Multilevel empirics for small banks in local markets*

Francesco Aiello[1], **Graziella Bonanno**[2]

[1] Department of Economics, Statistics and Finance, University of Calabria, I-87036 Arcavacata di Rende (CS), Italy (e-mail: f.aiello@unical.it)
[2] Department of Computer, Control, and Management Engeneering, 'Antonio Ruberti' Sapienza University, I-00185 Rome, Italy (e-mail: bonanno@dis.uniroma1.it)

Abstract. Small banks are embedded in narrow markets and hence benefit from proximity to their customers. By referring to multilevel approach, this paper evaluates how much the performance of Italian mutual co-operative banks is determined by geographical and individual characteristics. The effect of local markets explains 28.27 per cent of bank heterogeneity in the empty multilevel model and 33 per cent in the most extended model. Moreover, it is found that efficiency increases with market concentration and demand density but decreases with branching in local markets.

JEL classification: G21, C13, D22, R19

Key words: Multilevel model, small banks, local markets, cost efficiency

1 Introduction

Two main interconnected facts help to explain why small banks are an intriguing case-study for economists. Both reasons come from the reforms that occurred over the world in the last 25 years. The first issue is that after consolidation, markets are dominated by big banks. However, the 2007 crisis reveals how the risky behaviour of big banks introduced a domino effect in the propagation of shocks. Second, the increased action of complex conglomerates would force small entities to disappear: in a world of big banks, small credit institutions are expected to fail. An important reform which reinforces these expectations regards the relaxing of geographic constraints in banking activity. Actually, banks may open branches anywhere, thereby inducing a territorial diversity in their organization and more competition in the periphery. If local markets become contestable, then small banks will lose their quasi-monopoly power, which in the past assured profitability (Coccorese 2009; Fiordelisi and Mare 2013; Silipo 2009).

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Despite all the market changes and differently from expectations, small banks persistence in several banking systems is counterintuitive. Then, it is meaningful to investigate the determinants of small banks' performance, given that they operate within an industry, which now is much more consolidated than in the past. Given their number and the niche they fill, it is important to assess how environmental changes affect small banks viability.

This paper focuses on the Italian mutual co-operative banks (MCBs), which are important players in the national industry.[1] Three main characteristics guide the operations and organization of MCBs. First, their governance is based the 'one member, one vote' rule, with widespread ownership across the members; second, they are embedded in the territory where they operate; and, finally, they act to achieve goals that are inspired by mutualism. In brief, the mission of an MCB is to provide value for its members, encourage social cohesion, and promote sustainable growth in the area that it serves (Alessandrini et al. 2009; Boscia and Di Salvo 2009). It is also noteworthy to say that much research empirically supports the hypothesis that small banks promote the growth of local economies (Berger et al. 2004; Destefanis et al. 2014; Meslier-Crouzille et al. 2012; Usai and Vannini 2005).

In order to examine the influence of local market conditions on MCB performance, we combine two strands of literature, one focusing on the evaluation of bank efficiency and the other investigating efficiency determinants.

While the literature on banking efficiency is extensive — Berger and Humphrey (1997), and Fethi and Pasourias (2010) — few consider regard Italy. The mixed evidence available shows that larger banks attain lower efficiency levels than small banks, and, importantly, MCBs perform better than other banks in controlling costs (Girardone et al. 2004; Dongili et al. 2008; Ayadi et al. 2010). These outcomes are often explained by the competitive advantages that MCBs have over their big bank counterparts, particularly with respect to their use of 'soft' rather than 'hard' information, their lean rather than complex organization, and the short operational distances between the smaller banks and their customers (Berger and Udell 2002; Berger et al. 2005; Carnevali 2005).

These competitive elements are of interest in Italy, as MCBs exploit them to ensure sizeable financing to small and medium-sized enterprises (SMEs) which are so numerous and important in the Italian economy. Indeed, loans from small banks to businesses increased by 4.8 per cent from 2008 to 2013, while those managed by the big banks grew by only 2.7 per cent. Over the same period, MCB credit lines to SMEs made up roughly 35 per cent of total MCB loans (Bank of Italy 2014). There is robust evidence of the role played by the MCBs was crucial in the 2007–2008 crisis, during which MCBs have contributed to financial stability and alleviated the credit constraints of SMEs (Hesse and Cihàk 2007; Ayadi et al. 2010; Catturani and Borzaga 2014; Groeneveld 2014). This is consistent with the general predictions of Petersen and Rajan (1994) and Berger et al. (2005) and is emphasized by the high proportion of SMEs in the Italian economy, which typically prefer credit relationships with small banks like the MCBs (Berger et al. 2005; Cole et al. 2004; Ferri and Messori 2000). The arguments in favour of MCBs, together with their anti-cyclical performance and resilience during the 2007–2008 crisis (Fonteyne 2007; Birchall 2013; ILO 2013), explain why they have gained attention from the academic community.

With regard the theme of 'what' explains bank efficiency, it is worth noting that there is no clear widely shared theory, but much is left to empirics. There has been a great deal of research on the relationships between efficiency and market concentration, external socio-economic conditions, banking structure, and access to banking services (Bos and Kool 2006: Dietsch and

[1] In 2013 there were 385 MCBs, while in the early '90s they were 700. However, the number of branches even doubled in ten years, rising from 2226 in 1993 to 4454 in 2013, In 2013 MCBs branches made up 14% of national branches, which is a value 4 percentage points higher than that of 1993.

Lozano-Vivas 2000; Girardone et al. 2004). While part of this literature will be reviewed together with the setting-up of our model (Hughes and Mester 2008) for a comprehensive survey), it is important here to say that the main focus of the paper is the effect of environmental factors on MCB performance. In this sense, the article by Battaglia et al. (2010) is comparable to ours as it focuses on MCB efficiency over the 2000–2005 period. They estimate stochastic frontiers by only referring to MCBs and, thus, proposing ‘within-the-group’ differences. As the authors argue, their method allows them to ‘avoid estimation bias in efficiency scores to strong heterogeneity in the sample’ (Battaglia et al. 2010, p. 1366). It is also worth mentioning that they calculate external variables at regional level.

Compared to the related literature, the contributions of this paper are threefold. The first feature refers to the empirical setting we propose, as the efficiency is first estimated by applying the stochastic frontier approach (SFA) and then regressed against individual and environmental factors. The novelty is not the two-stage procedure in itself, but what we do in each step. Cost efficiency is estimated by referring to the SFA specification proposed by Battese and Coelli (1995). In contrast to Battaglia et al. (2010), our SFA considers all banks, thereby implying that the estimations of individual performance control for what happens in the national system. This assures the comparability of results across groups and, thus, allows discernment of ‘within’ and ‘between’ group differences (Bos and Kool 2006). In the second step, MCB efficiency is regressed against a set of factors that influence performance. The main interest is to evaluate the effect of the local conditions that we measured by using several variables at provincial level.

This introduces the second contribution of the study, which is related to the decision to consider the province (NUTS 3) as the reference area for MCBs. An analysis based on larger territories suffers from aggregation bias as the nearer the MCBs are to their markets, the more precise the investigation of the efficiency-environment nexus will be. Briefly, the decision to focus on MCBs and limit the territory of interest to the provincial level gives a better understanding of the effect of the local conditions on individual performance, as MCBs act as single market entities (Dick 2008; Amel and Starr-McCluer 2002). From an empirical perspective, the required information to be analysed comes from the MCB balance-sheets, which are reliable from a territorial perspective. Indeed, the accounting data incorporate the environmental effects, as they are the result of the financial relationship between MCBs and the ‘residents’.

In the second stage of the analysis, we use cost efficiency as the dependent variable of multilevel models (MLMs). The use of MLMs represents the third novelty because they fit well with the structure of our data. Indeed, small banks operate in a market and thus represent a good example of hierarchy: they are at the lowest level of the hierarchy while the higher level is the local market (Goldstein 2003; Luke 2004). While this embeddedness makes it easy to argue that environmental factors influence individual performance, it is puzzling that the related literature refers to single equation models that are too limited to handle the multilevel nature of data featuring the small banks’ behaviour. On the contrary, the embeddedness can be properly treated by MLMs, which are very attractive also from an economic perspective, because they address how the micro, mid and macrospheres of economic systems evolve and interact. Indeed, if the first-level of unit-of-analysis, the small bank, is embedded in a local market, then its performance cannot be addressed without taking into consideration the interactions from the micro to the macro-level, and vice versa, as MLMs do (Baldwin and Okubo 2006; Beugelsdijk 2007).[2]

[2] The links between agents and external factors are modeled from different perspectives. For instance, the endogenous growth theory proves the existence of increasing returns due to spillovers between firms and other organizations (Romer 1986). However, it refers to single equation macro models and focuses on aggregate patterns, although they have microfoundations. Again, the existence of micro-macro interactions is recognized by the evolutionist school. However, here the links are one-way, as they flow from the individual to the aggregate level (Dosi and Nelson 2010). This implies that the ‘overall’ patterns are just those from aggregations, while any other environmental factor is left out of the analysis.

In this respect, MLMs make an important contribution to many empirical studies aimed at understanding the individual performance and the links between micro and macro-patterns (Maas and Hox, 2004; Knoben 2009; Raspe and van Oort 2011a, 2011b; Aiello et al. 2014; Goedhuys and Srholec 2015; Srholec 2015).

As MLMs have never been used to study the role of context in banking, this paper tries to fill this gap. MCBs are observed over time and, thus, we refer to an MLM for longitudinal data, given that multiple measurements at different time points (level 1) are nested within small banks (level 2), which are further nested in local markets (level 3). While panel data have many advantages over cross-sectional study (Hsiao 2003), their use in MLM approach allows for the investigation of heterogeneity by taking into account the links across the units of a hierarchical order of data (Skrondal and Rabe-Hesketh 2008). In order to represent time changes, a growth linear MLM with a random intercept as well as random slopes is considered. Furthermore, the analysis includes a set of predictors that we retrieved from the literature (Aiello and Bonanno 2016).

The period under scrutiny involved the years of crisis 2006–2011. This was a period of severe instability, whose effect on MCBs have not been studied in depth (the exception is Barra et al. 2016). This paper contributes to the debate first by updating the analysis of the level and dynamics of MCB performance and secondly by modeling time as a determinant of MCB efficiency.

The paper is organized as follows: Section 2 presents models and data; Sections 3 and 4 discuss the results; Section 5 concludes.

2 The empirical setting: models and data

2.1 Estimating a cost frontier in banking

In the first step of the econometric analysis we consider a very large sample of Italian banks and obtain cost efficiency scores by estimating an SFA, thereby allowing banks to be distant from the frontier also for randomness (Aigner et al. 1977; Meeusen and van de Broek 1997).

The choice to use cost efficiency as measure of MCB performance depends on three reasons. The first is that profits are not the ultimate aim of MCBs. Indeed, profits go to a special mutual aid fund (Fondo Sviluppo Spa set up by Federcasse and Conf Co-operatives) for the promotion and development of co-operation (Guitérrez 2008). Second, and more in general, the use of efficiency scores is driven from the conclusive debate according to which efficiency measures have advantages over accounting ratios (Berger and Humphrey 1997). For example, frontier estimations, which are based on microfounded theories (Farrell 1957; Kumbhakar and Lovell 2000), can accommodate multiple inputs and multiple outputs and the results are more objective and all inclusive (Thanassoulis et al. 1996). Finally, financial ratios are appropriate when the decision unit manages one input to generate a single output (Mousa 2015), which is not the case of banks.

We refer to the SFA specification proposed by Battese and Coelli (1995), which yields a cleaner efficiency measure compared with the model where one first estimates inefficiency and, second, uses the estimated efficiency-score as the dependent variable in subsequent regression (Greene 1993).

The main equation, that is to say the cost frontier, is based on a 3-inputs-3-outputs model. The variables have been classified according to the intermediation approach (Sealey and Lindley 1977). The dependent variable is total costs. The outputs are loans to customers, commission income and securities (sum of loans to other banks, equities and bonds). The inputs are labour, capital and deposits. The inefficiency equation only controls for bank type (MCBs, Popolari banks and limited (Ltd) companies) and location effects. The following function F_c (.) indicates the cost of producing an output y given a price w:

$$\mathrm{Cost}_{it} = F_c(y, w)\ \ e^{v_c} e^{u_c}. \tag{1}$$

From Equation (1), the efficiency can be expressed as the ratio of the minimum cost of a potentially efficient bank to the cost actually observed:

$$CE = \frac{F_c(y, w)e^{v_c}}{F_c(y, w)e^{v_c} e^{u_c}} = e^{-u_c}. \tag{2}$$

We use the Translog function to model the frontiers.[3] It satisfies the assumptions of non-negativity, concavity and linear homogeneity (Kumbhakar and Lovell 2000). After taking into account the constraint of homogeneity in relation to input-prices ($\sum_n \omega_n = 1$), the cost frontier in the log-linear form (w_r is the price of deposits) is:

$$\begin{aligned}\log\left(\frac{\mathrm{Cost}}{w_r}\right) &= \beta_0 + \sum_j \beta_j \log y_j + \sum_n \omega_n \log\frac{w_n}{w_r} + \\ &+ \frac{1}{2}\left[\sum_j \sum_s \beta_{js} \log y_j \log y_s + \sum_n \sum_q \omega_{nq} \log\frac{w_n}{w_r} \log\frac{w_q}{w_r}\right] + \\ &+ \textstyle\sum_n \sum_j \alpha_{nj} \log\frac{w_n}{w_r} \log y_j + u + v,\end{aligned} \tag{3}$$

where *Cost* is total bank costs; y_j represents the *jth* output, with j = 1,2,3; w_n is the cost of the *nth* input, with n = 1,2,3; α, β and ω are the parameters to be estimated; u is the inefficiency; v is the random error. Using a Translog, the linear homogeneity also requires standard symmetry ($\beta_{js} = \beta_{sj}$ and $\omega_{nq} = \omega_{qn}$) and linear restrictions of the cost (or profit) function ($\sum_n \omega_{nq} = 0$ and $\sum_n \alpha_{nj} = 0$). Finally, we assume that v_{it} is normally distributed with mean zero and u_{it} is distributed as a truncated normal. Again, v_{it} and u_{it} are independently and identically distributed:

$$v_{it} \sim iid\ \left(0,\ \ \sigma_v^2\right), \tag{4}$$

$$u_{it} \sim N^+\left(z'\eta,\ \ \sigma_u^2\right), \tag{5}$$

where $z'\eta$ is the linear predictor of inefficiency. The econometric specification of the inefficiency component is:

$$u_{it} = \eta_1 z_{ltd} + \eta_2 z_{pop} + \eta_3 z_{centre} + \eta_4 z_{south} + e_{it}, \tag{6}$$

where Z_{ltd} and Z_{pop} are two dummy variables equal to unity if the *i*th bank belongs to the group of Ltd or Popolari, respectively (the base group comprises the MCBs), whereas Z_{centre} and Z_{south} are equal to unity if the headquarter of the *i*th bank is in the centre or in the South of Italy (the base group is formed by banks located in the North of the country). These dummy variables guarantee that the efficiency scores are net of any geographical and institutional fixed effect. Moreover, e_{it} is the erratic component. Finally, efficiency is time-variant, ensuring a change in relative ranking among banks. In other words, this accommodates the case where an initially inefficient bank becomes more efficient over time. Regression was performed through the

[3] The LR test allows us to accept the translog functional form over the Cobb-Douglas at 1%.

Table 1. Banking frontiers in Italy. Translog estimates in 2006–2011

	Cost
β_0	–3.713***
β_1 (Loans)	0.729***
β_2 (Commission income)	–0.241***
β_3 (Securities)	0.442***
ω_1 (Labour cost/cost of deposits)	1.128***
ω_2 (Cost of capital/cost of deposits)	0.344***
β_{11}	0.092***
β_{12}	–0.100***
β_{13}	–0.086***
β_{22}	0.056***
β_{23}	–0.004
β_{33}	0.047***
ω_{11}	–0.025
ω_{12}	–0.095***
ω_{22}	0.122***
α_{11}	–0.060***
α_{12}	0.084***
α_{13}	–0.030***
α_{21}	0.068***
α_{22}	–0.065***
α_{23}	0.008
Z_{LtD}	0.092***
Z_{Pop}	0.157***
Z_{centre}	–0.127***
Z_{south}	0.032
σ^2	0.064***
$\gamma = \frac{\sigma_u^2}{\sigma^2}$	0.323***
Log-likelihood	229.414
LR test	47.814***
	(14.33)+

Source: Our elaborations on data from ABI.
Notes: Significance levels: *** = 0.01; ** = 0.001; * = 0.05; . = 0.1; no indication = 1; + 1% LR critical value as in Kodde and Palm (1986).

simultaneous estimation of Equations (3) and (6) and by using more than 3,700 bank-observations. Results are in Table 1.

Regarding the appropriateness of the stochastic model, the ratio of the variance of the inefficiency to the variance of the composite error (Gamma) is high, indicating that inefficiency significantly contributes to determine the distance from the frontier. This evidence is confirmed by the likelihood ratio test, which verifies the correct model specification of an SFA. The null hypothesis, H_0, of this test is that all the parameters in Equation (6) are equal to zero: if this hypothesis is accepted, then the OLS estimates will be consistent because the composite error comprises only randomness. LR is 47.814 and, therefore, H_0 is rejected at 1 per cent (Table 1).

Furthermore, after observing that the coefficients of the Translog frontier are almost all significant, it is important to underline that the estimation of Equation (6) yields positive signs for the dummy variables Z_{Ltd} and Z_{pop}, implying that the average level of efficiency is higher for MCBs than for Ltd and Popolari as in Ayadi et al. (2010), Girardone et al. (2004) and Dongili et al. (2008). Moving on to explain the geographical effect, banks with their main office in the Centre of Italy obtain lower inefficiency levels than banks of Northern Italy.

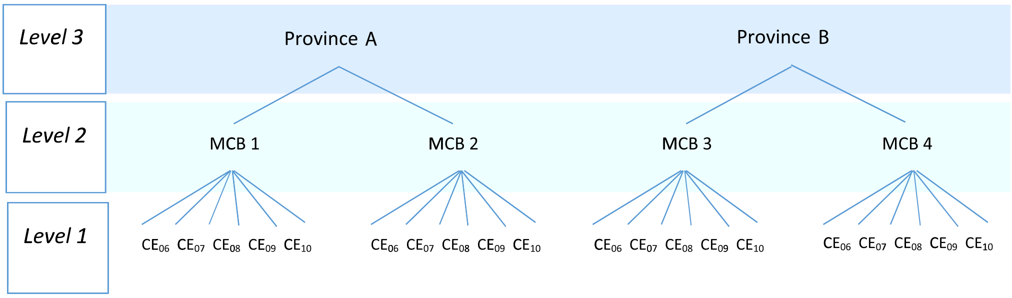

Fig. 1. The hierarchy for MCBs over 2006–2011

2.2 *The multilevel model*

The second step of the empirical setting aims at understanding how territorial conditions affect MCBs cost efficiency. To this end, we use MLMs because small banks are embedded in local market, thereby representing a typical example of hierarchy (Goldstein 2003). MLMs fit well this structure of data, yielding more reliable estimates than single equation model. Indeed, variables at any level of the hierarchy are not simply add-ons to the same single level equation, but are linked together in ways that make the simultaneous existence of distinct level-one and level-two equations explicit. This allows the evaluation of whether, and to what extent, local factors matter in determining individual performance. On the one hand, the role of contextual factors is detected by testing hypothesis operating at different levels; on the other hand, MLMs decompose heterogeneity in the output variable, providing a highly informative outcome on 'how much' contextual and individual factors contribute to small banks performance (Heck and Thomas 2000; Richter 2006; Bickel 2007; Rabe-Hesketh and Skrondal 2008). Furthermore, MLMs address: (*i*) the issue of error correlation across small banks, thereby controlling for spatial dependence, and correct the measurement of standard errors (Hox 2002)[4] and (*ii*) the ecological and atomistic fallacies (Maas and Hox 2004; Snijders and Berkhof 2008).

The MLM used in this paper has been specified in order to maximize the fitting to data. The analysis focuses on Italian MCBs which are observed over the 2006–2011 period. Then, as MCBs are embedded in local markets, the hierarchy is composed of three levels. The multiple measurements of individual cost efficiency at different time points represents the level 1 of the hierarchy. Punctual-time observations are nested within small banks, which are the level 2 of the model. Further, MCBs are nested in local markets, which represent the level 3 of the structure. This hierarchy is standard in MLMs literature for panel data (Steele 2008). Figure 1 describes the case.

Based on these considerations, the basic model is:

$$y_{tij} = \beta_{0ij} + e_{tij}, \tag{7}$$

[4] Small banks operating in a market are likely to be more similar than banks located in different areas, implying that residuals are not independent. This is addressed by multilevel models, which, controlling for territorial effects, ensure more efficient estimates than single equation models (Rabe-Hasketh and Skrondal 2008). Furthermore, single-level regressions yield an inflated significance of level-two coefficients because the diagnostics refers to the number of level-one observations instead of the number of higher-level units. Conversely, MLMs distinguish between sample size at the different levels of data aggregation. One consequence of failing to recognize hierarchical structures is that standard errors of OLS coefficients will increase the risk of type I errors (Hox 2002).

where y_{tij} is the vector, at time t, of the MCB cost efficiency of the i-th MCB (I = 1…Nj) operating in the j-th province, with t = 2006…2011, I = 1…Nj and j = 1…p. The erratic component $e_{tij} \sim N(0, \sigma_e)$ is meant to capture the randomness due to time.

In Equation (7), the parameter β_{0ij} varies across banks and provinces. It is made of a constant (γ_{000}) plus the random variations due to province level (u_{00j}) and bank level (u_{0ij}), i.e. $\beta_{0ij} = \gamma_{000} + u_{00j} + u_{0ij}$. Thus, Equation (7) becomes:

$$y_{tij} = \gamma_{000} + u_{00j} + u_{0ij} + e_{tij}. \tag{8}$$

γ_{000} is the overall efficiency mean, u_{0ij} is a random departure from the overall mean due to the i-*th* MCB, u_{00j} is a random departure from the overall mean due to the j*th* province. Equation (8) is named 'empty', in the sense that is a specification without explanatory variables. It allows the decomposition of the unobserved variance of y into three components, i.e. the variance of e_{tij} (σ_e^2), the so-called within-group variance, the variance of u_{00j} (σ_{uj}^2), also known as between-group variance for provinces and the variance of u_{0ij} (σ_{ui}^2), which is the between-group variance for MCB-level.

Since data follow a longitudinal structure, the MLM specification controls for time effect. Thus, time is an augmenting variable of Equation (8), which becomes:

$$y_{tij} = \gamma_{000} + u_{00j} + u_{0ij} + \delta_{.ij} Time + e_{tij}, \tag{9}$$

where $\delta_{.ij}$ is the slope associated with Time, varying across banks and provinces. In each level, it comprises a random component related to the departure from the common trend. When looking at MCB level, the term $\delta_{.ij}$ can be expressed as:

$$\delta_{.ij} = \delta_{.0j} + u_{.ij} \} \text{ level-two model} \tag{10}$$

Substituting Equation (10) in Equation (9) yields:

$$y_{tij} = \gamma_{000} + u_{00j} + u_{0ij} + \delta_{.0j} Time + u_{.ij} Time + e_{tij}. \tag{11}$$

Further, at the province level, the term $\delta_{.0j}$ of Equation (11) is:

$$\delta_{.0j} = \delta_{.00} + u_{.0j} \} \text{ level-three model} \tag{12}$$

Substituting Equation (12) in Equation (11) one gets the full mixed model:

$$y_{tij} = \gamma_{000} + u_{00j} + u_{0ij} + \delta_{.00} Time + u_{.0j} Time + u_{.ij} Time + e_{tij}. \tag{13}$$

Compared to Equation (9), Equation (13) includes the $u_{.ij}$ and $u_{.0j}$ terms, which are the departure from the common linear trend due to the i-*th* MCB and to the j-*th* province respectively.

Finally, when extending the model with variables at bank level (MCB_{tij}) and at province level (P_{tij}), the dependent variable can be predicted by:

$$y_{tij} = \gamma_{000} + \beta_1 MCB_{tij} + \beta_2 P_{t.j} + \delta_{.00} Time + u_{00j} + u_{0ij} + u_{.0j} Time + u_{.ij} Time + e_{tij}. \tag{14}$$

The econometric model (14) is composed of a deterministic part – $\gamma_{000} + \beta_1 MCB_{tij} + \beta_2 P_{t.j} + \delta_{.00} Time$ – which contains all the fixed coefficients – and by a stochastic component – which is represented by u-terms and e_{tij}. Besides e_{tij}, the stochastic part is the sum of two components: the $u_{00j}+u_{.0j}Time$ is the random part associated with level-three of the model, while $u_{0ij}+u_{.ij}Time$ relates to the level-two model.

Another advantage of MLMs is that they permit to measure the proportion of the response variance that lies at each hierarchical level. To this end, we refer to the intra-class correlation (ICC), which is calculated level-by-level and differ model-by-model. For instance, as far as the provinces are concerned, the ICC is given by the ratio of the variance at that level, σ^2_{ui}, to the total variance, that is:

$$ICC_j = \frac{\sigma^2_{uj}}{\sigma^2_{uj} + \sigma^2_{ui} + \sigma^2_e}. \tag{15}$$

Similarly, the ICCs for MCB and time level are, respectively:

$$ICC_i = \frac{\sigma^2_{ui}}{\sigma^2_{uj} + \sigma^2_{ui} + \sigma^2_e}; \tag{16}$$

$$ICC_t = \frac{\sigma^2_{e}}{\sigma^2_{uj} + \sigma^2_{ui} + \sigma^2_e}. \tag{17}$$

Of course, when considering the full mixed model (Equation (14)), the ICCs take into account the entire structure of variance. Regarding models with randomness in both intercepts and slopes, the ICC is computed by knowing that $\sigma^2_{uj} = \sigma^2_{uj}\text{intercept} + \sigma^2_{uj}\text{slope}$ and $\sigma^2_{ui} = \sigma^2_{ui}\text{intercept} + \sigma^2_{ui}\text{slope}$. At the opposite side, when estimating the empty model (Equation (8)), the variance is given by $\sigma^2_{uj} = \sigma^2_{uj}\text{intercept}$ and $\sigma^2_{ui} = \sigma^2_{ui}\text{intercept}$. In between these two extremes, there are other MLM specifications, depending on whether modeling the slopes randomness due to time.

Estimations of Equation (14) rely on standard assumptions on the error terms, such as homoscedasticity and the normality of the distribution. Moreover, for consistency of the estimates it is assumed that: (*i*) the independent variables at each level are uncorrelated with the random effects (error terms) on the other levels; (*ii*) the level-one independent variables are uncorrelated with the level-one error term. The same applies for level-two and level-three; and (*iii*) the error terms, among levels, are independent (van Landeghem et al. 2006; Maas and Hox 2004). Here, it is noteworthy to highlight that the complexity of the stochastic part of Equation (14) makes difficult to test the orthogonality assumptions, suggesting to read with care the results as they may be sensitive to endogeneity bias. In other words, Equation (14) might be viewed as a convenient way of summarizing statistical regularities among variables, suggesting that the estimates must be read as associations rather than causality.[5] However, we provide further evidence by applying the approach proposed by Mundlak (1978), which is a consistent solution of addressing the so-called level-2 endogeneity problem. It consists in adding the group mean of MCB variables as additional regressors. As proven by Baltagi (2001), the Wald test on these additional slopes can be used to verify the assumption of exogeneity of individual MCB variables. As Mundlak (1978) works well in a cross-sectional framework (see e.g., Rabe-Hesketh and Skrondal 2008; Snijders and Berkhof 2008; Grilli and

[5] An approach to handle the endogeneity issue is the fixed effect estimator. Nevertheless, it does not allow for any group-level covariate since these covariates would be perfectly collinear with the group variables, which explain the group-level variability. Therefore, fixed-effect estimator leads no scope for group-level observables. This explains why the random effect estimator is widely used in multilevel literature, although the difficulty of handling the conditional distribution introduces some risk of yielding biased inference (Grilli and Rampichini 2011).

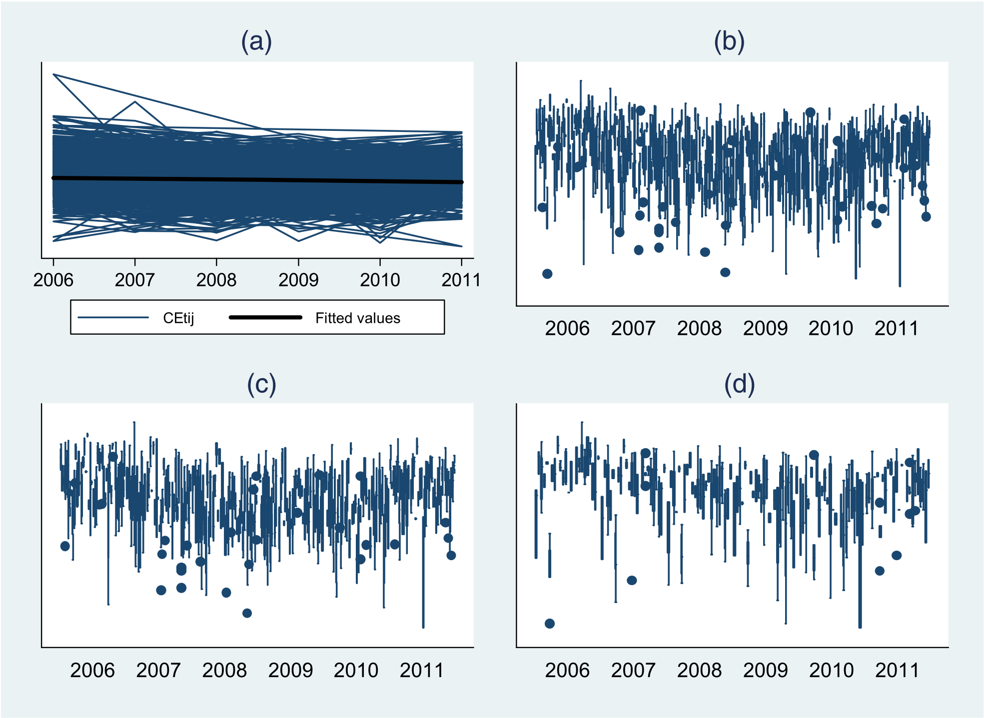

Fig. 2. MCB cost efficiency by time and province (2006–2011)

Rampichini 2011; Hanchane and Mostafa 2012; Aiello and Ricotta 2016), we perform some MLM regressions by considering a 2-level hierarchy with small banks at the first level and provinces at the second level. These auxiliary estimations are meant to be just a robustness check of the empirical evidence obtained when estimating the Equation (14).[6]

2.3 Data at bank level

Microdata are from the Italian Banking Association (ABI), which collects balance-sheets of about 97 per cent of Italian banks and of more than 400 MCBs per year. On average, MCBs are more than 63 per cent of the sample (the remaining are corporations (32%) and Popolari banks (6%)). It is noteworthy to point out that MCB size is, on average, 295 m euro, that is to say about thirty times smaller than the size of other banks (6,903 m euro). As far as the individual variables that will enter in our econometric setting are concerned, we find that MCB activities are weakly diversified: income diversification is 0.21, while MCB loan diversification is 0.32. MCB ability to transform deposits into loans is, on average, 1.51. Interestingly, the ratio equity/total assets is significantly low (0.018) (see footnote 6).

Furthermore, MCB cost efficiency is 0.80, thereby meaning that MCBs should reduce the inputs of 20 per cent offering the same banking services. The dynamics of efficiency in 2006–2011 is displayed in Figure 2 (Panel A). It is clear that there is a considerable inter-MCBs heterogeneity at the beginning year 2006 and a high variation over time. Figure 2 also plots the MCB cost efficiency by province and year. Panels B–D of Figure 2 indicate that the within and between group heterogeneity is high across all Italian provinces (panel B), in Northern (panel C)

[6] Results show that there is no evidence of level-2 endogeneity in cross-section regressions. They are provided as supplementary material at http://www.ecostat.unical.it/aiello/pubb/pubbl.htm.

or in Southern provinces (panel D). This representation of cost-efficiency further legitimate the use of MLM for longitudinal data, whose estimations provide a test of the variability in intercepts and growth terms – as depicted in panel A – and of the role of any hierarchical level of data in explaining individual outputs.

2.4 Data at provincial level

The estimation of Equation (14) requires a set of variables capturing the local market conditions. This paper refers to provinces (NUTS 3) as reference market of MCBs because the greater the proximity of MCBs to markets the more precise will be the investigation of the individual efficiency-environment nexus.

This said, here we document some characteristics of banking markets across 103 provinces. An important effect of the restructuring reform is the spatial diffusion of financial services. The number of bank branches by square kilometre is on average 0.0014 in 2006–2011, with considerable variation across provinces. An additional indicator is the ratio 'Bank Branches/Municipalities' per province, which is, on average, more than 5. Further evidence comes from market concentration. The Hirschman-Herfindahl (HH) index calculated using, by year, total bank assets per bank in every province is 0.368, falling in the range 0.229–0.593.[7] Finally, there has been a relevant increase of big banks participation in the periphery. The top-3 national banks owned 21 per cent of bank branches operating in every Italian province (see footnote 6).

Another issue concerns the transformation of deposits into loans. High values of this ratio mean that the banking sector is issuing more of its deposits in loans, which, in turn, means it releases more income. Over 2006–2011 the provincial ratio loans/deposits is on average 1.548. The highest value (3.046) is in Milan, whereas the lowest (0.729) refers to the province of Trieste. A related issue to offering funds is that loans are not always repaid. In Italy, non-performing loans are 6.38 per cent of total loans in 2006–2011, with a different incidence across provinces. Finally, there is also great heterogeneity when looking at the credit provided by banks: the loans-to-GDP ratio ranges from the highest value of Milan (3.454) to the lowest values (0.392) of Vibo Valentia. Analogous evidence emerges when restricting the computations to the 66 provinces included in the econometric analysis, whose summary is provided as supplementary material (see footnote 6).

We have learned that banking behaviour is extremely heterogeneous across provinces, further motivating the understanding of the nexus between local determinants and MCB performance.

3 Heterogeneity in MCB performance: the empty MLM and the time-effect

This section refers to the estimations obtained when considering different MLM specifications.[8] Column 1 of Table 2 refers to the random-intercept empty model in which the second level is

[7] Since total assets by the i*th* bank in every province *j* (*TAij*) are not freely available in Italy, in computing the HH index we follow Carbò Valverde et al. (2003) and consider this formula: $TA_{ij} = TA_i \times b_{ij}$, where TAi is the balance-sheet amount of total asset (*TA*) of the *i*th bank and bij is the proportion of branches of bank *i* in province *j* ($bij = BBij/BBj$).

[8] In running MLM regressions, the dependent variable – that is the MCBs cost efficiency – has been transformed using the following formula: $CE^{Trans} = ln[CE/(1\text{-}CE)]$. This is because I is never zero or unity, thereby making inappropriate the use of a Tobit model, which, on the contrary, performs well only if the upper and lower bounds come from non-observability (Maddala 1991; McDonald 2009).

Table 2. Explaining heterogeneity in cost efficiency of Italian MCBs (2006–2011). Results from the empty model and MLMs with intercept and slope time randomness

	Dep. variable: cost efficiency				
	No time effect	Time effect			
		Intercepts	Intercepts and II level slopes	Intercepts and III level slopes	Intercepts, II and III level slopes
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	1.469	1.525	1.531	1.595	1.595
	(42.82)	(41.35)	(40.92)	(36.26)	(36.26)
Time		−0.016	−0.016	−0.036	−0.036
		(−4.13)	(−4.03)	(−5.42)	(−5.42)
Random effects					
Variance					
Provinces (intercept)	0.0600	0.0599	0.0631	0.0943	0.0943
Provinces (slope)				0.0016	0.0016
MCBs (intercept)	0.0502	0.0503	0.0473	0.0518	0.0518
MCBs (slope)			0.0005		1.62E-25
Time random effect	0.1022	0.1013	0.0991	0.0918	0.0918
Total	0.2124	0.2115	0.2099	0.2396	0.2396
ICC					
Provinces	28.27%	28.31%	30.08%	40.05%	40.05%
MCBs	23.62%	23.80%	22.73%	21.63%	21.63%
Time	48.11%	47.89%	47.19%	38.32%	38.32%
LR test (p-value)	0.000	0.000	0.000	0.000	0.000
AIC	1960.09	1954.361	1953.77	1849.90	1851.90
Observations	2,334	2,334	2,334	2,334	2,334
N. of groups:					
MCB level	414	414	414	414	414
Province level	66	66	66	66	66

Source: Our elaborations on data from ABI and Bank of Italy.
Notes: z-value are in brackets. LR test is for the choice between ML and linear regression (H0). AIC = -2(lnL-k), where lnL is the log-likelihood value and k is the number of estimated parameters.

formed by 414 MCBs and the third level by 66 provinces (the latter depends on the spatial distribution MCBs, which are not located in every province). There are 2,334 observations. In column 2, time enters into the deterministic part of the model to depict growth. Columns 3–5 refer to the estimations adding randomness in the second and/or third level slopes. The AIC statistics is used to choose the best performing regression.

The first outcome to be discussed is the likelihood-ratio test, which compares the MLM with OLS regression. If the null hypothesis is true, OLS can be used instead of a variance-components model. The results support the use of multilevel methodology and indicate that the intercept should be considered as a group-by-group variant coefficient. This holds for each model, thereby supporting the conclusion that MCB behaviour follows a hierarchical structure. It is also remarkable to highlight that the coefficient of time is always negative, indicating that during the years of the Lehman crisis the MCBs register significant losses in efficiency. While the nexus between crisis and small banks efficiency deserves to be investigated better, as done by Barra et al. (2016), it is interesting to point out that our evidence is in line with the results provided by Tabak et al. (2013), which focus on US savings banks over the period 2001–2009.

The province-specific unobservable factors capture 28.27 per cent of the MCB heterogeneity in efficiency, while the remainder is explained by MCBs (23.62%) and time (48.11%; Table 2, column 1). Moving from one model to another, the portion of variance explained by each level varies a lot. For instance, the ICC index of the provinces is 40.05 per cent when time enters as source of randomness of provincial intercepts and slopes (models 4 and 5), while the role of unaccounted MCB factors remains broadly the same, falling in the range 21.63 per cent of models 4 and 5 and 23.80 per cent of model 2.[9] The role of unobservable-province factors is confirmed in cross-section regressions (see footnote 6).

4 The full multilevel model

This section presents the results obtained when the MLM is augmented through a set of individual and provincial variables.[10] Starting from a specification in which time is treated as a source of randomness at any level, the aim of this section is twofold. First, the evidence of Section 3 indicates that the proportion of efficiency variability explained by unobservable specific effect is high. Therefore, after considering a set of efficiency determinants, we expect to grasp part of this black-box of unaccounted individual heterogeneity. Second, our main interest remains in understanding the role of location, net of the role exerted by observables.

While results of Table 3 refer to MLM regressions for the entire sample of MCB and provinces, Table 4 displays the estimates obtained when performing a sensitivity analysis. Table 3 follows the presentation of Table 2, whereas Table 4 uses the full specification of the mixed-model (that is to say the one with the lowest AIC of Table 3). The sensitivity analysis of Table 4 is performed by splitting the sample according to: (*i*) bank location (northern and southern provinces in columns 1 and 2, respectively); (*ii*) MCB efficiency distribution (1st quartile in column 3, 2nd and 3rd quartiles in column 4 and 4th quartile in column 5); and (*iii*) MCB size distribution in columns 6–8 (dividing the sample by using three areas of size distribution, as for efficiency distribution).[11]

First of all, it is meaningful to highlight that the multilevel approach allows the possibility of calculating the coefficient of determination and obtaining, at any level of the hierarchy, a proportional reduction in the estimated total residual variance when moving from the ‘empty model’ to an extended specification of the model (Rabe-Hesketh and Skrondal 2008). The overall fit of Model 5 is 31.69 per cent and is the result of a different contribution at each level: while individual MCB variables absorb 9.8 per cent of the variance estimated at the 2-level of the hierarchy, the R^2 at provincial-level is 20 per cent. Interestingly, the set of observables at the provincial level used in Table 3 contributes to explain always more than 20 per cent of efficiency variability that we observe at that level, with a peak of 40 per cent in Model 2. Table 4 points out that the goodness of fit differs a lot according to the sub-sample of MCB we refer to. Finally, it is noteworthy to say that the observables do not affect the relative

[9] The AIC is low in models 4 and 5 (about 1850) and high (from 1953 to 1960) in models 1–3, suggesting that the best fitting refer to MLMs with time randomness in both MCBs/provincial intercepts and slopes.

[10] In the extended model (Equation (14)), the following individual-bank level regressors are included: a proxy for the bank ‘Size’, which is the logarithm of Total Assets; ‘Loans Diversification’, calculated as (1-Loans/Total Assets); ‘Income Diversification’ as [Income Commissions/(Income Commissions + Net Interests Income)]; ‘Equity/Total Assets’, as indicator of capital adequacy. As far as the province level is concerned, we use ‘Market Concentration’, which is measured by the Hirschman-Herfindahl index calculated using, by year, the total assets per bank; ‘Branch Density’ expressed as the number of branches per square kilometres; ‘Demand Density’ calculated by the ratio between total deposits and square kilometres; ‘Market Risk’, measured as Bad Loans/Total Loans and, finally, ‘Local Economic Development’ measured by the provincial GDP *per capita*.

[11] We replicate Tables 3 and 4 by addressing the issue of missing values in MLM for longitudinal data (Kwok et al. 2008; Little and Rubin 2002). To this end, we employ the Stata command ‘mi impute’ (Royston 2009). There are 221 missing values over the 2006–2011 period, corresponding to less than 10 per cent of the sample. Including missing values does not affect the results (findings with missing values are available upon request).

Table 3. Explaining heterogeneity in cost efficiency of Italian MCBs (2006–2011). Evidence from MLMs with bank and provincial-specific variables

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	3.183***	3.144***	3.272***	3.172***	3.240***
	(15.99)	(15.71)	(15.28)	(15.74)	(15.63)
Fixed-effects					
Time		−0.010	−0.0127*	−0.0447***	−0.0435***
		(−1.75)	(−2.20)	(−5.50)	(−5.37)
MCBs level					
Size	−0.198***	−0.193***	−0.206***	−0.190***	−0.197***
	(−13.03)	(−12.55)	(−12.41)	(−12.36)	(−12.40)
Loans diversification	0.159	0.136	0.124	0.00939	0.0108
	(1.59)	(1.34)	(1.19)	(0.09)	(0.11)
Income diversification	3.691***	3.643***	3.680***	3.395***	3.442***
	(33.31)	(32.02)	(32.63)	(29.66)	(30.20)
Equity/total assets	−3.654***	−3.569***	−3.799***	−3.453***	−3.569***
	(−12.96)	(−12.53)	(−13.43)	(−12.27)	(−12.75)
Province level					
Market concentration	0.200**	0.241***	0.229***	0.178***	0.179***
	(5.03)	(5.20)	(5.04)	(3.66)	(3.76)
Branch density	−121.84***	−129.9***	−128.4***	−168.0***	−163.8***
	(−4.07)	(−4.31)	(−4.13)	(−4.37)	(−4.30)
Demand density	0.002**	0.003***	0.003***	0.004***	0.004***
	(3.24)	(3.61)	(3.50)	(3.91)	(3.85)
Market risk	−0.220	0.221	0.745	2.275***	2.258***
	(−0.73)	(0.56)	(1.85)	(4.90)	(4.93)
Local econ. development	−0.018**	−0.019**	−0.015*	−0.002	−0.002
	(−2.40)	(−2.59)	(−2.07)	(−0.27)	(−0.29)
Random-effects					
Variance					
Provinces (intercept)	0.0371	0.0357	0.0373	0.0456	0.0466
Provinces (slope)				0.0015	0.0014
MCBs (intercept)	0.0435	0.0432	0.0409	0.0430	0.0446
MCBs (slope)			0.0014		0.0006
Time random effect	0.0608	0.0686	0.0537	0.0545	0.0518
Total	0.1414	0.1475	0.1333	0.1446	0.1451
ICC					
Provinces	26.23%	24.22%	27.98%	32.57%	33.08%
MCBs	30.76%	29.29%	31.72%	29.74%	31.19%
Time	43.01%	46.49%	40.30%	37.68%	35.73%
R^2	0.3368	0.3053	0.3721	0.3189	0.3169
R2 level 3	0.2761	0.4049	0.3786	0.2153	0.2006
R2 level 2	0.1330	0.1385	0.1570	0.1423	0.0980
R2 level 1	0.0469	0.3286	0.4740	0.4665	0.4927
LR test (p value)	0.000	0.000	0.000	0.000	0.000
Log restricted-lik	−435.01	−437.77	−416.01	−372.17	−365.54
AIC	896.03	903.53	862.03	774.35	763.07
Number of groups					
Provinces	66	66	66	66	66
MBCs	414	414	414	414	414
Number of observations	2334	2334	2334	2334	2334

Source: Our elaborations on data from ABI and Bank of Italy.
Notes: Significance levels: *** = 0.01; ** = 0.001; * = 0.05; . = 0.1; no indication = 1.

values of ICCs. Data of Table 3 show that the proportion of MCB heterogeneity in efficiency explained by location effect remains high, varying from 24.22 per cent (Model 2) to 33.08 per cent (Model 5).

Table 4. Explaining heterogeneity in cost efficiency of Italian MCBs (2006–2011). Evidence from MLMs with bank and provincial-specific variables. A sensitivity analysis

	Banks location		Cost efficiency distribution (by quartile)			Size distribution (by quartile)		
	North	South	1st	2nd and 3rd	4th	1st	2nd and 3rd	4th
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	2.512***	4.442***	4.634***	1.419**	2.012***	0.699**	1.917***	2.852***
	(10.95)	(8.95)	(5.84)	(2.90)	(3.30)	(3.13)	(16.71)	(15.78)
Fixed-effects								
Time	–0.0298***	–0.0891***	–0.0658***	–0.0369***	–0.00952	0.0115	–0.00152	–0.0416***
	(–3.39)	(–5.26)	(–3.93)	(–3.61)	(–0.71)	(1.13)	(–0.33)	(–5.84)
MCBs level								
Size	–0.159***	–0.274***	–0.294***	–0.0733	–0.120**	–0.0189	–0.059***	–0.083***
	(–9.40)	(–6.71)	(–4.12)	(–1.86)	(–2.62)	(–1.13)	(–6.88)	(–5.69)
Loans diversification	0.330**	–0.704***	–0.487*	0.552***	0.247	0.158	0.158*	–0.101
	(2.70)	(–3.59)	(–2.47)	(3.75)	(1.12)	(1.20)	(2.36)	(–1.09)
Income diversification	3.438***	3.528***	3.678***	3.743***	3.282***	1.589***	1.058***	1.049***
	(24.97)	(16.27)	(14.71)	(22.9)	(17.16)	(8.05)	(10.18)	(7.83)
Equity/total assets	–1.661***	–4.376***	–4.067***	–1.02	0.345	–1.492***	–1.061***	0.151
	(–3.38)	(–10.92)	(–8.48)	(–0.62)	(0.16)	(–4.70)	(–4.48)	(0.57)
Province level								
Market concentration	0.178***	0.302*	0.329*	0.271***	–0.049	–0.001	0.054	0.196*
	(3.57)	(1.97)	(2.33)	(4.58)	(–0.73)	(–0.02)	(1.45)	(2.40)
Branch density	–114.8**	–57.66	–137.4	–202.8***	–48.32	25.86 –0.9	–50.10**	–72.22*
	(–3.04)	(–0.25)	(–1.31)	(–3.83)	(–1.05)		(–2.65)	(–2.13)
Demand density	0.003**	0.017**	0.004	0.005**	0.001	–0.001	0.001*	0.002
	(2.66)	(2.82)	(1.08)	(3.16)	(1.14)	(–0.78)	(2.35)	(1.86)
Market risk	2.697***	1.630*	1.917*	1.696**	2.096*	0.685	0.368	0.769*
	(4.13)	(2.12)	(2.20)	(2.80)	(2.09)	(1.12)	(1.22)	(1.98)
Local econ. develop.	0.009	–0.014	–0.031	0.011	0.001	0.008	0.002	–0.019*
	(1.00)	(–1.09)	(–1.70)	(1.09)	(0.01)	(0.69)	(0.38)	(–1.96)

(Continues)

Table 4. (Continued)

	Banks location		Cost efficiency distribution (by quartile)			Size distribution (by quartile)		
	North	South	1st	2nd and 3rd	4th	1st	2nd and 3rd	4th
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Random-effects								
Variance								
Provinces (intercept)	0.0320	0.0457	0.0025	0.0035	0.0040	0.0456	0.0506	0.0657
Provinces (slope)	0.0010	0.0015	0.0003	0.00006	0.00006	0.0010	0.0014	0.0020
MCBs (intercept)	0.0370	0.0472	0.0130	0.0051	0.0065	0.0323	0.0479	0.0246
MCBs (slope)	0.0003	0.0015	6.21E-23	0.00010	2.95E-25	0.0009	0.0005	0.0006
Time random effect	0.0520	0.0478	0.0400	0.0189	0.0249	0.0871	0.0383	0.0331
Total	0.1223	0.1437	0.0558	0.0277	0.0355	0.1669	0.1387	0.1260
ICC								
Provinces	26.98%	32.85%	5.02%	12.86%	11.44%	27.94%	37.49%	53.73%
MCBs	30.50%	33.89%	23.30%	18.79%	18.33%	19.87%	34.90%	19.99%
Time	42.52%	33.26%	71.68%	68.35%	70.22%	52.19%	27.61%	26.27%
LR test (p value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log restricted-lik	–239.50	–95.34	15.81	472.82	158.78	–218.13	–78.95	–7.11
AIC	510.99	222.69	0.39	–913.63	–285.56	468.25	189.90	46.22
Number of groups								
Provinces	42	24	57	65	58	46	60	42
MBCs	312	102	222	380	232	122	241	119
Number of observations	1784	550	584	1166	584	557	1181	596

Source: Our elaborations on data from ABI and Bank of Italy.
Notes: Significance levels: *** = 0.01; ** = 0.001; * = 0.05; . = 0.1; no indication = 1.

Results presentation begins with the market concentration, which enters into regressions to gauge the effect of the consolidation process observed in Italian banking.[12] This is an issue also addressed by Dongili et al. (2008), Turati (2008) and Casu and Girardone (2009). The uncertainty of the outcome is due to the fact that, on the one hand, the consolidation increases individual size with an expected increase in efficiency levels. On the other hand, high concentration can cause an increase in banks market power and, therefore, a reduction of efficiency (Turati 2008). From our regressions, it emerges a positive correlation between banking concentration and efficiency, indicating that MCBs operating in provinces with more concentrated banking markets attain higher cost efficiency. This evidence is consistent with the efficient structure hypothesis (Berger 1995; Goldberg and Rai 1996) and holds whatever the sample (Table 4). Phrased differently, in local concentrated banking markets, each MCB is forced to be efficient, with the result that in provinces with high market concentration there would be many efficient MCBs. Arguments that increased market concentration leads to efficiency improvements are in Casu and Girardone (2009) and Demirgüç-Kunt and Levine (2001).

Regarding the accessibility to banking services, it is reasonable to argue that banking efficiency in the local market is affected by the branching that has occurred in Italy over the last 20 years. Here, the hypothesis is if the higher the number of branches the less MCB efficiency. This is why a large number of branches exerts negative effects on efficiency because the operating costs to provide banking services increase. Moreover, local markets with many branches would suffer from over dimensioning which acts against efficiency. However, the hypothesis may be different as big banks participation in small markets can be positive due to the increases in capital brought by big banks, the expertise brought in, risk management and increases in competition (Delis and Papanikolaou 2009; Hannan and Prager 2009). The estimated parameter of branch density is always negative (Tables 3 and 4), indicating an inverse association between individual efficiency and the huge branch opening process occurred throughout the country. This evidence might be due to the fact that the presence of many branches forces MCBs to invest increasing amount of resources for serving more customers, whose expectations is to increase the benefits from loans and deposits at better advantageous conditions than those applied by other bank branches. Other things being fixed, the increased number of bank branches in local markets and the MCB strategies act against their costs.

Another issue regards the demand effect. The hypothesis is that MCBs operating in markets with a lower density of demand face higher expenses to find customers asking for banking services (Fries and Taci 2005). Thus, the greater the density of demand, the higher will be the banking efficiency levels. We find that efficiency and demand density are positively related (Table 3). This supports the hypothesis according to which MCBs working in provinces with high levels of deposits face, *ceteris paribus*, lower costs in mobilizing deposits and making loans. Interesting, the positive link remains positive only in the middle of cost efficiency and size distributions, while the evidence is inconclusive in the tails (Table 4).

In order to gauge the effects of market risk on individual efficiency, the variable Market Risk enters into MLM equation. It is expressed as the non-performing loans to total loans. Here, the question to be understood is whether MCBs gain or lose from operating in local markets with poor credit quality. It is likely that MCBs operating in risky markets are exposed

[12] As the main scope of the paper is the evaluation of spatial effects on MCB performance, we restrict the discussion regarding the role played by individual variables. In brief, we find that MCB cost efficiency tends to decrease with size (Pilloff 1996). Furthermore, MCBs gain from diversifying their business other than intermediation within the income statement (income diversification). With regard to diversification, the evidence is mixed. In the five MLM specifications used in Table 3, the estimated parameter is not significant, inducing no interpretation. However, this average effect hides some specificities that the sensitivity analysis helps to capture. Finally, the impact of equity/total assets is negative, suggesting that an increased amount of capital act as a binding restriction and thus is perceived by MCBs as a cost (Berger and Mester 1997; Acharya and Viswanathan 2011).

to potential efficiency losses caused by higher costs of screening and monitoring activities. Results differ according to the MLM specification. If the time-effect introduces disturbances in slopes (model 5 of Table 3), then the statistical link between MCB cost efficiency and local markets riskiness will be positive. This finding is driven by banks lying in the upper tail of size distribution, while it is robust to efficiency distribution and MCB location (Table 4). Overall, this might be due to the fact that MCBs save costs from the nature of the relationships with their customers. These relationships protect MCBs from market riskiness, as they are long-dated and based on the use of soft information.

Finally, the level of economic development is an important factor of bank performances, because it affects numerous aspects related to the demand and supply of banking services (mainly deposits and loans). It is expected that provinces with higher income *per capita* are assumed to have a banking system operating in a mature environment and resulting in more competitive interest rates and profit margins. They can also exert more financial activity. Results are mixed and not robust, given that a significant link has been found only in models 2 and 3 of Table 3. In contrast with expectations, our evidence may be affected by the fact that operating in rich areas implies higher operating and financial costs that MCBs would incur in offering services (Dietsch and Lozano-Vivas 2000).

5 Conclusions

This study shows that heterogeneity in MCB efficiency is explained by unobserved and observed spatial factors. On this perspective, several points stand out. Estimations from the empty model prove that provinces explain about one-third of the unaccounted heterogeneity in efficiency, while this proportion is one-fifth in the most extended multilevel model. Furthermore, the analysis emphasizes the positive link between efficiency and concentration in local markets. Other robust insights come from the demand density and the branch density, which positively and negatively affect efficiency respectively. Importantly, these results are robust to any MLM specification and across different samples of banks. As Tabak et al. (2013) argue for US saving banks, the conclusion we can confidentially draw is that geography matters a lot in determining Italian MCB efficiency.

While the study is not centred on evaluation, some policy considerations follow from these results. Indeed, the finding that high market concentration is positively linked to MCB efficiency could be considered as an implication of reforms carried out over the last 15 years. In this sense, a virtuous circle seems to be at work: market concentration in the periphery makes MCBs in those markets more efficient and then viable. This might be seen as a result of big banks action in the periphery: they gain from geographic expansion (Berger and DeYoung 2001; Deng and Elyasiani 2008) and then force a recovery of small banks efficiency. This evidence, in line with the intentions of the regulator as the scope to maintain market efficiency is an expected result of market consolidation. At the same time, MCB viability preserves the small market to be served. However, the negative effect of branching on MCB efficiency acts against the full effectiveness of reforms, as the impressive branch opening is seen as a threat for efficiency.

A number of extensions to this paper could be made. For instance, future work could use MLM for longitudinal data to estimate cross-country bank efficiency with the aim to compare the MLM evidence with the results from single equation model. An analysis on EU should induce important implications for policy makers because a homogeneous regulation in banking across EU members does not fit all. Another avenue for future research would combine multilevel models and spatial econometrics in a longitudinal framework, similarly to what Corrado and Fingleton (2012) propose for cross-sectional data. Finally, something other than size, diversification and capital structure influences MCB efficiency. While this might be seen as a caveat of this paper, it leaves room for future research with the aim of refining the measurement issues relating to other bank level aspects, such as management competence and organizational practices. Analysing these issues in greater depth could minimize the ‘sizable’ and ‘unobservable’ black box of small banks’ behaviour.

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Resumen. Los bancos pequeños están arraigados en mercados pequeños y, por lo tanto, se benefician de la proximidad a sus clientes. Con referencia al enfoque multinivel, este artículo evalúa el grado en que el desempeño de los bancos cooperativos mutualistas italianos está determinado por características geográficas e individuales. El efecto de los mercados locales explica el 28,27 por ciento de la heterogeneidad bancaria en el modelo multinivel vacío y el 33 por ciento en el modelo más amplio. Además, se encontró que la eficiencia aumenta con la concentración del mercado y la densidad de la demanda, pero disminuye con las sucursales en los mercados locales.

抄録:小規模銀行(small bank)は小規模のマーケットに入り込んでおり、顧客との近接性から恩恵を得ている。本稿では、マルチレベルアプローチを参照して、イタリアの相互扶助の協同組合銀行(mutual co-operative bank)の業績が、地理学的特色と銀行別の特色によって、どの程度決定されるのかを評価する。現地のマーケットの効果は、銀行の異質性が、空のマルチレベルモデルでは27-28%、最も拡張したモデルでは33%となることを示している。また、マーケットの規模と需要密度とともに効率は上がるが、地域のマーケットが事業拡大すると効率は下がることも認められた。