255 BCCs were never subject to a merger or acquisition, and they represent our reference group. In this sample, data on regional population and size have been taken from Istat (the Italian National Statistical Institute).

All economic figures have been deflated using the 2005 GDP deflator. Descriptive statistics for the variables entering the regressions in the two stages are provided in Table 2.

INSERT TABLE 1 HERE

INSERT TABLE 2 HERE

5. Estimation results

In line with the standard procedure characterizing the stochastic frontier analysis, Equation (4) has been estimated by maximum likelihood. Table 3 reports the results for both the BC and the ALS stochastic frontier models. The majority of the estimated coefficients are statistically significant at the 1% level.

INSERT TABLE 3 HERE

Yearly averages of the efficiency scores for both models are shown in Table 4. It is evident a (decreasing) trend for the efficiency scores estimated through the BC model; they are also much lower and exhibit a higher variability than those derived from the ALS model, which show a more irregular pattern over time but are higher and less variable. Over the whole sample, the correlation between the two measures of cost efficiency is +0.4236.

INSERT TABLE 4 HERE

Interestingly, from Table 5 we can also note that BCCs (but also popular banks, another type of credit institutions with cooperative features, even if to a lesser extent) are characterized by a higher level of cost efficiency compared to commercial and savings banks, and this holds for every year. It therefore seems that in the whole sample period BCCs have shown the best performance in terms of cost efficiency, which upholds the general appropriateness of either their size and their business model.

INSERT TABLE 5 HERE

In order to assess whether M&As among BBCs have helped to reach an even higher level of efficiency, we employ the estimated cost efficiency scores as dependent variables of Equation (5). The empirical results – deriving from both the tobit estimation and the OLS with the logistic transformation of CE_{it}'s – are reported in Tables 6 and 7 (which refer to the BC model and the ALS model, respectively).

INSERT TABLE 6 HERE
INSERT TABLE 7 HERE

When considering the Battese and Coelli scores, the coefficient of *PREMERGE* is negative and statistically significant at the 1% level in both regressions, meaning that BCCs which are going to be involved for the first time in a merger are characterized by lower efficiency compared to the reference group, i.e. those that will never merge in our time interval. Particularly, according to the tobit model, the predicted value of CE_{it} is 0.0139 points lower for the *PREMERGE* group (corresponding to a difference of about 2.5 percent of the sample mean). Considering the estimation with the logistic transformation of CE_{it}, the value of -0.0604 for the *PREMERGE* coefficient means that, holding the other variables at a fixed value, the odds of CE_{it} for the *PREMERGE* group over the odds of the reference group is exp(-0.0604) = 0.9414, or – in terms of percent change – that the odds for the *PREMERGE* group are 5.86% lower than the odds for BCCs that have never initiated a merger process. Therefore, if we set $CE_{it}/(1–CE_{it}) = 0.9414$ for the first set of BCCs and $CE_{it}/(1–CE_{it}) = 1$ for the second, we find that the value of CE_{it} for the *PREMERGE* group is 0.0151 points lower than the reference group, a result virtually identical to the one derived from the tobit regression.

However, the empirical results also suggest that both a first merge and a second merge (in our analysis, the latter regards those cooperative banks that had been already previously involved in one merger) do not allow to achieve a higher cost efficiency than the reference group: actually, in the tobit estimation once and twice merged BCCs are still significantly less efficient, while in the OLS with logistic CE_{it}'s their level of efficiency is undistinguishable from the reference group but certainly not higher. A significant improvement in cost efficiency can be observed only after the third merger, and this gain is even higher with the fourth merge (as in both specifications the coefficient of *POSTMERGE*4 is bigger than that of *POSTMERGE*3), thanks to which – still according to the tobit model – the predicted value of CE_{it} raises of about 0.03 points compared to the never-merged BCCs, an increase of 5.5 percent with respect to the sample mean (the increase in the efficiency scores amounts to 0.04 according to the regression based on the odds of CE_{it}).

With reference to the Aigner-Lovell-Schmidt scores, both estimations indicate that a pre-merger BCC is as efficient as those that decide not to merge (since the coefficient of *PREMERGE* is not significantly different from zero), and also that one or two consecutive mergers lead to a more inefficient firm. Gains in efficiency are possible only after four successive mergers.

The above findings allow to conclude that, even if a BCC is not efficient in minimizing costs, a M&A process does not appear to be the best efficiency-enhancing solution, at least for small-scale operations. It is true that significant improvements can be achieved with more consecutive mergers, but they would imply an increase in the average bank's size, which would probably modify the intrinsic nature of BCCs, currently based on relationship banking and strong ties with local communities and hence unavoidably requiring a smaller size. Particularly, bigger BCCs might begin to overlook marginal borrowers, i.e. their current main clientele that is normally served by smaller banks but is very often neglected by large-sized banks, with the twofold consequence of a severe detrimental impact on local development and inequality and the BCCs' discharge of their ethics and mission. Perhaps a better solution would be the careful improvement of banks' way of managing businesses, especially considering that on average BCCs' cost efficiency scores are nonetheless higher than other types of banks.

Regarding the control variables, the coefficients of ln*TOTAST* and its squared are negative and positive, respectively, both always significant at the 1% level, confirming the presence of nonlinearities in the relationship between BCCs' size and efficiency. In particular, the empirical results emphasize that cost efficiency scores decrease as total assets grow, up to a minimum that varies according to the model. However, the lowest level of total assets from which we record an increase in the level of efficiency is about 3,771 millions euro (in the tobit estimation with the ALS efficiency scores, while for the other regressions this figure is much higher); considering that in our sample only 2 BCCs over 8,275 have a (slightly) bigger size than this threshold, we conclude that in Italy an increase of BCCs' size would not allow an improvement in the quality of organization and management, whereas it would generally lead to worse cost performances, thus validating our former evidence that mergers are not efficiency-enhancing, at least on the cost side and up to a certain point.

The share of non-performing loans over total loans (*NPL*) exhibits the expected negative coefficient (always significant at least at the 10% level): bad loans are negatively correlated with cost efficiency and signal an inadequate management quality. The coefficient of *BRBUS* is also in line with our conjecture: as its coefficient is always positive (and highly significant), we deduce that BCCs are more efficient also when they can count on more business at the branch level. The equity to assets ratio (*EQAST*) also shows a positive and significant coefficient: as anticipated, more capitalized BCCs are also more cost efficient, probably due to the fact that managers are compelled to implement more efficient programs and procedures because of the stronger monitoring by cooperative members.

The impact of the deposits to assets ratio (*DEPASS*) on cost efficiency is significantly negative, from which we infer that, as BCCs' deposits increase, they impose efficiency losses to banks. Quite to contrary, as the coefficient of *LOANAST* is positive and significant, BCCs with a higher proportion of loans experience a higher cost efficiency. Thus, the overall evidence is that cooperative banks are more efficient when they focus mainly on the traditional activity of loan granting (which is normally based on relationship lending), while a higher fraction of deposits among liabilities produce inefficiencies on the cost side. Finally, population density (*POPDENS*) exerts a significant negative impact on cost efficiency; this evidence proves that the complexity of crowded markets more than offsets the advantage of reaching more customers (Coccorese and Pellecchia, 2010, p. 192).

6. Conclusions

Against the mainstream tenet that banking consolidation delivers efficiency gains in banking, another strand of literature admonishes that consolidation might cause losses via reduced banking diversity and less support for marginal banking customers. The latter losses might materialise especially when consolidation reduces the role of savings and, particularly, cooperative banks since these banks – via their retail and relationship banking orientation – are most effective at favouring the financial inclusion of the marginal borrowers.

However, an even more radical question is asking whether, in reality, mergers among mutual cooperative banks do deliver efficiency gains. In fact, for the reasons specified above, one can suspect that M&As among mutual cooperative banks have the same meaning as M&As among shareholder value oriented banks.

In this paper we aimed at empirically testing the effects of mergers among credit cooperative banks, particularly their aftermath on the level of cost efficiency. We have focused our attention on the Italian banking industry in the period 1993-2013, during which an important process of consolidation has taken place, which involved also many cooperative banks.

We have first estimated bank-level cost efficiency scores for the whole Italian banking system through a translog stochastic frontier model, finding that BCCs have performed much better than the other types of banks. Next, we have focused on the sub-sample of cooperative banks and used a set of merger status dummy variables (never merged, before the first merger, merged once, merged twice...), along with a group of control variables, to explain their efficiency scores, using both a tobit regression and a logistic model due to the fact that the dependent variable ranges between 0 and 1.

Our results are robust with respect to model specification, and make clear that BCCs decide to merge when their efficiency is lower than other cooperative banks, but also that there is need of at least three consecutive mergers – hence, a much bigger dimension – in order to become more efficient than those never involved in a M&A process. However, even if such significant mergers could be convenient in terms of cost efficiency, they would probably imply a loss of identity for BCCs, since the larger size appears in direct conflict with their traditional mission of supporting small firms and households in the local area of business, which could be therefore undermined as regards social and economic development.

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TABLE 1 – *Number of observations (banks) by year*

Year	Whole sample (first stage)	Only BCCs (second stage)
1993	392	135
1994	711	417
1995	724	470
1996	725	480
1997	729	478
1998	708	436
1999	673	434
2000	646	426
2001	641	415
2002	632	410
2003	577	395
2004	602	398
2005	589	383
2006	606	390
2007	626	397
2008	614	379
2009	601	390
2010	546	377
2011	575	380
2012	505	333
2013	505	352
Total	*12,927*	*8,275*
Number of banks	1,087	687
Average obs. per bank	11.89	12.05

TABLE 2 – *Descriptive statistics*

Variable	Mean	Std. Dev.	Minimum	Median	Maximum	Obs.
C (1)	132.61	683.41	0.4101	11.6716	17,475.72	12,927
Q (1)	2,012.02	11,513.16	2.3105	154.84	301,930.80	12,927
*W*1 (2)	0.0315	0.0190	0.0054	0.0241	0.0803	12,927
*W*2 (3)	64.4144	8.2655	38.9255	63.6512	114.42	12,927
*W*3 (3)	461.53	416.20	156.31	378.42	6,309.26	12,927
TREND (4)	10.6249	5.9064	1	10	21	12,927
PREMERGE (4)	0.2655	0.4416	0	0	1	8,275
*POSTMERGE*1 (4)	0.1942	0.3956	0	0	1	8,275
*POSTMERGE*2 (4)	0.0398	0.1954	0	0	1	8,275
*POSTMERGE*3 (4)	0.0098	0.0985	0	0	1	8,275
*POSTMERGE*4 (4)	0.0018	0.0425	0	0	1	8,275
TOTAST (1)	257.03	306.95	4.3029	157.47	4087.02	8,275
NPL (2)	0.0263	0.0290	0.0010	0.0173	0.5704	8,275
BRBUS (1)	36.1682	20.5067	3.3225	32.4777	304.11	8,275
EQAST (2)	0.1110	0.0333	0.0168	0.1062	0.3635	8,275
DEPAST (2)	0.5684	0.1044	0.3023	0.5607	0.9132	8,275
LOANAST (2)	0.6668	0.1263	0.2550	0.6738	0.9425	8,275
POPDENS (5)	0.2053	0.1114	0.0357	0.1771	0.4270	8,275

(1) Millions euro (2005 values) - (2) Ratios - (3) Thousands euro (2005 values) - (4) Units - (5) Inhabitants per square kilometer
Source: ABI, Bank of Italy, Istat.

TABLE 3 – *Estimation results of the cost function*

Variable	**Coefficient**	**BC MODEL (Battese-Coelli)**		**ALS MODEL (Aigner-Lovell-Schmidt)**	
		Coeff.	***z*-value**	**Coeff.**	***z*-value**
Constant	a_0	0.5965	1.40	2.5518	4.21 ***
ln$Q$	a_Q	0.8565	27.48 ***	0.9607	35.87 ***
ln(W_1/ W_3)	a_1	1.1238	11.13 ***	1.8933	11.94 ***
ln(W_2/ W_3)	a_2	-0.5721	-4.98 ***	-1.0631	-6.36 ***
ln*TREND*	a_T	-0.0003	0.00	0.0441	0.38
(ln$Q$)^2/2	a_{QQ}	0.0113	5.55 ***	0.0115	11.74 ***
(ln(W_1/W_3))^2/2	a_{11}	0.1048	7.45 ***	0.2055	9.27 ***
(ln(W_2/W_3))^2/2	a_{22}	0.0138	0.62	0.0859	2.71 ***
(ln*TREND*)^2/2	a_{TT}	-0.1622	-17.31 ***	-0.2092	-16.42 ***
ln(W_1/W_3)*ln(W_2/W_3)	a_{12}	-0.0956	-6.00 ***	-0.1660	-6.87 ***
ln$Q$*ln(W_1/W_3)	a_{Q1}	0.0159	6.70 ***	0.0134	3.84 ***
ln$Q$*ln(W_2/W_3)	a_{Q2}	0.0172	4.47 ***	0.0162	3.68 ***
ln$Q$*ln*TREND*	a_{QT}	-0.0245	-12.23 ***	-0.0064	-2.51 **
ln*TREND**ln(W_1/W_3)	a_{T1}	-0.0372	-3.44 ***	-0.0208	-1.24
ln*TREND**ln(W_2/W_3)	a_{T2}	-0.0324	-2.53 **	0.0138	0.73
Log-likelihood		5,918.47		802.51	
N. obs.		12,927		12,927	
N. banks		1,087		1,087	

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

TABLE 4 – *Estimated values of the cost efficiency scores (CE) by year*

Year	*BC model*	*ALS model*
1993	0.5019	0.8367
1994	0.5462	0.8288
1995	0.5476	0.8369
1996	0.5403	0.8298
1997	0.5362	0.8267
1998	0.5312	0.8178
1999	0.5189	0.8155
2000	0.5119	0.8191
2001	0.5044	0.8242
2002	0.5012	0.8172
2003	0.4910	0.8218
2004	0.4834	0.8255
2005	0.4835	0.8259
2006	0.4776	0.8367
2007	0.4782	0.8254
2008	0.4760	0.8224
2009	0.4654	0.8314
2010	0.4674	0.8436
2011	0.4632	0.8262
2012	0.4576	0.8048
2013	0.4549	0.7727

All figures are averages across the whole country.

TABLE 5 – *Estimated values of the cost efficiency scores (CE) by bank type*

Type	*BC model*	*ALS model*
Commercial banks	0.3891	0.7920
Popular banks	0.3916	0.8245
Savings banks	0.3335	0.8193
BCCs	0.5558	0.8291

All figures are averages across the whole country.

TABLE 6 – *Estimation results for BC Model (Battese-Coelli)*

Variable	Coefficient	TOBIT ESTIMATION		LOGISTIC TRANSFORMATION	
		Coeff.	*z*-value	Coeff.	*z*-value
PREMERGE	b_0	-0.0139	-8.67 ***	-0.0604	-7.40 ***
*POSTMERGE*1	b_1	-0.0070	-5.26 ***	-0.0071	-1.05
*POSTMERGE*2	b_2	-0.0081	-3.71 ***	-0.0007	-0.07
*POSTMERGE*3	b_3	0.0094	2.52 **	0.0702	3.42 ***
*POSTMERGE*4	b_4	0.0298	4.64 ***	0.1642	4.73 ***
ln*TOTAST*	b_5	-0.3565	-27.52 ***	-1.9997	-26.53 ***
(ln*TOTAST*)^2	b_6	0.0098	18.50 ***	0.0595	19.51 ***
NPL	b_7	-0.0494	-1.85 *	-0.3379	-2.23 **
ln*BRBUS*	b_8	0.1184	53.64 ***	0.6082	36.65 ***
EQAST	b_9	0.0881	3.70 ***	0.6188	4.44 ***
DEPAST	b_{10}	-0.1616	-20.48 ***	-0.8312	-16.60 ***
LOANAST	b_{11}	0.1688	22.66 ***	0.7349	17.58 ***
POPDENS	b_{12}	-0.1359	-3.56 ***	-0.5616	-3.19 ***
Log-likelihood		13,403.57			
Adj. R^2				0.7920	
N. obs.		8,275		8,275	
N. banks		687		687	

Dependent variable: *CE*
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level.
Bootstrapped standard errors (in parentheses) are based on 1000 replications.
Regional and time dummies are included in all estimations but are not reported.

TABLE 7 – *Estimation results for ALS Model (Aigner-Lovell-Schmidt)*

Variable	Coefficient	TOBIT ESTIMATION		LOGISTIC TRANSFORMATION	
		Coeff.	*z*-value	Coeff.	*z*-value
PREMERGE	b_0	-0.0013	-1.29	-0.0106	-1.62
*POSTMERGE*1	b_1	-0.0073	-6.35 ***	-0.0423	-6.04 ***
*POSTMERGE*2	b_2	-0.0147	-7.14 ***	-0.0936	-7.65 ***
*POSTMERGE*3	b_3	-0.0041	-1.24	-0.0093	-0.42
*POSTMERGE*4	b_4	0.0213	4.34 ***	0.1454	4.17 ***
ln*TOTAST*	b_5	-0.0699	-7.26 ***	-0.4704	-7.14 ***
(ln*TOTAST*)^2	b_6	0.0023	5.83 ***	0.0147	5.44 ***
NPL	b_7	-0.1633	-8.00 ***	-1.1372	-8.52 ***
ln*BRBUS*	b_8	0.0488	36.24 ***	0.3815	43.53 ***
EQAST	b_9	0.2433	12.51 ***	1.8287	14.82 ***
DEPAST	b_{10}	-0.0781	-14.69 ***	-0.6335	-18.76 ***
LOANAST	b_{11}	0.3944	69.60 ***	2.7539	78.21 ***
POPDENS	b_{12}	0.0562	2.27	0.1041	0.63
Log-likelihood		16,422.09			
Adj. R^2				0.7761	
N. obs.		8,275		8,275	
N. banks		687		687	

Dependent variable: *CE*
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level.
Bootstrapped standard errors (in parentheses) are based on 1000 replications.
Regional and time dummies are included in all estimations but are not reported.

FIGURE 1 – *Number of banks and BCCs (Italy, years 1993-2013)*

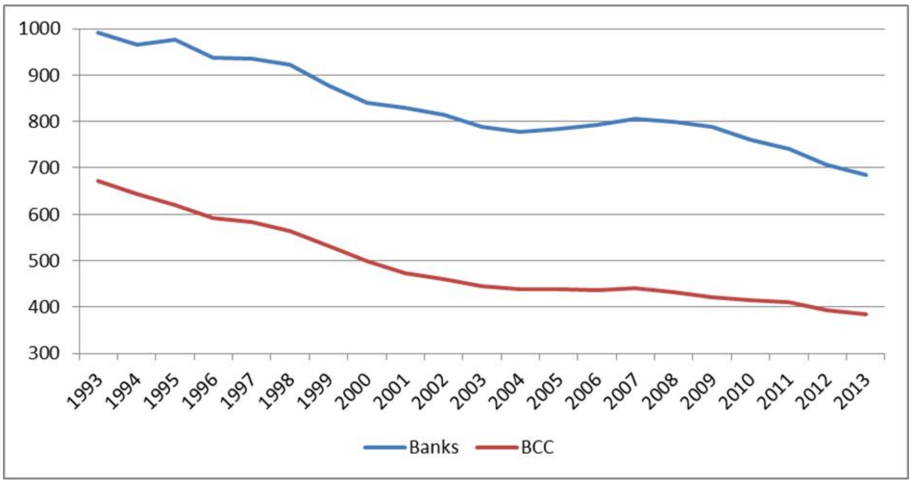

FIGURE 2 – *M&A operations involving BCCs (Italy, years 1994-2013)*