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ABSTRACT

In this paper we study the intense wave of mergers among Italian mutual cooperative banks (Banche di Credito Cooperativo, BCCs) and try to assess whether those mergers were 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 BCCs' ethics and mission.

KEYWORDS: Banking; Cooperative banks; Mergers; Efficiency

JEL CLASSIFICATION NUMBERS: D40, G21, G34

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1. Introduction

Following banking deregulation and liberalization, trends to consolidate 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 et al., 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 credit rationing of borrowers, particularly SMEs.

Therefore, there seems to be a potential trade-off between the beneficial effects of consolidation – if it helps improve banking efficiency – and its unfavourable consequences – if it dilutes banking diversity. This paper centres on one side of that potential trade-off testing whether, indeed, consolidation through Mergers and Acquisitions (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 in Italy. 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 recent years pressures emerged for reforming the Italian credit cooperative system, as BCCs are regarded to be "too many and too little". Particularly, a recent reform by the Italian government aims to promote mergers so to increase their overall efficiency, even though concerns arise that bigger BCCs might undermine network economies and make relationship lending unsustainable, thus lessening (or even offsetting) the efficiency gains from mergers.

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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 1,079 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 688 BCCs on a set of merger status dummy variables (never merged, before the first merger, merged once, merged twice, etc.) as well as on a vector of control variables. Our main result is that mergers may increase BCCs' cost efficiency only after a cooperative bank has merged at least three successive times with other BCCs, that is to say after reaching a remarkably larger size. However, we regard this possible bigger size as a factor generating harmful effects 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. Thus, in plain words, the intense wave of mergers among BCCs probably wasn't worth a dime.

The paper is organized as follows. In Section 2 we provide an outline of the existing literature on M&As in the banking sector, with a special focus on the empirical evidence regarding efficiency and performance effects. Section 3 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 Section 4. Section 5 illustrates data and variables, while the empirical results are presented and discussed in Section 6. Finally, Section 7 recapitulates our main conclusions.

2. M&As in the banking industry: a literature review

In the past few decades, changes in the structural and regulatory environment have pushed banks of several countries to expand especially through M&As, trusting that this consolidation route would be beneficial in terms of reduction in expenses, more earning stability, increase in market power, economies of scale and scope. The investigation of the causes of financial consolidation has driven to different classifications of the factors leading to M&As, giving rise to a number of papers focusing also on the related effects on banks' performance. In this section we review some of this literature, about which we provide further details in the Appendix.

Berger et al. (1999) suggest that M&As in financial markets may be mainly due to both value maximizing and non-value maximizing motives. Value maximization through consolidation can be achieved thanks to increasing firms' market power in setting prices and/or efficiency. Non-value maximizing motives prevail when stakeholders other than shareholders directly affect consolidation

decisions, particularly managers (for empire-building, or when corporate control is relatively weak) and governments (which can obstruct some types of M&As, or encourage them in certain periods, e.g. during financial crises, even acquiring troubled financial institutions). They also identify five key changes that may help explain M&A activities: technological progress (e.g., larger scale and scope economies in financial services, and higher efficiency), improvements in financial condition of institutions (due to e.g. increased profitability, low interest rates, or high stock prices), excess capacity or financial distress (actually, consolidation may represent an efficient way of overcoming such problems), international consolidation of markets (as a consequence of the overall globalization of markets), and deregulation (banks' new ability to expand geographically may force inefficient banks to improve their efficiency by acquiring other institutions, by being acquired, or by improving management practices internally).

In their study of US domestic acquisitions, Thu Nguyen et al. (2012) find that 73% of them are related to market timing (i.e. when the managers of the acquirer firm try to take advantage of market mispricing), 59% hinge on agency motives (i.e. when M&As increase the acquirer management's welfare at the expense of the acquirer's shareholders) and/or hubris (whereby managers launch acquisitions even when there is no synergy with the acquiring firm and/or overpay for targets), and 3% are responses to industry and economic shocks (like deregulation, system-wide fundamental transformations, price changes). Moreover, they show that about 80% of the M&As have multiple motives. They conclude that it is very difficult to have a clear picture of merger motivations, because value-increasing and value-decreasing motives frequently coexist.

According to Fiordelisi (2009) M&As among banks usually have the following aims: revenue enhancement (increasing market share and market power, but also exploiting network externalities), cost savings (e.g., lower costs in marketing, sales and distribution, human resource management by achieving: lower excess capacity, scale economies via size growth, scope economies via increased number of products offered, and X-efficiency linked to scale and scope economies), new growth opportunities (by tapping new financial products, new delivery channels, and new markets). Besides, conforming to Berger et al. (1999), Fiordelisi admits that M&A transactions may be motivated by other goals due to stakeholders' influence, such as managers and government.

In order to detect the consequences of consolidation, scholars use accounting measures (e.g. ROA, ROE, cost/assets ratios), or investigate changes in X-efficiency, the latter being the distance from the best-practice efficient frontier.[1] However, the empirical evidence on the impact of M&As on profitability and efficiency is mixed, and cannot provide a conclusive answer. Actually,

[1] Extensive literature reviews on this and related topics are those by Berger et al. (1999), Beccalli and Frantz (2009), and DeYoung et al. (2009).

DeYoung et al. (2009) observe that the extant literature offers no consistent evidence on whether, on average, the involved financial firms benefit from M&As, but also on whether the customers of these firms benefit or whether societal risks have increased or decreased as a result of those M&As. They ascribe the mixed findings to the different methodologies and time periods used in previous studies (e.g., if M&As are observed at early stages in the consolidation process, they appear as disequilibrium or pre-equilibrium phenomena).

Pilloff (1996) finds that performance measures and consolidated abnormal returns exhibit little to no change on average. However, the fact that abnormal returns are highest for mergers with the greatest opportunities for expense reduction is viewed as signalling that mergers increase efficiency. Vander Vennet (1996) notices that domestic mergers among equal-sized EU banks significantly increase the performance of the merged banks. Improvement of cost efficiency are found in cross-border acquisitions but not in domestic ones, which most likely means that domestic takeovers have been influenced predominantly by defensive and managerial motives such as size maximization.

Akhavein et al. (1997) find that profit efficiency increases especially when the involved banks exhibit low prior efficiency. Altunbas et al. (1997) observe only limited opportunities for cost savings from big-bank mergers, while an increase in total costs appears the most likely outcome. DeYoung (1997) employs a thick cost frontier methodology to estimate pre- and post-merger X-inefficiency. He finds that cost efficiency has improved in only a small majority of mergers, suggesting that motivations other than cost efficiency drove US bank mergers in the late 1980s. Also, efficiency gains were concentrated in mergers where acquiring banks made frequent acquisitions, suggesting the presence of experience effects. Peristiani (1997) studies the post-merger performance of acquiring banks that participated in a merger. Specifically, he measures cost X-efficiency by means of a “distribution-free approach”, and proves that acquirers failed to improve post-merger X-efficiency, though acquiring banks did experience moderate gains in scale efficiency relative to a control sample.

Berger (1998) shows evidence that M&As increase profit efficiency relative to other banks, but have little effect on cost efficiency. Moreover, efficiency gains are more noticeable when the participating banks are relatively inefficient ex ante. Resti (1998) indicates that, on average, buyers look less efficient than their targets, and that merged banks appear to have increased their post-merger cost efficiency; however, efficiency scores tend to decrease again in the third year after the merger. Rhoades (1998) examines nine case studies, selected among large horizontal bank mergers (i.e. those which are most likely to yield efficiency gains), and shows that all nine M&As induced significant cost cutting; but, only four of them did improve cost X-efficiency.

Kwan and Eisenbeis (1999) find that the better-performing institutions tended to target the higher-performing banks, but the resulting mergers did not significantly improve profit performance or efficiency. In turn, Huizinga et al. (2001) report an increase in cost efficiency of merged banks, while profit efficiency improves only marginally. Cuesta and Orea (2002) test the trend of technical efficiency at Spanish savings banks, and discover an initial decreasing followed by an increase of technical efficiency indexes, concluding that merged banks became more efficient.

Focarelli et al. (2002) find no evidence of an improvement in profits, because the post-merger increase in revenues (due to a larger market for services and the growth of loans relative to total assets) is offset by an increase in staff costs. However, mergers are followed by an increase in ROE, determined by a reduction in capital, and a long-run increase in profitability for acquired banks, due to a permanent decrease in bad loans (with a long-term reduction in lending, especially to small firms). Diaz et al. (2004) scrutinize bank performance following both the acquisition of another bank and the acquisition of other non-banking financial institutions; their main result is an increase in acquirers' long-term profitability, more significantly for bank acquisitions.

Investigating the performance record of M&As and focusing also on changes in the operating performance for the involved banks, Campa and Hernando (2006) find significant improvements in profitability and efficiency beginning on average two years after the transaction was completed. Knapp et al. (2006) explore the impact of mean reversion on the evaluation of post-merger performance of bank holding companies, and conclude that post-merger results significantly outperform the industry in the first five post-merger years. Altunbas and Marquez (2008) also detect improved post-merger accounting profitability (in terms of ROE).

In the five post-merger years, Beccalli and Frantz (2009) find a slight deterioration in ROE, cash flow return and profit efficiency, but a marked improvement in cost efficiency (especially for domestic deals). By means of various criteria, Lozano-Vivas et al. (2011) examine the effectiveness of both domestic and cross-border bank mergers, and find that, on average, both types of mergers reduce cost and profit inefficiency (though there are no improvements in cost, ROA, or ROE). In addition, banks involved in cross-border M&As are more efficient than domestic ones, and banks involved in M&As are more cost efficient than those that are not.

Overall, our review of the empirical literature on M&As in banking emphasizes the variety of approaches and the heterogeneity of results achieved so far. Thus, we concur with DeYoung et al. (2009) that one cannot generalize the results outside each specific framework under investigation, even though there are frequent indications of efficiency gains, especially for Europe.

However, for our specific purpose we should ask whether M&As have specific effects on the performance of credit cooperatives. Lang and Welzel (1999) find no evidence of cost efficiency

gains for cooperative banks in the post-merger phase, but only a levelling off of differences among the merging units. Fried et al. (1999) observe that service provision following a merger doesn't deteriorate for members of acquiring credit unions, while improving for at least three years for members of acquired credit unions. They then conclude that the mergers occurred during the sample period were generally beneficial, even if almost half of acquiring credit unions and 20% of acquired credit unions experienced a post-merger decline in service provision. In a similar study, Ralston et al. (2001) indicate that merging Australian credit unions did not achieve greater post-merger efficiency gains over 1993-1998. This suggests that M&As among credit unions do not guarantee better efficiency results than those achievable via internal growth.

Taken together, Fried et al. (1999) and Ralston et al. (2001) seem to indicate that mergers alone cannot ensure the survival of credit unions in the third millennium. Rather, as Ralston et al. (2001) suggest, credit unions might better achieve the twin goals of efficiency and member service satisfaction by aligning with other small financial institutions and centralized bodies to purchase aggregated services and to outsource specialized technology support and product innovation.

Still, Garden and Ralston (1999) find that, on average, credit union mergers do not result in an increase in X-efficiency or allocative efficiency relative to other credit unions. Cabo and Rebelo (2005) notice that merged credit cooperatives had a heavy administrative cost structure and faced profitability problems, and also that the post-merger impact on their performance fails to show any positive influence on cost reduction, credit management and solvency ratio. Koetter (2008) shows that every second merger is a success in terms of either cost or profit efficiency, even if the margin of success in terms of the former is narrow, while mergers boost in particular the change in profit efficiency.

Again, the (narrow) empirical evidence available for mergers among credit cooperative banks does not allow clear-cut conclusions on their efficiency effects, yet it appears that the cases where M&As can be beneficial are even more limited than for bank M&As in general. However, the available indications on the determinants of financial institution mergers suggest that the motives for M&As among cooperative banking institutions differ substantially from their joint stock peers, mainly due to the behavioural differences between private and mutual organizations (Worthington, 2004). It has been observed that in cooperative financial sectors structural changes are largely due to 'friendly' mergers, towards which regulatory authorities exert a large degree of acquiescence (Thompson, 1997), but it cannot be forgotten that decision rules in cooperative enterprises are based on democratic principles, rather than ownership concentration, and this factor leads to the maximization of member utility instead of profits. In some sense, these aspects make the analysis of the interactions among credit cooperative banks – hence, of their mergers – quite complex. For

example, according to Jones and Kalmi (2012) integration in a network – rather growth via mergers – allows cooperative banks to maintain a smaller feasible scale, which may be good in terms of maintaining member participation, a value that might be depleted by mergers.[2]

3. Credit cooperative banks in Italy: features 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 (Kalmi, 2016).

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 currently features more than 4,000 local and regional banks, about 62,000 branches, and 49 million members. Although comparing international data may be difficult, 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 former banks generally have profit maximization as their 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, mutual cooperative banks play a prominent role (together with 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.

[2] See also Kalmi (2016) for an in-depth discussion of the role of cooperative banking networks.

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 is adopted;
- 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 or interregional – Federations representing, promoting, assisting and monitoring 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, three Central Institutions (Gruppo Bancario Iccrea, Cassa Centrale Banca of Trento, and Cassa Centrale Raiffeisen of Alto Adige) cater wide-ranging support to the BCCs offering services and products specifically designed for them.

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 in Italy. At the end of 2014, 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) located in 2,703 municipalities (46% of municipalities with at least one bank branch). Those municipalities are mostly small-medium sized urban centres (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 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 maturity, bearing the related credit risk) rather than the originate-to-distribute model (where banks distribute their loans to other market participants through securitizations, thus transferring the credit risk to other parties). In addition, they are characterized by long-lasting fiduciary relationships with customers (largely BCCs members).

The above features favoured mostly their typical customers, i.e. small enterprises and households. Presently, again at the end of 2014, 9.6% of loans granted to Italian enterprises were 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 figures regarding Italian BCCs (still referring 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 thousand euro (78.3 thousand 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 banking 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 million 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. In accordance with the principle of mutuality and in consonance with a cohesion contract, it mainly directs and coordinates the BCCs in its Group.

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, are believed to 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 by replacing inefficient management, exploiting scope economies (due to product-mix synergies), and gaining scale economies (as larger organizations could reduce per-unit operating expenses). In addition, mergers might allow diversification of costs and risks, by both broadening the scope of the consolidated bank's asset portfolio, and expanding the geographic scope of its operations.

However, smaller-sized cooperative banks might answer local needs better: a BCC usually features a high degree of homogeneity among members, who belong to the same local community and/or social group, and are typically its borrowers. Through better screening and monitoring of borrowers, this enhances the BCCs efficiency/effectiveness to serve small and marginal borrowers, also helping reduce financial exclusion because, as BCCs normally engage in relationship banking, they are better equipped to deal with borrowers' self-selection and moral hazard.

In this respect, its bigger size – and the related larger business area – following a merger could impair BCCs' ability to effectively cope with informationally opaque borrowers, with adverse consequences even on their performance. Or, put it differently, today BCCs are disadvantaged by their small size, specialization, and high concentration of credit risks, but are also largely not substitutable providers of loans to local borrowers.

Our empirical investigation aims at providing insight on the possible efficiency gains that BCCs could achieve through mergers. If they are substantial (i.e. a bigger size is a desirable outcome), this would support possible future consolidation of the cooperative credit sector. If instead the gains are negligible, mergers should be weighed against their (detrimental) effect of undermining network economies and relationship lending, thus damaging local communities and economies.

Recent figures on the Italian banking industry tell us that, over 1993-2013, the number of Italian BCCs dropped from 671 to 385 (-42.6%), in analogy to the overall banking sector (Figure 1).

INSERT FIGURE 1 HERE

Between 1994 and 2013 Bank of Italy's Supervisory Bulletins report a large number of M&A operations among BCCs (including the transfers of assets and liabilities): 325 M&As involving only BCCs (about 16 per year on average), with a maximum of 39 in 1999 (Figure 2).

INSERT FIGURE 2 HERE

4. Empirical strategy

Given the above framework, we are going to investigate the effects of M&As on BCCs through an empirical assessment of the post-merger changes in cost efficiency at the merged BCCs, compared to the concurrent cost efficiency changes at those BCCs that never merged. A preliminary methodology step to that analysis consists in ascertaining that never-merged BCCs (group A) did not appear ex ante to be systematically different from merged BCCs (group B). If that were not the case, comparing between the two groups might be less meaningful. Indeed, the *t*-tests for difference in means – using banks' age as the discriminating variable – that we ran for each year over 1993-2013 reject the hypothesis that group A BCCs and group B BCCs belong to two different populations for eighteen years over twenty-one.[3]

In order to gauge the worthiness of mergers among BCCs, we 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).

As Maudos et al. (2002) underline, for many years bank differences in costs have been studied by estimating scale (and scope) economies, while more recently the focus has also moved towards the analysis of X-efficiency (Leibenstein, 1966), i.e. the ability of a bank to minimize the distance between its (observable) behaviour and the efficient behaviour as assumed by economic theory. Such analysis currently represents a key tool for empirical research on firms' performance, as the deviations from the efficient frontier are an important source of efficiency divergences. Actually, Berger et al. (1993) maintain that differences in managerial ability to control costs or maximize revenues appear to be greater than the cost effects of the choice of scale and scope production.

In particular, our approach consists in estimating a cost frontier function where a stochastic efficiency term captures bank-specific distances between actual costs and the best-practice frontier costs (yielding the efficiency scores), and then using such scores to quantify the change in efficiency after a merger involving BCCs, in order to gauge whether the merger was successful.

In view of the panel structure of our dataset, for estimating BCCs' cost efficiency levels we employ the stochastic frontier model of Battese and Coelli (1992), through which we obtain 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.

[3] Exceptions are 1995, 1996 e 2001. Results are not reported but are available upon request.

In the banking context, if we assume that, for bank i at time t, production costs are a 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 final 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 $\gamma < 0$, a 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 accordance with many recent banking studies we use a standard translog specification with three inputs and one output:[4]

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

where $i = 1,...,N$ and $t = 1,...,T$ indicate banks and years, respectively, C is total cost, Q is output, W_h are factors prices, and $TREND$ is a time trend included to account for technical change,[5] while v_{it} and u_{it} are the error and inefficiency terms, respectively.

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

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:

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

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).

These authors 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 with no 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 $CE_{it} = E\left[\exp(-u_{it})\,|\,\varepsilon_{it}\right]$, where ε_{it} is the overall

[5] 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).

error term.[6] 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 BCCs by regressing their efficiency scores on a set of five dummy variables that identify the sample cooperative banks by groups according to their M&A status, 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 BCCs 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 take 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 never involved in M&A activities during the sample period – i.e. our reference group – all 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 history 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).

Regarding control variables, total assets (*TOTAST*) are included to account for banks' size, and its quadratic term aims to capture possible nonlinearities in the size-efficiency relationship. Bigger BCCs need a widespread branch network, thus having 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 size. The ratio of non-performing loans to 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 the average of customer loans plus customer deposits per branch,

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

and is a proxy for the business characterizing the representative bank office; credit institutions managing more resources per office should 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: we conjecture 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 promote efficiency.

The variables *DEPAST* and *LOANAST* – deposits to assets ratio and loans to assets ratio, respectively – focus on the core activities of BCCs. Deposits are the main source of financing for cooperative banks, but gathering and managing them well requires a good organization. Loan management is even more crucial, as lending requires specific effort and organizational capabilities by the staff, and produces significant long-term effects on both revenues and costs. Hence, the impact on cost efficiency is not clear a priori. We also include in the regression population density (*POPDENS*), the number of inhabitants (thousand units) per square kilometre.[7] On one hand, offering banking services should be less costly in higher-density markets; 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 predictable a priori. Finally, δ_i is a group of provincial dummy variables,[8] while γ_t is a group of year dummies.

Since by construction the variable CE_{it} lies between 0 and 1, a standard OLS regression would be inappropriate, and a double-censored tobit estimation is recommended.[9] However, 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 (McDonald, 2009). In this case, an alternative strategy is using the OLS estimation where the dependent variable is replaced by its logistic transformation, given by

[7] As relevant geographical markets for BCCs, we consider the more than one hundred Italian provinces. For all cooperative banks that operate in more than one province, we weighted both population and land area according to the distribution of branches. See also Maudos (1998) and Coccorese and Pellecchia (2009).

[8] BCCs are attributed to the province where the majority of branches is located. However, nearly 97% of the sample BCCs have at least one half of their total branches in the same province, and 70% operate exclusively in one province.

[9] «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.

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

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

In what follows, we will use both approaches 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.

5. Data and variables

Banks' balance sheet as well as profit and loss account data come from ABI (the Italian Banking Association), and cover the years 1993-2013. For estimating the efficiency scores, we considered all types of credit institutions (commercial, popular, savings and cooperative banks): this allows better assessing cost performances since we take into account the whole Italian banking industry instead of just a limited subgroup. The above data were matched with those published yearly by the Bank of Italy, particularly the number of branches of each bank. All information on M&As among BCCs were gathered from the various issues of the Bank of Italy's Supervisory Bulletins.

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.

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) was computed dividing personnel expenses by the number of employees. Finally, the price of capital (W_3) was proxied by the ratio between other operating costs and number of branches. Output Q was measured by total loans.

To correct for outliers, we dropped the observations for which output and/or factors prices were lower than the 1st centile or larger than the 99th centile. After this data selection process, the (unbalanced) sample comprises 13,191 observations on 1,079 banks observed over 21 years. On average, it includes about 12 observations for each bank (Table 1).

As for the second stage estimation, the size of the sample drops because it is restricted to include only BCCs. Indeed, 8,451 observations are available, referring to 688 BCCs (Table 1), among which we recorded 318 M&As: particularly, during the sample period 175 BCCs 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, 254 BCCs were never involved in a merger or acquisition, and they represent our reference group. In this sample, data on provincial population and size have been taken from Istat (the Italian National Statistical Institute).

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

INSERT TABLES 1 AND 2 HERE

6. Estimation results

We will first present the results of our baseline regressions (sub-section 6.1) and then perform some additional checks to verify the robustness of our results (sub-section 6.2).

6.1 Baseline results

Following the standard procedure of the stochastic frontier analysis, Equation (4) was estimated by maximum likelihood. Table 3 reports the results for both BC and ALS stochastic frontier models. Most 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. A (decreasing) trend emerges for the efficiency scores estimated through the BC model; they are also much lower and exhibit 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 positive and rather high (+0.4019).

INSERT TABLE 4 HERE

Interestingly, from Table 5 we also note that BCCs (but also popular banks, another type of credit institutions with cooperative features, even though not mutual) exhibit higher levels of cost efficiency compared to commercial and savings banks, and this holds for every year. For example, as cost efficiency scores are given by the ratio of the minimum potential total cost to the observed

total cost, for BCCs the value $CE = 0.55$ from the Battese-Coelli model means that on average the minimum cost amounts to 55% of the observed one, i.e. that for cooperative banks the observed cost is 82% higher than the minimum potential cost. Instead, for commercial banks, the average efficiency score of 0.38 means that their costs are 163% higher than the minimum attainable level.

It therefore seems that in the whole sample period BCCs showed the best performance in terms of cost efficiency, which upholds the general appropriateness of their size and/or business model.

INSERT TABLE 5 HERE

To assess whether M&As among BBCs helped to reach even higher levels 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 (for the BC and the ALS model, respectively). We estimated Equation (5) both without and with control variables. However, in what follows we focus on the regression results from the full specifications.

INSERT TABLES 6 AND 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 exhibit lower efficiency compared to the reference group, i.e. those that will never merge in our time interval. Specifically, in the tobit model the predicted value of CE_{it} is 0.0174 points lower for the *PREMERGE* group (corresponding to a difference of about 3.2% of the BCC sample mean). Considering the estimation with the logistic transformation of CE_{it}, the value of -0.0787 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(-0.0787) = 0.9243, or – in terms of percent change – that the odds for the *PREMERGE* group are 7.57% lower than the odds for BCCs that never merged. Therefore, if we set $CE_{it}/(1-CE_{it}) = 0.9243$ for the first group 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 0.0197 points lower than the reference group, a result quite close to the one derived from the tobit regression.

However, the empirical results also suggest that both a first merger and a second merger (in our analysis, the latter regards those BCCs 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. Instead, significant improvements 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 0.0356 points compared to the never-merged BCCs, an increases of about 6.6% with respect to the sample mean (the increase in the efficiency scores amounts to 0.0465 according to the regression based on the odds of CE_{it}).

With reference to the Aigner-Lovell-Schmidt scores, both estimations again indicate that a pre-merger BCC is less efficient than those that decide not to merge (since the coefficient of *PREMERGE* is significantly different from zero at the 5% level), also confirming that one or two consecutive mergers lead to a more inefficient firm. Gains in efficiency are possible here only after four successive mergers.

The above findings allow to conclude that, even if a BCC is not efficient in minimizing costs, an 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. In particular, 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 business, especially considering that on average BCCs' cost efficiency scores are nonetheless higher than other types of banks.

Regarding 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 2,570 millions euro (in the tobit estimation with the ALS efficiency scores; for the other regressions this figure is much higher); considering that in our sample only 7 observations over 8,451 – corresponding to just three BCCs over 688 in 2013 – are characterized by 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. Quite to the contrary, small scale BCCs seem to be able to operate more efficiently.

The share of non-performing loans over total loans (*NPL*) exhibits the expected negative coefficient, even if it is not significant when using the Battese-Coelli efficiency scores: hence, bad loans appear to be negatively correlated with cost efficiency and signal an inadequate management quality. The coefficient of *BRBUS* also supports our conjecture: as its sign 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 (*DEPAST*) on cost efficiency is significantly negative, from which we infer that, as BCCs' deposits increase, they impose efficiency losses to banks. Quite to the contrary, as the coefficient of *LOANAST* is positive and significant, BCCs with a higher proportion of loans enjoy higher cost efficiency. Thus, the overall evidence is that BCCs are more efficient when they focus mainly on the traditional activity of loan granting (which is normally based on relationship lending), while higher shares of deposits in liabilities produce inefficiencies on the cost side. Finally, higher population density (*POPDENS*) appears to reduce cost efficiency, which means that for BCCs the complexity of crowded markets more than offsets the advantage of reaching more customers (Coccorese and Pellecchia, 2010, p. 192). However, the estimated coefficient for this variable is significant only when using the Aigner-Lovell-Schmidt scores.

6.2 Robustness checks

To make sure that our baseline results may be trusted, we will now perform three robustness checks. The first one consists in separating the mergers where BCCs spontaneously chose to engage in M&A from those in which one of the parties was "forced" in the merger by its own crisis. Next, we attune our specification to consider that M&As might actually exert initial negative effects on efficiency that might be (more than) offset by subsequent efficiency gains over time. As a final robustness check, we abandon the more sophisticated efficiency score approach and run our regressions on a naïve measure of cost efficiency.

The mergers considered in our sample can be split into two main groups: the 'voluntary' mergers, occurred as autonomous choices of two or more BCCs, and the 'induced' mergers, when a

BCC acquires some or all the business of another BCCs subject to special crisis management procedures. Namely, we consider cases of Special Administration (SAs) and of Compulsory Administrative Liquidation (CALs). SAs and CALs can be adopted by the regulatory authority in case of serious (for SAs, characterizing an early stage of bank crisis) or exceptionally serious (for CALs, occurring when the crisis is irreversible) capital losses and/or administrative irregularities or regulatory violations. SAs may end with the combination (merger or acquisition) of the troubled bank with a sound bank, while CALs often ends with the sale of assets and liabilities to another bank (in some sense, it can be regarded as a merger); normally, both procedures end up with friendly agreements and/or mergers.

To assess whether such M&As are to be regarded as different in terms of efficiency, we first divided the merged BCCs into two groups according to whether they were involved in 'voluntary' or 'induced' mergers, then estimated two tobit models that included the same reference set of BCCs (i.e. those that never merged). The first group is much bigger (400 BCCs) than the second (just 25 BCCs), also because we have been compelled to exclude 9 BCCs that were involved in both types of mergers. Tables 8 and 9 report the estimation results for BC and ALS efficiency scores.

INSERT TABLES 8 AND 9 HERE

First, note that for the 'induced' mergers there is evidence of an efficiency effects just for one merger: considering the BC scores, before and after M&As cost efficiency is not statistically different from that of never merged BCCs (while both coefficients were negative and significant for the whole sample); with the ALS scores, we observe the same qualitatively results of the whole sample, but note a remarkable efficiency drop following the first (and unique) merge. Hence, at best 'induced' mergers do not change the efficiency of the new BCC. Regarding the 'voluntary' mergers, the coefficients of the dummy variables pre- and post-merger keep the same sign and significance of those of Tables 6 and 7, but for *POSTMERGE*3 and *POSTMERGE*4 the coefficients are lower, implying that the efficiency effects of mergers are even lower than before.

In turn, Koetter (2008) suggests that efficiency might deteriorate in the immediate aftermath of a merger but be able to recover – exhibiting the largest difference from non-merging banks – after some time has elapsed. To evaluate whether this happens in our sample, we again estimate the tobit specification with both the BC and ALS efficiency scores, but replacing each post-merge dummy variable with five-year dummies associated to the time periods elapsed after the mergers. For example, the dummy variable *POSTMERGE*1 was substituted by the dummy variables *POSTMERGE*1_1to5 (equal to 1 from the first to the fifth year after the first merger, and to 0

elsewhere), *POSTMERGE*1_6to10 (equal to 1 from the sixth to the tenth year after the first merger, and to 0 elsewhere), and so on. The empirical evidence of such experiment is shown in Table 10.

INSERT TABLE 10 HERE

With the BC efficiency scores, it comes out that after a merger BCCs are generally better off in the first five years, but their efficiency worsens monotonically later in time. For example, *POSTMERGE*1_16over exhibits a value more than twice lower than *POSTMERGE*1_6to10 (besides, it is three times lower than the corresponding *POSTMERGE*1 in Table 6). The same happens to the group of the *POSTMERGE*2 dummies (here *POSTMERGE*2_16over is ten times lower than *POSTMERGE*2 in Table 6), but also to *POSTMERGE*3 and *POSTMERGE*4 groups of binary variables. Hence, contrary to the conjecture, it appears that a merger spreads out its effects in the very first years, after which at best BCCs come back to the old level of cost efficiency.

The pattern characterizing the same dummies when employing the ALS scores is quite different. For the cooperative banks that merged once, efficiency worsens up to ten years after the merger, but then a recovery leads them to a (weak) improvement after fifteen years. Similar outcomes emerge for BCCs that merged twice and three times, while for those that merged four times the efficiency gains are obtained soon after the last merger but persist just for five years.

The above estimations emphasize different trends for post-merger efficiency depending on measurement techniques in line with the idea of DeYoung et al. (2009), for whom it was the use of diverse methodologies that led previous studies to contrasting empirical evidence on whether involved financial firms benefit from M&As. However, to our end, finding efficiency gains due to BCC mergers is undeniably very hard. To better support this conclusion, we have performed other tobit estimations using post-merger one-year dummies for the time elapsed from each M&A. The trends characterizing the estimated coefficients during time are portrayed in Figure 3, where panel a) considers the Battese-Coelli efficiency scores and panel b) those by Aigner-Lovell-Schmidt.

INSERT FIGURE 3 HERE

While the post-merger efficiency trends reflect those already highlighted (descending for BC scores, ascending for ALS scores), two phenomena emerge sharply: first, there is a noteworthy difficulty for BCCs involved in mergers to reach at least the same level of cost efficiency of the never merged banks; second, clear efficiency improvements are associated only to four consecutive mergers. As we find that the target banks often exhibit an inferior performance but the acquirers are

unable to remedy this situation, in agreement with Vander Vennet (1996) it is straightforward to observe that these M&As fail to purge the system from inefficient banks.

Finally, we estimated OLS regressions for the post-merger periods (with just one dummy variable for each merger, with five-year dummies, and with one-year dummies) where the dependent variable is represented by an accounting measure, namely the ratio between non-interest operating costs and total assets (*COSTAST*), which replaces the frontier-based measures. This is a widely adopted measure for a quick assessment of the operational efficiency of banks intensely used by practitioners and sometimes also in the economic literature, where the interest expenses have been overlooked as they can be highly correlated with market rates rather than the management ability. Table 11 displays the results when using both the unique and the five-year dummies, while Figure 3, panel c), depicts the trends associated to the estimated values of the one-year dummies.

INSERT TABLE 11 HERE

Our previous results, particularly those obtained with the ALS cost efficiency scores, are broadly confirmed: according to Table 11, pre-merge cost/assets ratios are always higher than at never merged BCCs. In addition, each merger causes an initial worsening in *COSTAST*, nonetheless it is recovered after some time (which is quite long when BCCs merge once or twice). Looking at Figure 3, panel c), we discover that it takes a long time for merged BCCs to reach a cost-to-assets ratio significantly better than at never merged BCCs (seventeen years for cooperative banks that merged twice, and nine years for those that merged three times).

7. Conclusions

Against the mainstream tenet that 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 marginal borrowers and marginal clientele in general.

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 mutual cooperative banks, particularly their impact on the level of cost efficiency. We focused on the Italian banking industry in the period 1993-2013, during which an important process of consolidation took place, which involved also many Banche di Credito Cooperativo (BCCs).

We first estimated bank-level cost efficiency scores for the whole Italian banking system through a translog stochastic frontier model, finding that BCCs performed much better than the other types of banks. Next, we concentrated on the sub-sample of BCCs and used a set of merger status dummy variables (never merged, before the first merger, merged once, merged twice...), along with a vector 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 proved robust with respect to various model specifications, and suggest that BCCs decide to merge when their efficiency is lower than other cooperative banks, but also that they need either at least three consecutive mergers – hence, a much bigger dimension – and a long time in order to become more efficient than those BCCs never involved in M&As. Therefore, conforming to Lang and Welzel (1999) and Koetter (2008), we find no evidence of clear and substantive efficiency gains from merging in the Italian cooperative credit sector (even for some M&As which took place years before), rather our results point essentially to a deterioration of efficiency in the aftermath of a merger and a later levelling off of discrepancies with respect to the previous merging banks. Hence, it emerges that a consolidation of the credit cooperative sector in Italy does not necessarily result in a more efficient – and therefore stable – industry, nor mergers among BCCs can be seen as a means of reducing costs.

Yet, even if sizeable mergers could be convenient in terms of cost efficiency, they would probably imply a loss of identity for BCCs. First, the philosophy of cooperation has the maximization of members' benefits as its first objective, and this might not be compatible with achieving gains in efficiency or containing costs. Second, the larger size appears in direct conflict with BCCs' traditional mission of supporting small firms and households in their local business area, which could be therefore undermined as regards social and economic development, while the smaller size represents an ideal answer for small communities where relatively intimate knowledge of each other's trustworthiness ensures that loans are only provided to borrowers who could be expected to repay them (Fonteyne, 2007).

A caveat is appropriate. We cannot rule out that mergers among BCCs deliver benefits outside the sphere of efficiency. For example, the fact that mergers help reduce credit concentration should not be underplayed as a factor that might have spared some crises at BCCs in the recent adverse macroeconomic conditions (Stefani et al., 2016). Nevertheless, it is a fact that BCCs mergers were

almost always promoted with the idea that they would deliver efficiency gains. Now, the lack of evidence of significant post-merger efficiency gains calls for a fundamental reassessment. The burden of the proof is for those who advocate those mergers: they should find other convincing arguments besides efficiency. Otherwise, we might conclude that the intense BCCs merger wave was largely the result of a wrong view and, possibly, those mergers were worth a dime.

REFERENCES

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

Akhavein J.D., Berger A.N., Humphrey D.B. (1997), The effects of megamergers on efficiency and prices: Evidence from a bank profit function, *Review of Industrial Organization* 12, 95-139.

Altunbas Y., Molyneux P., Thornton J. (1997), Big-bank mergers in Europe: An analysis of the cost implications, *Economica* 64, 317-329.

Altunbas Y., Marquez D. (2008), Mergers and acquisitions and bank performance in Europe: The role of strategic similarities, *Journal of Economics and Business* 60, 204-222.

Amel D., Barnes C., Panetta F., Salleo C. (2004), Consolidation and efficiency in the financial sector: A review of the international evidence, *Journal of Banking and Finance* 28, 2493-2519.

Ayadi R., De Groen W.P., Sassi I., Mathlouthi W., Rey H., Aubry O. (2016), *Banking Business Models Monitor 2015: Europe*, Montreal: International Research Centre on Cooperative Finance, HEC.

Battese G.E., Coelli T.J. (1992), Frontier production function, technical efficiency and panel data with application to paddy farmers in India, *Journal of Productivity Analysis* 3, 153-169.

Beccalli E., Frantz P. (2009), M&A operations and performance in banking, *Journal of Financial Services Research* 36, 203-226.

Berger A.N. (1998), The efficiency effects of bank mergers and acquisitions: A preliminary look at the 1990s data, in: Amihud Y., Miller G. (eds.), *Bank Mergers and Acquisitions*, Dordrecht: Springer, 79-111.

Berger A.N., Hunter W.C., Timme S.G. (1993), The efficiency of financial institutions: A review and preview of research past, present, and future, *Journal of Banking and Finance* 17, 221-249.

Berger A.N., Demsetz R.S., Strahan P.E. (1999), The consolidation of the financial services industry: Causes, consequences, and implications for the future, *Journal of Banking and Finance* 23, 135-194.

Brown R.S., Caves D.W., Christensen L.R. (1979), Modelling the structure of costs and production for multiproduct firms, *Southern Economic Journal* 46, 256-273.

Cabo P., Rebelo J. (2005), Why do agricultural credit cooperatives merge? The Portuguese experience, *Annals of Public and Cooperative Economics* 76, 491-516.

Campa J.M., Hernando I. (2006), M&As performance in the European financial industry, *Journal of Banking and Finance* 30, 3367-3392.

Caves D.W., Christensen L.R. (1980), Flexible cost functions for multiproduct firms, *Review of Economics and Statistics* 62, 477-481.

Christensen L.R., Jorgenson D.W., Lau L.J. (1971), Transcendental logarithmic production frontiers, *Review of Economics and Statistics* 55, 28-45.

Coccorese P., Pellecchia A. (2009), Multimarket contact and profitability in banking: Evidence from Italy, *Journal of Financial Services Research* 35, 245-271.

Coccorese P., Pellecchia A. (2010), Testing the 'quiet life' hypothesis in the Italian banking industry, *Economic Notes* 39, 173-202.

Cuesta R.A., Orea L. (2002), Mergers and technical efficiency in Spanish savings banks: A stochastic distance function approach, *Journal of Banking and Finance* 26, 2231-2247.

DeYoung R. (1997), Bank mergers, X-efficiency, and the market for corporate control, *Managerial Finance* 23, 32-47.

DeYoung R., Evanoff D.D., Molyneux P. (2009), Mergers and acquisitions of financial institutions: A review of the post-2000 literature, *Journal of Financial Services Research* 36, 87-110.

Diaz B.D., Olalla M.G., Azofra S.S. (2004), Bank acquisitions and performance: Evidence from a panel of European credit entities, *Journal of Economics and Business* 56, 377-404.

Fiordelisi F. (2009), *Mergers and Acquisitions in European Banking*, London: Palgrave Macmillan.

Focarelli D., Panetta F., Salleo C. (2002), Why do banks merge?, *Journal of Money Credit and Banking* 34, 1047-1066.

Fonteyne W. (2007), Cooperative banks in Europe: Policy issues, *IMF Working Paper*, n. 07/159, International Monetary Fund, Washington.

Fried H.O., Knox Lovell C.A., Yaisawarng S. (1999), The impact of mergers on credit union service provision, *Journal of Banking and Finance* 23, 367-386.

Garden K., Ralston D. (1999), The X-efficiency and allocative efficiency effects of credit union mergers, *Journal of International Financial Markets Institutions and Money* 9, 285-301.

Huizinga H.P., Nelissen J.H.M., Vander Vennet R. (2001), Efficiency effects of bank mergers and acquisitions in Europe, *Tinbergen Institute Discussion Paper*, n. 01-088/3, Tinbergen Institute, Amsterdam.

Hunter W.C., Timme S.G. (1986), Technical change, organizational form, and the structure of bank production, *Journal of Money, Credit and Banking* 18, 152-166.

Jones D.C., Kalmi P. (2012), Economies of scale versus participation: A co-operative dilemma?, *Journal of Entrepreneurial and Organizational Diversity* 1, 37-64.

Kalmi P. (2016), The role of stakeholder banks in the European banking sector, in: Miklaszewska E. (ed.), *The Role of Institutional Diversity in the Banking Market. A Small Country, Small Bank Perspective*, London: Palgrave Macmillan, forthcoming.

Kauko K. (2009), Managers and efficiency in banking, *Journal of Banking and Finance* 33, 546-556.

Knapp M., Gart A., Chaudhry M. (2006), The impact of mean reversion of bank profitability on post-merger performance in the banking industry, *Journal of Banking and Finance* 30, 3503-3517.

Koetter M. (2008), An assessment of bank merger success in Germany, *German Economic Review* 9, 232-264.

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

Kwan S., Eisenbeis R.A. (1999), Mergers of publicly traded banking organizations revisited, *Federal Reserve Bank of Atlanta Economic Review*, fourth quarter, 26-37.

Lang G., Welzel P. (1999), Mergers among German cooperative banks: A panel-based stochastic frontier analysis, *Small Business Economics* 13, 273-286.

Leibenstein H. (1966), Allocative efficiency vs. "X-efficiency", *American Economic Review* 56, 392-415.

Lozano-Vivas A., Kumbhakar S.C., Fethi M.D., Shaban M. (2011), Consolidation in the European banking industry: How effective is it?, *Journal of Productivity Analysis* 36, 247-261.

Maudos J. (1998), Market structure and performance in Spanish banking using a direct measure of efficiency, *Applied Financial Economics* 8, 191-200.

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

McDonald J. (2009), Using least squares and tobit in second stage DEA efficiency analyses, *European Journal of Operational Research* 197, 792-798.

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

Michie J., Oughton C. (2013), Measuring diversity in financial services markets: A diversity index, *Centre for Financial and Management Studies Discussion Paper* n. 113, SOAS, University of London.

Montes, C.P. (2014), The effect on competition of banking sector consolidation following the financial crisis of 2008, *Journal of Banking and Finance* 43, 124-136.

Pagan A. (1984), Econometric issues in the analysis of regressions with generated regressors, *International Economic Review* 25, 221-247.

Peristiani S. (1997), Do mergers improve the X-efficiency and scale efficiency of U.S. banks? Evidence from the 1980s, *Journal of Money Credit and Banking* 29, 326-337.

Pilloff S.J. (1996), Performance changes and shareholder wealth creation associated with mergers of publicly traded banking institutions, *Journal of Money Credit and Banking* 28, 294-310.

Ralston D., Wright A., Garden K. (2001), Can mergers ensure the survival of credit unions in the third millennium?, *Journal of Banking and Finance* 25, 2277-2304.

Resti A. (1998), Regulation can foster mergers, can mergers foster efficiency? The Italian case, *Journal of Economics and Business* 50, 157-169.

Rhoades S.A. (1998), The efficiency effects of bank mergers: An overview of case studies of nine mergers, *Journal of Banking and Finance* 22, 273-291.

Sealey C.W., Lindley J.T. (1977), Inputs, outputs, and a theory of production and cost at depository financial institutions, *Journal of Finance* 32, 1251-1266.

Stefani M.L., Vacca V., Coin D., Del Prete S., Demma C., Galardo M., Garrì I., Mocetti S., Pellegrino D. (2016), Le banche locali e il finanziamento dei territori: evidenze per l'Italia (2007-2014), *Bank of Italy Occasional Paper*, n. 324, Banca d'Italia, Rome.

Thompson S. (1997), Takeover activity among financial mutuals: An analysis of target characteristics, *Journal of Banking and Finance* 21, 37-53.

Thu Nguyen H., Yung K., Sun Q. (2012), Motives for mergers and acquisitions: Ex-post market evidence from the US, *Journal of Business Finance and Accounting* 39, 1357-1375.

Turk Ariss R. (2010), On the implications of market power in banking: Evidence from developing countries, *Journal of Banking and Finance* 34, 765-775.

Vander Vennet R. (1996), The effect of mergers and acquisitions on the efficiency and profitability of EC credit institutions, *Journal of Banking and Finance* 20, 1531-1558.

Worthington A.C. (2004), Determinants of merger and acquisition activity in Australian cooperative deposit-taking institutions, *Journal of Business Research* 57, 47-57.

APPENDIX – *Causes and effects of M&As among banks: a review of the literature*

A) Studies on commercial banks

Paper	Methodology	No. M&As	Countries	Time period	Main results on M&As
Berger et al. (1999)	Survey of extant studies	-	Mostly US	-	Value & non-value maximizing motives coexist. Five key changes explain M&As: technical progress, improving institutions' financial condition, excess capacity or financial distress, international consolidation of markets, deregulation.
Thu Nguyen et al. (2012)	Identifying M&A motivation from ex-post market data	3,520	US	1984-2004	Multiple motives (some value-increasing, some value-decreasing) coexist: market timing; agency motives and/or hubris.
Fiordelisi (2009)	Survey of extant studies	-	EU	Since '90s	Main aims: revenue enhancement, cost savings, new growth opportunities.
DeYoung et al. (2009)	Survey of extant studies	-	US, EU	Since '90s	No clear evidence of benefit from M&As for involved banks, customers, or society.
Pilloff (1996)	Accounting ratios analysis	48	US	1982-1991	Little performance change but more efficiency (highest abnormal returns for M&As with greatest opportunities for expense cut).
Vander Vennet (1996)	Post-merger performance analysis	492	EU	1988-1993	M&As among equal-sized banks increase performance. More cost efficiency in cross-border M&As.
Akhavein et al. (1997)	Stochastic Frontier Analysis (SFA) on profit efficiency	57	US	1981-1989	Profit efficiency increases especially when the involved banks exhibit low prior efficiency.
Altunbas et al. (1997)	X-efficiency analysis (hybrid translog cost function)	Simulation	FR, DE, IT, ES	1988	Only limited opportunities for cost savings in big-bank M&As, while an increase in total costs appears the most likely outcome.
DeYoung (1997)	X-efficiency analysis (thick cost frontier methodology)	348	US	1987-1988	Cost efficiency gains slightly prevail (M&As have other motives) and mostly regard serial acquiring banks (experience effects).
Peristiani (1997)	X-efficiency analysis (distribution-free approach)	4,900	US	1980-1990	Acquirers fail to improve post-merger X-efficiency, but experience moderate gains in scale efficiency.
Berger (1998)	X-efficiency analysis on cost and profit	639	US	1991-1995	M&As increase profit- but not cost-efficiency. More efficiency gains when the involved banks are relatively inefficient ex ante.
Resti (1998)	DEA approach	67	IT	1986-1995	Buyers less efficient than targets. Post-merger efficiency gains are unstable.
Rhoades (1998)	X-efficiency analysis (on a few case studies)	9	US	1985-1995	All M&As led to significant cost cutting; but, only a minority of them did improve cost X-efficiency.
Kwan and Eisenbeis (1999)	Event study analysis of mergers causing stock abnormal returns	94	US	1989-1996	Most M&As are among better-performing institutions, but do not significantly improve profit performance or efficiency.
Huizinga et al. (2001)	X-efficiency analysis on cost and profit	52	EU	1994-1998	Increase in cost efficiency of merged banks, but profit efficiency improves only marginally.
Cuesta and Orea (2002)	Stochastic output distance function	n.a.	ES	1985-1998	Initially decreasing followed by an increase of technical efficiency indexes. Overall, merged banks became more efficient.
Focarelli et al. (2002)	X-efficiency analysis on cost and profit	201	IT	1985-1996	No gain in profits at acquirers, but increase in profitability for acquired banks, due to a permanent drop in NPL ratios.
Diaz et al. (2004)	Panel data profitability analysis	240	EU	1993-2000	Stable gain in acquirers' profitability, more significantly for bank acquisitions and for domestic M&As.
Campa and Hernando (2006)	Event study analysis of abnormal returns + OLS on financial ratios	244	EU	1998-2002	Short term positive abnormal returns + Profit and cost efficiency gains two years after the transaction was completed.
Knapp et al. (2006)	Correcting post-merger profitability for mean-reversion	80	US	1987-1998	Results significantly outperform the industry in the first five post-merger years.
Altunbas and Marquez (2008)	Strategic analysis of post-merger performance determinants	262	EU	1992-2001	Improved post-merger accounting profitability (in terms of ROE).
Beccalli and Frantz (2009)	X-efficiency analysis on cost and profit	714	EU	1991-2005	Slight drop in profit efficiency but marked cost efficiency gain (especially for domestic deals) in the five post-M&A years.
Lozano-Vivas et al. (2011)	SFA on cost and profit	117	EU	1998-2004	Both domestic and cross-border M&As give cost and profit efficiency gains. Cross-border M&As banks are more efficient.

B) Studies on cooperative banks

Paper	Methodology	No. M&As	Countries	Time period	Main results on M&As
Lang and Welzel (1999)	X-efficiency analysis on cost and profit	283	DE	1989-1997	No evidence of cost efficiency gains in the post-merger phase, but only a levelling off of differences among the merging units.
Fried et al. (1999)	DEA approach	348	US	1988-1995	Post-merger service provision doesn't deteriorate for members at acquiring credit unions (CUs), while improving for at least three years at acquired CUs. But almost half of acquiring CUs and 20% of acquired CUs suffer post-merger decline in service provision.
Ralston et al. (2001)	DEA approach	31	AUS	1993-1994	No post-merger efficiency gains.
Garden and Ralston (1999)	DEA approach	16	AUS	1992-1997	On average, credit union mergers do not result in an increase in X-efficiency or allocative efficiency relative to other CUs.
Cabo and Rebelo (2005)	Multinomial logit on determinants of M&As and their impact	64	PT	1995-2001	Merged credit coops had high costs and low profitability, but post-merger impact doesn't improve performance.
Koetter (2008)	X-efficiency analysis on cost and profit	1,340	DE	1994-2005	About 50% success in terms of either cost or profit efficiency. More gains in profit efficiency than in cost efficiency.

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

Year	Whole sample (first stage)	Only BCCs (second stage)
1993	430	147
1994	753	437
1995	751	490
1996	744	494
1997	743	490
1998	735	454
1999	699	447
2000	660	437
2001	650	422
2002	633	414
2003	591	403
2004	605	403
2005	588	387
2006	606	396
2007	620	398
2008	609	384
2009	609	394
2010	561	380
2011	579	381
2012	513	340
2013	512	353
Total	*13,191*	*8,451*
Number of banks	1,079	688
Average obs. per bank	12.22	12.28

TABLE 2 – *Descriptive statistics*

Variable	Mean	Std. Dev.	Minimum	Median	Maximum	Obs.
C [(1)]	129.63	676.68	0.37	11.33	17,475.72	13,191
Q [(1)]	1,977.27	11,418.65	2.31	148.76	301,930.80	13,191
W1 [(2)]	0.0317	0.0191	0.0060	0.0241	0.0802	13,191
W2 [(3)]	64.2503	8.0494	37.1140	63.5862	104.99	13,191
W3 [(3)]	433.16	264.03	131.38	374.82	2,722.01	13,191
TREND [(4)]	10.5405	5.9310	1	10	21	13,191
PREMERGE [(4)]	0.2697	0.4438	0	0	1	8,451
POSTMERGE1 [(4)]	0.1942	0.3956	0	0	1	8,451
POSTMERGE2 [(4)]	0.0388	0.1932	0	0	1	8,451
POSTMERGE3 [(4)]	0.0096	0.0974	0	0	1	8,451
POSTMERGE4 [(4)]	0.0018	0.0421	0	0	1	8,451
TOTAST [(1)]	253.24	305.01	4.3029	153.43	4,087.02	8,451
NPL [(2)]	0.0264	0.0290	0.0010	0.0173	0.5704	8,451
BRBUS [(1)]	35.6977	20.3407	3.3225	32.0675	264.33	8,451
EQAST [(2)]	0.1205	0.0354	0.0167	0.1160	0.3045	8,451
DEPAST [(2)]	0.5689	0.1042	0.3023	0.5614	0.9132	8,451
LOANAST [(2)]	0.6646	0.1276	0.2550	0.6720	0.9647	8,451
POPDENS [(5)]	0.2357	0.2714	0.0356	0.1717	2.6396	8,451

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

TABLE 3 – *Estimation results for the cost function*

Variable	Coefficient	BC MODEL (Battese-Coelli)		ALS MODEL (Aigner-Lovell-Schmidt)	
		Coeff.	*z*-value	Coeff.	*z*-value
Constant	a_0	0.1112	0.27	0.8908	1.50
ln*Q*	a_Q	0.7574	24.35 ***	0.9338	35.61 ***
ln(W_1/ W_3)	a_1	0.8122	8.22 ***	1.4152	9.06 ***
ln(W_2/ W_3)	a_2	-0.4569	-4.04 ***	-0.8752	-5.27 ***
ln*TREND*	a_T	-0.2619	-3.49 ***	-0.2107	-1.81 *
$(\ln Q)^2/2$	a_{QQ}	0.0159	7.74 ***	0.0104	10.62 ***
$(\ln(W_1/W_3))^2/2$	a_{11}	0.0622	4.48 ***	0.1446	6.57 ***
$(\ln(W_2/W_3))^2/2$	a_{22}	0.0338	1.46	0.0602	1.83 *
$(\ln TREND)^2/2$	a_{TT}	-0.1413	-15.40 ***	-0.2177	-17.24 ***
ln(W_1/W_3)*ln(W_2/W_3)	a_{12}	-0.0873	-5.52 ***	-0.1541	-6.38 ***
ln*Q**ln(W_1/W_3)	a_{Q1}	0.0142	6.12 ***	0.0120	3.49 ***
ln*Q**ln(W_2/W_3)	a_{Q2}	0.0149	3.86 ***	0.0033	0.73
ln*Q**ln*TREND*	a_{QT}	-0.0199	-9.99 ***	-0.0052	-2.07 **
ln*TREND**ln(W_1/W_3)	a_{T1}	-0.0620	-5.80 ***	-0.0507	-3.03 ***
ln*TREND**ln(W_2/W_3)	a_{T2}	-0.0172	-1.36	0.0287	1.51
Log-likelihood		6,171.25		895.83	
N. obs.		13,191		13,191	
N. banks		1,079		1,079	

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	0.4838	0.8334
1994	0.5223	0.8285
1995	0.5258	0.8367
1996	0.5194	0.8285
1997	0.5179	0.8278
1998	0.5153	0.8182
1999	0.5028	0.8149
2000	0.4979	0.8198
2001	0.4894	0.8228
2002	0.4872	0.8184
2003	0.4830	0.8207
2004	0.4771	0.8257
2005	0.4768	0.8254
2006	0.4722	0.8377
2007	0.4738	0.8261
2008	0.4759	0.8223
2009	0.4684	0.8335
2010	0.4657	0.8444
2011	0.4639	0.8258
2012	0.4604	0.8033
2013	0.4604	0.7740

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	0.3771	0.7915
Popular banks	0.3790	0.8236
Savings banks	0.3159	0.8189
BCCs	0.5462	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	Coeff.	*z*-value	Coeff.	*z*-value
PREMERGE	b_0	0.0056	1.88 *	-0.0174	-11.53 ***	0.0262	1.79 *	-0.0787	-10.29 ***
*POSTMERGE*1	b_1	-0.0810	-37.02 ***	-0.0059	-4.20 ***	-0.3581	-26.82 ***	-0.0044	-0.65
*POSTMERGE*2	b_2	-0.1175	-30.69 ***	-0.0065	-2.71 ***	-0.5048	-22.77 ***	0.0055	0.46
*POSTMERGE*3	b_3	-0.1277	-17.83 ***	0.0125	2.77 ***	-0.5558	-20.14 ***	0.0668	2.99 ***
*POSTMERGE*4	b_4	-0.1726	-10.80 ***	0.0356	5.48 ***	-0.7393	-10.60 ***	0.1864	4.82 ***
ln*TOTAST*	b_5	-		-0.4047	-31.69 ***	-		-2.2375	-29.43 ***
(ln*TOTAST*)^2	b_6	-		0.0116	22.10 ***	-		0.0687	22.48 ***
NPL	b_7	-		-0.0212	-0.86	-		-0.1925	-1.34
ln*BRBUS*	b_8	-		0.1122	51.36 ***	-		0.5647	36.16 ***
EQAST	b_9	-		0.1573	6.79 ***	-		1.0073	8.61 ***
DEPAST	b_{10}	-		-0.1452	-18.83 ***	-		-0.7206	-15.64 ***
LOANAST	b_{11}	-		0.1442	19.18 ***	-		0.6184	15.03 ***
POPDENS	b_{12}	-		-0.0053	-1.00	-		-0.0277	-1.14
Log-likelihood		8,720.14		14,198.45					
Adj. R^2						0.4528		0.8154	
N. obs.		8,451		8,451		8,451		8,451	
N. banks		688		688		688		688	

Dependent variable: *CE*
*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level.
z-values are based on bootstrapped standard errors (with 1,000 replications).
Provincial 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	Coeff.	*z*-value	Coeff.	*z*-value
PREMERGE	b_0	-0.0013	-0.67	-0.0020	-1.97 **	-0.0166	-1.35	-0.0165	-2.34 **
*POSTMERGE*1	b_1	-0.0209	-11.94 ***	-0.0085	-7.45 ***	-0.1519	-14.90 ***	-0.0502	-6.47 ***
*POSTMERGE*2	b_2	-0.0341	-12.93 ***	-0.0162	-7.10 ***	-0.2398	-11.47 ***	-0.0967	-7.06 ***
*POSTMERGE*3	b_3	-0.0217	-3.45 ***	-0.0116	-3.59 ***	-0.1542	-5.09 ***	-0.0588	-2.70 ***
*POSTMERGE*4	b_4	-0.0180	-1.27	0.0099	1.89 *	-0.1428	-2.19 **	0.0818	2.17 **
ln*TOTAST*	b_5	-		-0.0801	-7.90 ***	-		-0.5559	-8.81 ***
(ln*TOTAST*)^2	b_6	-		0.0027	6.54 ***	-		0.0181	7.03 ***
NPL	b_7	-		-0.1338	-6.79 ***	-		-0.9363	-7.46 ***
ln*BRBUS*	b_8	-		0.0454	30.55 ***	-		0.3691	39.36 ***
EQAST	b_9	-		0.3095	19.99 ***	-		2.2767	21.54 ***
DEPAST	b_{10}	-		-0.0581	-12.02 ***	-		-0.5117	-15.06 ***
LOANAST	b_{11}	-		0.4126	77.61 ***	-		2.8687	83.80 ***
POPDENS	b_{12}	-		-0.0125	-2.60 ***	-		-0.0943	-3.16 ***
Log-likelihood		12,847.07		17,186.65					
Adj. R^2						0.3750		0.7984	
N. obs.		8,451		8,451		8,451		8,451	
N. banks		688		688		688		688	

Dependent variable: *CE*
*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level.
z-values are based on bootstrapped standard errors (with 1,000 replications).
Provincial and time dummies are included in all estimations but are not reported.

TABLE 8 – *Type of merger: tobit estimation results for BC Model (Battese-Coelli)*

Variable	Coefficient	VOLUNTARY MERGERS		INDUCED MERGERS	
		Coeff.	*z*-value	Coeff.	*z*-value
PREMERGE	b_0	-0.0173	-11.54 ***	0.0030	0.39
*POSTMERGE*1	b_1	-0.0068	-5.75 ***	0.0027	0.53
*POSTMERGE*2	b_2	-0.0044	-1.38	-	
*POSTMERGE*3	b_3	0.0099	2.31 **	-	
*POSTMERGE*4	b_4	0.0301	3.92 ***	-	
ln*TOTAST*	b_5	-0.3896	-27.01 ***	-0.4197	-20.12 ***
(ln*TOTAST*)^2	b_6	0.0109	18.77 ***	0.0122	14.54 ***
NPL	b_7	-0.0104	-0.51	-0.1487	-3.05 ***
ln*BRBUS*	b_8	0.1128	65.91 ***	0.1171	37.92 ***
EQAST	b_9	0.1681	7.10 ***	0.0744	2.61 ***
DEPAST	b_{10}	-0.1473	-16.87 ***	-0.1234	-11.13 ***
LOANAST	b_{11}	0.1407	17.53 ***	0.0749	6.96 ***
POPDENS	b_{12}	-0.0046	-0.72	0.0077	1.18
Log-likelihood		13,718.02		7,355.16	
N. obs.		8,133		4,280	
N. banks		654		279	

Dependent variable: *CE*
*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level.
z-values are based on bootstrapped standard errors (with 1,000 replications).
Provincial and time dummies are included in all estimations but are not reported.

TABLE 9 – *Type of merger: tobit estimation results for ALS Model (Aigner-Lovell-Schmidt)*

Variable	Coefficient	VOLUNTARY MERGERS		INDUCED MERGERS	
		Coeff.	*z*-value	Coeff.	*z*-value
PREMERGE	b_0	-0.0020	-1.95 *	-0.0052	-1.09
*POSTMERGE*1	b_1	-0.0078	-6.46 ***	-0.0347	-6.81 ***
*POSTMERGE*2	b_2	-0.0148	-5.50 ***	-	
*POSTMERGE*3	b_3	-0.0117	-5.03 ***	-	
*POSTMERGE*4	b_4	0.0060	1.11	-	
ln*TOTAST*	b_5	-0.0822	-9.34 ***	-0.1108	-9.31 ***
(ln*TOTAST*)^2	b_6	0.0028	7.79 ***	0.0040	8.43 ***
NPL	b_7	-0.1257	-6.09 ***	-0.1268	-3.71 ***
ln*BRBUS*	b_8	0.0458	30.84 ***	0.0445	24.06 ***
EQAST	b_9	0.3141	19.96 ***	0.2919	16.40 ***
DEPAST	b_{10}	-0.0587	-11.61 ***	-0.0282	-4.26 ***
LOANAST	b_{11}	0.4121	62.93 ***	0.3895	50.06 ***
POPDENS	b_{12}	-0.0084	-1.66 *	0.0154	1.89 *
Log-likelihood		16,545.89		9,030.27	
N. obs.		8,133		4,280	
N. banks		654		279	

Dependent variable: *CE*
*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level.
z-values are based on bootstrapped standard errors (with 1,000 replications).
Provincial and time dummies are included in all estimations but are not reported.

TABLE 10 – *Tobit estimation results with five-year effects of mergers*

Variable	Coefficient	BC efficiency scores			ALS efficiency scores		
		Coeff.	*z*-value		Coeff.	*z*-value	
PREMERGE	b_0	-0.0161	-10.94	***	-0.0022	-2.25	**
*POSTMERGE*1_1to5	b_{11}	0.0025	1.43		-0.0081	-7.36	***
*POSTMERGE*1_6to10	b_{12}	-0.0084	-4.02	***	-0.0122	-8.88	***
*POSTMERGE*1_11to15	b_{13}	-0.0176	-8.61	***	-0.0088	-4.64	***
*POSTMERGE*1_16over	b_{14}	-0.0181	-4.70	***	0.0041	1.40	
*POSTMERGE*2_1to5	b_{21}	0.0064	2.42	**	-0.0167	-5.87	***
*POSTMERGE*2_6to10	b_{22}	-0.0112	-3.61	***	-0.0202	-6.11	***
*POSTMERGE*2_11to15	b_{23}	-0.0367	-8.33	***	-0.0097	-2.19	**
*POSTMERGE*2_16over	b_{24}	-0.0741	-6.53	***	0.0090	0.27	
*POSTMERGE*3_1to5	b_{31}	0.0233	5.00	***	-0.0151	-3.77	***
*POSTMERGE*3_6to10	b_{32}	-0.0047	-0.97		-0.0085	-2.59	***
*POSTMERGE*3_11over	b_{33}	-0.0173	-2.74	***	0.0044	0.59	
*POSTMERGE*4_1to5	b_{41}	0.0359	6.00	***	0.0114	2.41	**
*POSTMERGE*4_6over	b_{42}	0.0308	1.73	*	0.0043	0.33	
ln*TOTAST*	b_5	-0.4092	-37.06	***	-0.0785	-6.30	***
(ln*TOTAST*)^2	b_6	0.0117	26.42	***	0.0027	5.20	***
NPL	b_7	-0.0202	-0.79		-0.1359	-6.45	***
ln*BRBUS*	b_8	0.1128	54.96	***	0.0451	40.67	***
EQAST	b_9	0.1554	7.22	***	0.3099	22.70	***
DEPAST	b_{10}	-0.1484	-15.77	***	-0.0573	-14.17	***
LOANAST	b_{11}	0.1435	17.25	***	0.4134	79.72	***
POPDENS	b_{12}	-0.0047	-0.95		-0.0122	-2.62	***
Log-likelihood		14,248.82			17,203.23		
N. obs.		8,451			8,451		
N. banks		688			688		

Dependent variable: *CE*
*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level.
z-values are based on bootstrapped standard errors (with 1,000 replications).
Provincial and time dummies are included in all estimations but are not reported.

TABLE 11 – *Estimation results with an alternative measure of efficiency*

Variable	Coefficient	Coeff.	*t*-value		Coeff.	*t*-value	
PREMERGE	b_0	0.0577	3.84	***	0.0645	4.27	***
*POSTMERGE*1	b_1	0.1652	11.98	***	-		
*POSTMERGE*1_1to5	b_{11}	-			0.2049	11.20	***
*POSTMERGE*1_6to10	b_{12}	-			0.1844	10.05	***
*POSTMERGE*1_11to15	b_{13}	-			0.1009	4.96	***
*POSTMERGE*1_16over	b_{14}	-			-0.0026	-0.10	
*POSTMERGE*2	b_2	0.2589	10.66	***	-		
*POSTMERGE*2_1to5	b_{21}	-			0.2824	10.53	***
*POSTMERGE*2_6to10	b_{22}	-			0.2520	6.06	***
*POSTMERGE*2_11to15	b_{23}	-			0.1828	3.00	***
*POSTMERGE*2_16over	b_{24}	-			0.2170	0.86	
*POSTMERGE*3	b_3	0.1755	5.14	***	-		
*POSTMERGE*3_1to5	b_{31}	-			0.2188	5.11	***
*POSTMERGE*3_6to10	b_{32}	-			0.1186	2.29	**
*POSTMERGE*3_11over	b_{33}	-			-0.0111	-0.27	
*POSTMERGE*4	b_4	0.1670	3.05	***	-		
*POSTMERGE*4_1to5	b_{41}	-			0.1808	3.17	***
*POSTMERGE*4_6over	b_{42}	-			-0.0001	0.00	
ln*TOTAST*	b_5	-0.2736	-1.71	*	-0.3105	-1.94	*
(ln*TOTAST*)^2	b_6	0.0031	0.48		0.0046	0.70	
NPL	b_7	3.0333	8.56	***	3.0344	8.55	***
ln*BRBUS*	b_8	-0.3972	-21.17	***	-0.3921	-20.93	***
EQAST	b_9	-0.0270	-0.12		-0.0569	-0.25	
DEPAST	b_{10}	1.0640	14.12	***	1.0453	13.86	***
LOANAST	b_{11}	1.5992	22.40	***	1.5905	22.25	***
POPDENS	b_{12}	0.2624	4.55	***	0.2584	4.48	***
R^2		0.6968			0.6980		
N. obs.		8,451			8,451		
N. banks		688			688		

Dependent variable: *COSTAST*
*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level.
t-values are based on robust standard errors.
Provincial and time dummies are included in all estimations but are not reported.

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

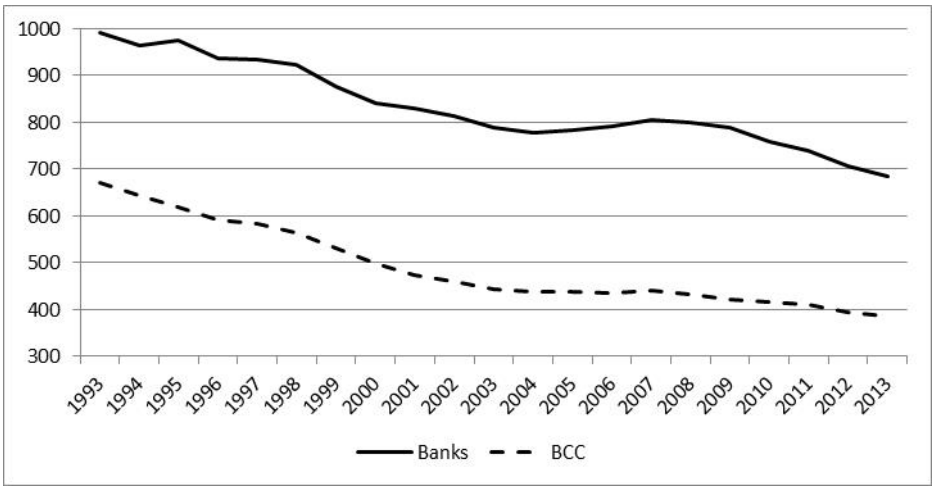


FIGURE 2 – *M&A operations involving BCCs (Italy, years 1994-2013)*

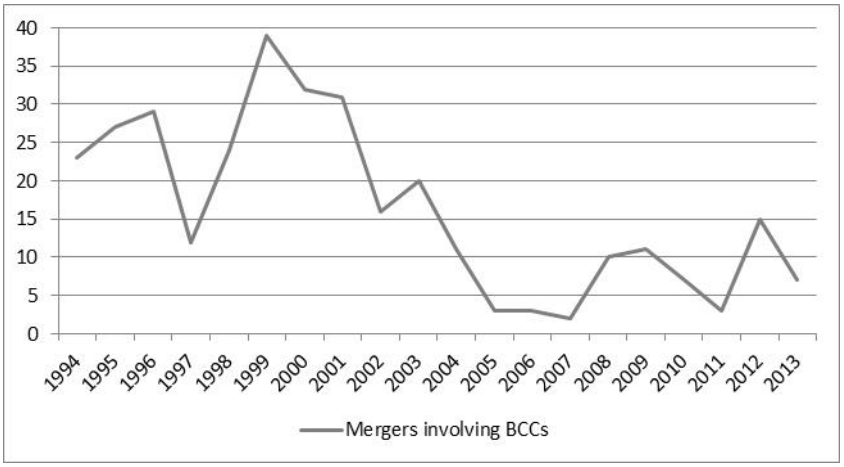
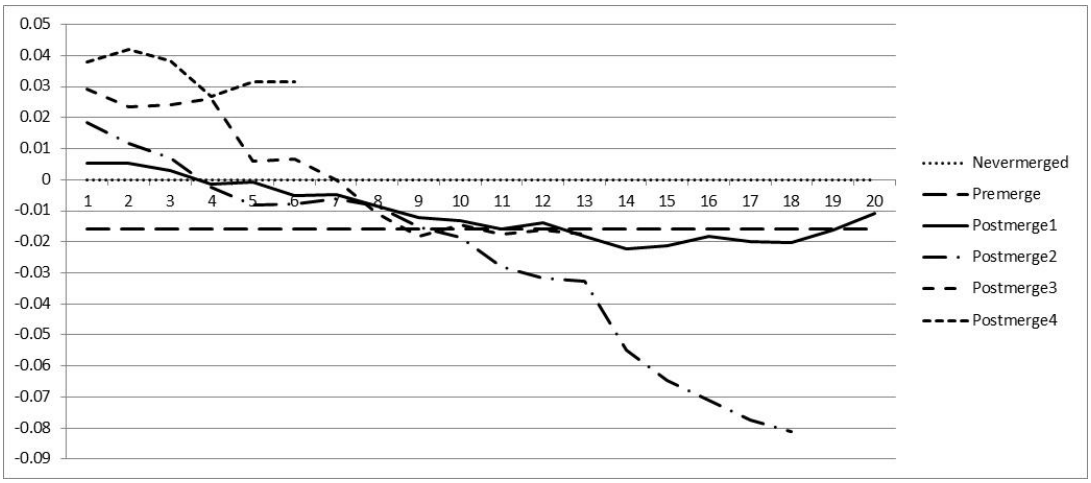
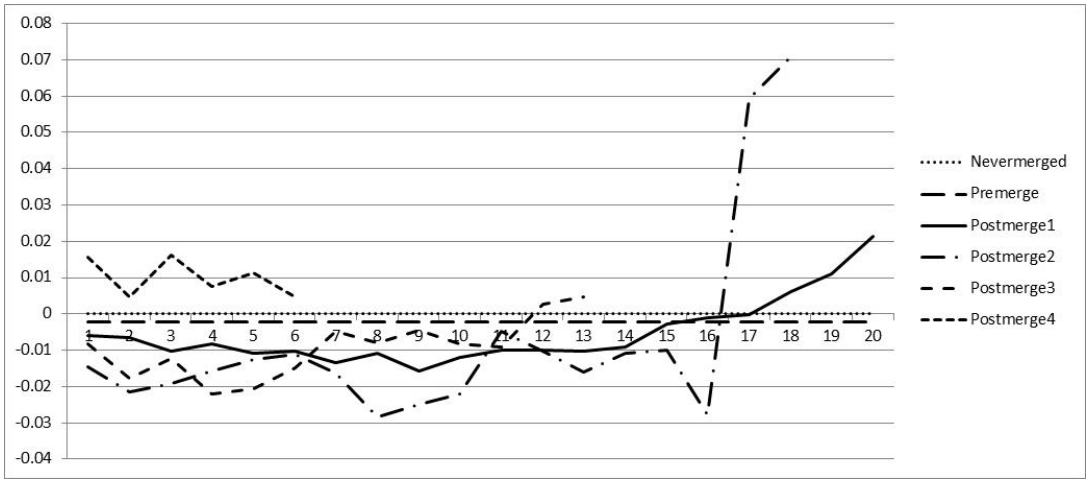


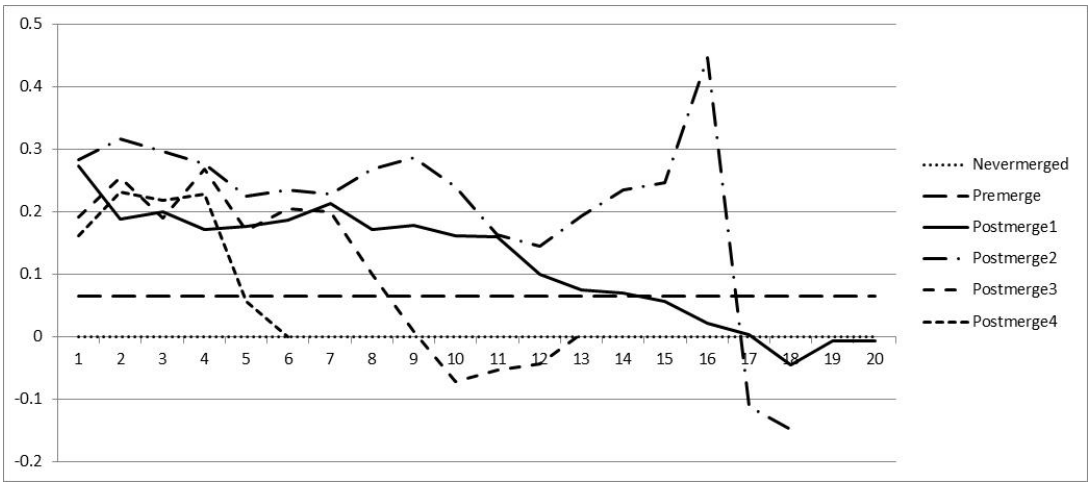
FIGURE 3 – *Yearly efficiency differentials with respect to never merged BCCs*



a) Measure of efficiency: Battese-Coelli scores (results obtained from tobit estimation)



b) Measure of efficiency: Aigner-Lovell-Schmidt scores (results obtained from tobit estimation)



c) Measure of efficiency: cost/assets ratio (results obtained from OLS estimation)