Received: 22 July 2021 | Revised: 9 January 2022 | Accepted: 16 February 2022

DOI: 10.1111/pirs.12669

FULL ARTICLE

Spatial dependence in the technical efficiency of local banks

Carmelo Algeri[1] | Luc Anselin[2] | Antonio Fabio Forgione[1] | Carlo Migliardo[1]

[1]Department of Economics, University of Messina, Via dei Verdi, 75, Messina, 98122, Italy

[2]Center for Spatial Data Science, University of Chicago, Chicago, IL, 60637, USA

Correspondence
Antonio Fabio Forgione, Department of Economics, University of Messina, Via dei Verdi, 75, Messina 98122, Italy.
Email: fforgione@unime.it

[Correction added on 16 May 2022, after first online publication: CRUI funding statement has been added.]

Abstract

Cooperative banks primarily compete with one another because they target niche markets that large banks typically ignore. The current study shows that in this competitive environment, the connection between financial intermediaries affects the operational efficiency of small banks. The findings indicate that the capitalization, diversification strategies, funding costs, liquidity, credit quality, and risk of bank neighbors have spillover effects on technical efficiency. Thus, bank networks trigger a cascading effect that demands the attention of bank stakeholders.

KEYWORDS
bank efficiency, DEA, spatial econometrics, spillover effects, two-stage bootstrap approach

JEL CLASSIFICATION
C24, C31, D24, G21, P13

1 | INTRODUCTION

The extensive use of the relationship lending procedure in loan issuance offers small banks a market edge over other banks, particularly when dealing with small and micro enterprises and household customers (e.g., Hauswald & Marquez, 2003; Schenone, 2010; Yosano & Nakaoka, 2019). Furthermore, small banks benefit from their customer relationships to collect a set of soft information (Agarwal et al., 2018; Baas & Schrooten, 2006; D'Aurizio et al., 2015; Ergungor & Moulton, 2014; Garcia-Appendini, 2011; Petersen, 2004) and to process private and inherently

All authors contributed equally.

qualitative information (see, among others, Cassar et al., 2015; Liberti, 2018). In comparison, larger banks, having a typically stronger hierarchy and greater distance between information collectors and decision-makers, tend to implement credit rationing policies toward opaque borrowers (Liberti & Petersen, 2019). Indeed, soft information regarding this kind of customer can be only extrapolated from personal interactions and, even when it is collected, it is challenging to transmit such information to the highest level of management (Agarwal et al., 2012; Berger & Udell, 1995; Stein, 2003). Moreover, large banks that adopt relationship lending practices must wear the additional costs of establishing adequate internal controls (Cerqueiro et al., 2009).

According to one stream of literature, small banks' proximity to their consumers may be an additional source of competitive advantage, because the financial burden borne by creditors and financial institutions rises as the distance from the bank's office increases (Almazan, 2002; Chiappori et al., 1995; Gehrig, 1998; Sussman & Zeira, 1995).

Once the credit relationship has been established, banks maintain advantages because they have acquired soft, non-transferable information on "opaque firms" (Elsas, 2005; Hasan et al., 2021; Ongena & Smith, 2001; Petersen & Rajan, 1994). From this perspective, local banks are advantaged over large and hierarchical banks in the credit market for small enterprises and households (Berger et al., 2005, 2017; Berger & Udell, 2002; Degl'Innocenti et al., 2018; Hasan et al., 2017; Kysucky & Norden, 2015; Liberti & Mian, 2008; Stein, 2002). In summary, local banks enjoy location-based cost advantages in lending to small customers and, thanks to the relationship lending technique, can achieve market power in niche markets with respect to large intermediaries (Coccorese & Santucci, 2019).

Against this background, small banks can dominate a market segment and achieve a monopolistic competition condition that can impair their Technical Efficiency (TE). Conversely, a cluster of close small banks can trigger market discipline and in turn improve banks' operational efficiency. Despite the awareness that local banks enjoy possible monopolistic rents because of their local roots, almost no research has been conducted to determine whether the efficiency of these banks is affected by spatial interdependence.

Accordingly, this article draws attention to the efficiency externalities induced by the financial characteristics of neighboring banks. For example, it is reasonable to infer that cooperative banks face stiff competition in the capital funding market, as bank regulation restricts the channels through which cooperative banks can raise capital. This implies that cooperative banks make an effort to attract shareholders from other mutual banks. As a result, if a direct competitor's risk-adjusted capitalization is higher, other cooperative banks may adopt a similar equity structure. Alternatively, a neighboring bank may offset a better capitalized bank's competitive advantage by providing additional services at a lower price, which reduces both cost and production efficiency.

Similarly, geographic efficiency effects occur as a result of income or funding diversification strategies. On one hand, neighboring banks that use unconventional funding sources gain a competitive edge over other banks, which suffer efficiency losses as a result. However, this scheme can hold for large banks, which can exploit their economies of scale and capability endowments to pursue diversification strategies that increase banks' productivity (Wu et al., 2020; Iosifidi et al., 2021). Equally, significant revenue generated by traditional bank activity from nearby banks may indicate that the competitive advantages of close rival banks are eroding, because small banks contend for the same lending market. On the other hand, in a homogeneous market segment where banks provide comparable services, an increase in a bank's funding rate induces banks in the same cluster to pursue a similar strategy or to reorganize the bank services to avoid losing market share. As a result, operational cost efficiency would suffer. In this regard, small banks that focus only on core banking activities avoid incurring the inefficient management of alternative funding and interest-bearing assets (Bernini & Brighi, 2018; McKee & Kagan, 2016; Van Cuong et al., 2020).

Finally, bank risk can have negative externality effects on banks' TE across a network of similar banks in the same geographic area. Specifically, efficiency can be harmed by increasing loan risk exposure, which results in higher screening and monitoring costs (Berger & DeYoung, 1997; Ding & Sickles, 2019), depleting nearby cooperative banks' confidence. Similar inefficiencies are caused by liquidity risk (Altunbas et al., 2007; Fernandes et al., 2018).

Despite the potential spillover effects of inefficiency, very few studies have examined the spatial efficiency effect in the banking industry. In this regard, a novel strand of the literature examines the spatial dependence of capital risk-adjusted measures and risk profiles (Ding & Sickles, 2019), as well as income diversification strategies

(Glass & Kenjegalieva, 2019; Glass et al., 2020). On a large extent, Tabak et al. (2013) provide evidence that location is a key factor in determining a bank's efficiency to a large extent. According to Burgstaller (2020), banks that are positioned farther away from their closest competitors are less efficient due to a lack of competition. Conversely, although Zhao et al. (2020) show the presence of geographical spillover effects, as neighboring contiguous banks show similar levels of efficiency and the regional market environment has an effect on the performance of Chinese urban commercial banks, the authors do not find significant relationships of the spatial lag of independent variables.

In general, the idea of co-movements in the efficiency scores of neighboring small banks should be strengthened in light of the bank financial statement profiles discussed above. In detail, the present study aims to provide further evidence of spatial dependence in the operational efficiency of small Italian cooperative banks (Credit Cooperative Banks, CCBs).[1] Furthermore, we apply a robust two-step methodology that first estimates the TE score via a nonparametric frontier technique and then regresses this score for a large group of explanatory covariates and spatial terms. The second step involves the application of Simar and Wilson's (2007) method of estimation with spatial variables; unlike other methodologies, this technique allows for the control of the assumption of the separability condition and the inclusion of a large set of bank efficiency determinants (e.g., Skevas & Grashuis, 2020).

In addition to the standard environmental variables that influence a bank's efficiency score, our empirical model incorporates their spatial lags to account for spillover effects: specifically, how the corporate profiles of nearby CCBs influence the i_{th} bank's efficiency, and vice versa.

Our main assumption is that CCBs experience competitive pressure from other CCBs because their relationship lending practices create niche markets in which large banks struggle to compete. Therefore, market discipline is more effective in the presence of other small banks as the main competitors. This effect needs to be explored via a methodology that allows for the control of the many bank characteristics that affect the performance score.

The findings indicate the existence of regional spatial externalities in the banks' operational efficiency score across all the estimated empirical models. Indeed, the spatial lagged explanatory factors are shown to be key drivers of the TE of local banks.

This article proceeds as follows. Section 2 overviews the literature. Section 3 describes the methodology. Section 4 introduces the data used in the specifications. The spatial dependence test results and the estimates of truncated bootstrap regression are reported in Section 5. Section 6 reports on the robustness check of the estimates using an alternative methodology to estimate the TE. Section 7 provides some concluding remarks.

2 | LITERATURE REVIEW

The determinants of bank efficiency are one of the top five themes in bank performance analysis (Ahmad et al., 2020). The vast literature is based on either parametric or nonparametric techniques (for reviews, see Ahmad et al., 2020; Aiello & Bonanno, 2018b; Bhatia et al., 2018), but few studies have investigated the role of spatial spillovers within this framework.

A novel body of research examines spatial effects on bank efficiency based on the stochastic frontier analysis (SFA) methodology. More specifically, Tabak et al. (2013) use a geographically weighted stochastic frontier model in a panel data framework to estimate the effect of unobserved environmental determinants of local US bank efficiency. This approach allows for more precise estimates, as it compares banks competing in the same local market and facing similar economic shocks. Their empirical strategy is based on a spatial distance weight matrix, the elements of which are defined by the Euclidean distance connections among spatial units within a specified bandwidth. However, their empirical model focuses only on the impact of the spatial frontier on the estimated coefficients, and overlooks the treatment of the presence of spatial effects within the environmental determinants. Interestingly, the study of Tabak et al. (2013) shows the shortcomings of nonspatial efficiency studies, particularly when applied to a

[1]CCBs operate in a limited area, apply the one-member-one-vote principle, are not allowed to distribute earnings, and mainly have their members as customers. In brief, CCBs tend to operate in a specific market and grant credit using relationship lending procedures.

financial intermediary operating exclusively in a local market. Aiello and Bonanno (2018a) follow an empirical strategy focused on multilevel models rather than spatial approaches to investigate the influence of bank clusters on the efficiency of small banks. Their results show that provincial-level characteristics, as well as market concentration, have an impact on the efficiency of Italian banks. Ding and Sickles (2019) models the spillover effect in the efficiency of US banks by introducing a spatial lag error term resulting in the product of residual vector and spatial weighting matrix (SWM). This specification captures the unobserved network heterogeneity. The adopted SWM is a binary contiguity weighting matrix in which the elements take the value of one if two banks are in the same network—namely, the j_{th} bank is one of the ten closest banks to i of at least ten banks—and zero otherwise. The results show a significant positive network multiplier effect in terms of Tier 1 ratio, NPL, and cost-efficiency performance. Therefore, a shock to a bank's nonperforming loans, or Tier 1, or cost-efficiency levels cause a positive aggregate shift in the bank network's impaired loans, or bank risk-weighted capital and cost efficiency, respectively. Glass and Kenjegalieva (2019) develop a novel methodology for decomposing total factor productivity in a spatial context and carry out an empirical application of the spatial stochastic frontier using bank-level data. The authors assume that spatial interactions between banks will diminish as their distance increases, and thus use a spatial matrix based on the inverse distance between the headquarters of large US banks. The effect of direct and indirect allocative efficiency spillovers is captured in their spatial Durbin specification, which integrates the regressors' spatial lags. Glass et al. (2020) show a geographical return to scale in medium and large US banks through a spatial cost function analysis, in which the spatial lags of the dependent and independent variables are related to the bank's indirect elasticity of output. Zhao et al. (2020) apply a spatial Durbin production frontier analysis to urban commercial Chinese banks, considering both spatial dependence and regional market environment effects on bank efficiency. Their translog function includes the spatial lags of the dependent and independent variables. Zhao et al. (2020) use a spatial contiguity matrix in which the spatial units are represented by geographical areas and contiguity indicates the sharing of common boundaries. A distinctive feature of the analysis of Tabak et al. (2013) is that it does not use spatial weights at bank level; that is, there is no SWM. Instead, the matrix ($n \times n$) has a row for each region, with the elements taking the value of 1 if the region borders another and 0 otherwise. With this approach they discovered that loans provided by Chinese urban commercial banks had a beneficial impact on nearby institutions.

The present study differs from Zhao et al. (2020) by examining the spatial effect of the efficiency determinant in a very different banking industry of a developed country with large regional development heterogeneity, characterized by big players controlling a larger share of bank services with small cooperative banks as microcredit financial intermediaries, which direct their services to niche clients. Our empirical strategy focuses mainly on the indirect effect of the efficiency determinant of Italian cooperative banks, among which the competitive interaction, and therefore probably also the spatial spillover effect, is stronger.

Another interesting and novel strand of the literature considers spatial analysis within the data envelope analysis (DEA) framework only among nonfinancial firms. Some studies use the standard single-step approach to relate efficiency to spatial proximity, without investigating the environmental variables related to efficiency (e.g., Fusco et al., 2018; Fusco et al., 2020). Another stream of the spatial DEA literature takes the two-step approach of estimating the efficiency score of each decision-making unit (DMU) and then considering an array of possible efficiency determinants, including a set of variables capturing spatial dependence (Skevas & Grashuis, 2020; Skevas & Oude Lansink, 2020). However, the spatial bank efficiency has not yet been investigated using nonparametric analysis. Therefore, our study represents a first attempt to investigate the co-movement efficiency effect in the banking industry using the DEA technique.

3 | ECONOMETRIC METHODOLOGY

This section introduces the methodological approach adopted for the current empirical study, which follows Simar and Wilson's (2007) Algorithm 1. The analysis proceeds in two stages. In the first stage, a nonparametric DEA frontier technique is used to obtain TE scores; this method is detailed in Appendix (A.1.1). In the second stage, the estimated efficiency scores of each bank are regressed on a group of covariates.[2] In our case, and similar to Skevas and Grashuis (2020) and Skevas and Oude Lansink (2020), the efficiency determinants also include the spatial lag terms (i.e., each regressor multiplied by the SWM), resulting in a spatial lag of X (SLX) specification.

Tobler's (1970) first law of geography states that all socioeconomic phenomena may exhibit spatial dependence because there can be a relationship between a single spatial unit and a neighboring one.[3] This necessitates the use of spatial econometric approaches, because it represents a source of bias in estimations based on data affected by spatial co-movement.

There are several spatial econometric models that allow for dealing with spatial spillover effects. However, the two-step approach of Simar and Wilson (2007) that we use makes many of these spatial models unsuitable because it is based on the assumption of error term independence, which cannot be applied to all spatial frameworks. Furthermore, the maximum likelihood estimation of the truncated regression cannot adapt to spatial dependence. These constraints limit the spatial model selection to the SLX model (Florax & Folmer, 1992; Gibbons & Overman, 2012; Halleck Vega & Elhorst, 2015), which assumes that it is the characteristics of economic units (i.e., the explanatory variables in the regression equation), and not their error terms or the TE of a neighboring unit(s), that are spatially correlated. The SLX model is expressed as follows:

$$\Delta = \mathbf{Z}\gamma + \mathbf{WZ}\rho + \varepsilon, \tag{1}$$

where Δ is the vector $(k \times 1)$ of TE scores for all DMUs obtained in the first stage of DEA, $\mathbf{Z}$ is a $k \times q$ matrix of efficiency determinants, $\boldsymbol{W}$ represents the SWM, γ, ρ, and τ are unknown parameter vectors to be calculated, and ε corresponds to a $k \times 1$ column vector of residuals.[4]

The SWM is a deterministic, nonnegative $n \times n$ matrix $(w_{ij} : i, j = 1, \ldots, n)$ that expresses various types of spatial connectivity, where the values on the principal diagonal are equal to zero $(w_{ii} = 0,\ \forall\ i = 1, \ldots, n)$ to discard self-influence effects (Cliff & Ord, 1968; Kelejian & Prucha, 2010).

Of the many different kinds of SWMs,[5] in our study we use a transformation of Anselin's (2003) k-nearest neighbors (k-NN) SWM[6] based on Euclidean metrics, in which the nonzero elements in the matrix are all the spatial entities within a specified orthodromic distance between the coordinates of the single units.

The k-NN matrix can overcome potential biases resulting from the different attitudes that people living in rural or mountain areas may have toward their willingness to travel when compared to citizens living in cities. Furthermore, it addresses the issue that in mountainous or isolated areas, linear distance can be meaningless.

The following is the generalization of a k-NN weight matrix $\boldsymbol{W}(k)$:

$$w_{ij}(k) = \begin{cases} 0, & \forall\ i \neq j \text{ if } d_{ij} > d_i(k) \\ 1, & \forall\ i \neq j \text{ if } d_{ij} \leq d_i(k), \end{cases} \tag{2}$$

[2]After estimating the efficiency score in the first stage, some earlier studies adopt either censored (Tobit) models or the linear regression technique (OLS) to analyze the efficiency determinants (see, for instance, Aly et al., 1990; Binam et al., 2003; Okeahalam, 2004 and Speelman et al., 2008). However, this empirical strategy is biased by the fact that the efficiency drivers are correlated with both output and input factors, and thereby these environmental variables are related to the regression model's residuals (Simar & Wilson, 2007). To address this estimation issue, Simar and Wilson's (2007) adopt a two-stage bootstrap truncated regression that is robust against the bias in the conventional methodology.

[3]Spatial econometrics examines the relationships between observations located in distinct territorial areas by embedding spatial autocorrelation and spatial heterogeneity in model specifications (Anselin, 1988; Elhorst, 2014).

[4]In the SLX model, unlike other spatial models, the coefficient interpretation is straightforward, with the estimated coefficients of the covariates representing direct influence and the spatial lag of the explanatory variables representing indirect influence (LeSage, 2014).

[5]Anselin (2002) provides a leading theory for determining the suitable SWM.

[6]The k-NN weight matrix is also used by Le Gallo and Ertur (2003), Baumont et al. (2004), Ertur and Koch (2006), and LeSage and Fischer (2008) to address several issues.

where d_{ij} is the great circle distance between the spatial units and $d_i(k)$ is the k_{th}-order smallest distance among cross-section entities i and j, so as every unit has k neighbors.

The k-NN connection implies that the SWM is not symmetric, because although y is x's closest neighbor, y's closest neighbor is not necessarily x (Ding & He, 2004). To address this disparity, the symmetric nearest neighbor (k-sNN) connection technique is used, which involves replacing $\boldsymbol{W}(k)$ with a new matrix called the k-sNN weight matrix, $\boldsymbol{W}(sk)$, computed as $\frac{[\boldsymbol{W}(k)+\boldsymbol{W}'(k)]}{2}$. Each spatial weight ($w_{ij}$) becomes equal to $\frac{(w_{ij}+w_{ji})}{2}$ as a result of this transformation. Consequently, some observations have more than k neighbors.

We choose a six-nearest-neighbor matrix (k=6) to correspond to the median number of neighbors in a queen contiguity matrix constructed for a Thiessen polygon tessellation of the point locations. We do not use the latter as it introduces several artificial linkages because of the different densities in the point pattern. As the Thiessen polygons correspond to a notion of market area (under highly simplifying assumptions), the median number of neighbors provides a proxy of the number of "spatial" competitors any given bank is likely to interact with. However, as the k-NN criterion does not consider the actual distance, we corrected for potential unrealistically long connections by intersecting the k-NN weights with a distance band of 73 km, which is the shortest distance for which no neighborless observations are possible (i.e., there are no isolates). We intersect the two k-NN matrices with a distance band spatial matrix, $\boldsymbol{W}(d)$, in which j is a neighbor of i if the distance between them is less than this critical distance.

Accordingly, the distance band weights of the matrix are:

$$w_{ij} = \begin{cases} 0, & \forall\, i \neq j \text{ if } d_{ij} > \lambda \\ 1, & \forall\, i \neq j \text{ if } 0 \leq d_{ij} \leq \lambda, \end{cases} \tag{3}$$

where λ is the critical cut-off distance.

The two matrices that result from this combination fully use the advantages of the k-NN technique and do not consider economic units located beyond the 73-km boundary.

Finally, the matrices have been row-standardized so that all rows add up to one. In this fashion, we normalize the outside influence on each spatial unit, making for meaningful comparisons between different spatial models estimated on the basis of different types of matrices.

Assuming a constant weights matrix by time period, the SWMs $nt \times nt$ in the panel data framework are defined in this way[7]:

$$\boldsymbol{W}_{nt} = \boldsymbol{I}_t \otimes \boldsymbol{W}_{\boldsymbol{n}}, \tag{4}$$

in which $\boldsymbol{I}_t$ is an identity matrix of size t, and $\boldsymbol{W}_{\boldsymbol{n}}$ is the $n \times n$ row-normalized weight matrix.

In the second stage, the steps of the single bootstrap technique are as follows. First, in Eq. (1), the maximum likelihood method[8] estimates the two-sided censored regression of TE on all the efficiency determinants (i.e., spatial and nonspatial variables).[9] In this step, $\hat{\gamma}$ of γ, $\hat{\rho}$ of ρ, and $\hat{\sigma}_\varepsilon$ of σ_ε are estimated. The two-sided truncated regression considers input- or output-oriented (Farrell) efficiency scores to be strictly positive and less than or equal to 1; that

[7]More information can be found in Anselin et al. (2007).

[8]Let $y = \mathbf{X}\omega + \epsilon$ be the general expression of a truncated regression specification, the corresponding log-likelihood function is as follows:

$$lnL = -\frac{n}{2}\log\left(2\pi\sigma^2\right) - \frac{1}{2\sigma^2}\sum_{j=1}^{n}\left(y_j - \mathbf{x}_j\omega\right)^2 - \sum_{j=1}^{n}\log\left\{\Phi\left(\frac{1-\mathbf{x}_j\boldsymbol{\omega}}{\sigma}\right) - \Phi\left(\frac{0-\mathbf{x}_j\boldsymbol{\omega}}{\sigma}\right)\right\}$$

[9]For each observed i, ε_i in the regression model (1) is distributed $N(0,\sigma_\varepsilon^2)$.

is, TE is bounded $(0,1]$. Second, the procedure simulates 2000 iterations of $(\hat{\gamma}^*, \hat{\rho}^*, \hat{\sigma}_\varepsilon^*)_n$ with $n=1,...,2000$. In particular:

- $\forall$ i, a residual ε_i belongs to a $N(0,\hat{\sigma}_\varepsilon^2)$ distribution left censored at $1-\mathbf{Z}\gamma-\mathbf{WZ}\rho$;
- The adjusted bootstrap TE score is equal to $\tilde{\Delta}=\mathbf{Z}\hat{\gamma}+\mathbf{WZ}\hat{\rho}+\varepsilon_i$;
- The parameters $(\hat{\gamma}^*, \hat{\rho}^*, \hat{\sigma}_\varepsilon^*)$ that define $\tilde{\Delta}$ have been estimated by a truncated regression based on the maximum likelihood procedure.

To complete the process, the bootstrap estimates and the original estimates ($\hat{\gamma}, \hat{\rho}$, and $\widehat{\sigma_\varepsilon}$) are combined to estimate their confidence intervals and standard errors γ, ρ, and σ_ε.[10]

The estimated coefficients of the bootstrap truncated regression model are only meaningful in terms of sign, not magnitude, which can be derived from the marginal effects estimates. In detail, the associated partial derivatives of the efficiency determinants are as follows:

$$\frac{\partial E(\tilde{\Delta}|\mathbf{Z},\ \tilde{\Delta}>1)}{\partial z}=\hat{\gamma}^*\times\left\{1-\left[\frac{\phi(1-\mathbf{Z}\hat{\gamma}^*/\hat{\sigma}_\varepsilon^*)}{1-\Phi(1-\mathbf{Z}\hat{\gamma}^*/\hat{\sigma}_\varepsilon^*)}\right]^2+\frac{\phi(1-\mathbf{Z}\hat{\gamma}^*/\hat{\sigma}_\varepsilon^*)}{1-\Phi(1-\mathbf{Z}\hat{\gamma}^*/\hat{\sigma}_\varepsilon^*)}\times\frac{1-\mathbf{Z}\hat{\gamma}^*}{\hat{\sigma}_\varepsilon^*}\right\}, \tag{5}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ represent the standard normal distribution and the standard normal cumulative distribution function, respectively.

4 | DATA AND EMPIRICAL SPECIFICATION

Our empirical analysis considers a sample of 230 CCBs from 2011 to 2020 for a total of 2300 observations.[11] This is a subsample of all Italian CCBs following two criteria: (1) financial data availability for all years of interest,[12] and (2) the exclusion of six isolated banks.[13] The sample is based on data provided by Orbis Bank Focus (Bureau van Dijk).[14] We constructed the geospatial data set by geo-referencing each CCB headquarters in terms of geographical coordinates.

Figure 1 shows the spatial network connecting all the CCB headquarters based on the criteria we used to design our three SWMs. The figure confirms our assumption that Italian CCBs are clustered in some areas, which supports the presence of spatial spillover effects that may affect CCB efficiency. Figure A1 depicts the local indicators of spatial association (LISA) statistics developed by Anselin (1995), and backs up the idea that Italian mutual banks' TE is influenced at the cluster level.

We estimate banks' efficiency performance using the DEA technique within the framework of the financial intermediation method (Sealey Jr & Lindley, 1977), in which banks provide services such as lending through the use of multiple inputs (i.e., deposits, labor, capital, etc.). In accordance with previous studies (*inter alia*, Asimakopoulos et al., 2018; Barth et al., 2013; Diallo, 2018; Drake et al., 2006; Kulasekaran & Shaffer, 2002), we adopt a particular model of bank intermediation with two outputs (i.e., total loans and other earning assets)[15] and four inputs (i.e., total

[10]Simar and Wilson (2007) offer a more comprehensive summary of the single bootstrap truncated regression.

[11]The sample does not consider the Popular banks, which are a particular kind of cooperative bank that presents differences from CCBs in terms of governance and business models, and do not strictly follow the mutuality principle. In addition, this kind of bank is rarely locally based.

[12]Indeed, the spatial model and the spatial dependence tests require a balanced panel (Elhorst, 2014).

[13]We excluded two CCBs located in Sardinia, and one in each of Elba island, Aosta Valley, Sicily, and Apulia.

[14]As some values are missing, we directly acquired the missing information from the balance sheets published on the websites of each the CCBs.

[15]The outputs have been selected following other studies (Casu & Girardone, 2004; Casu et al., 2004) and on the given available data. Some research studies measuring bank efficiency adopt alternative outputs (such as other noninterest or income) to avoid penalizing banks engaged in nontraditional banking activities (Barth et al., 2013). However, as our analysis focuses on small cooperative banks that are mainly involved in traditional banking activities, we consider only two outputs.

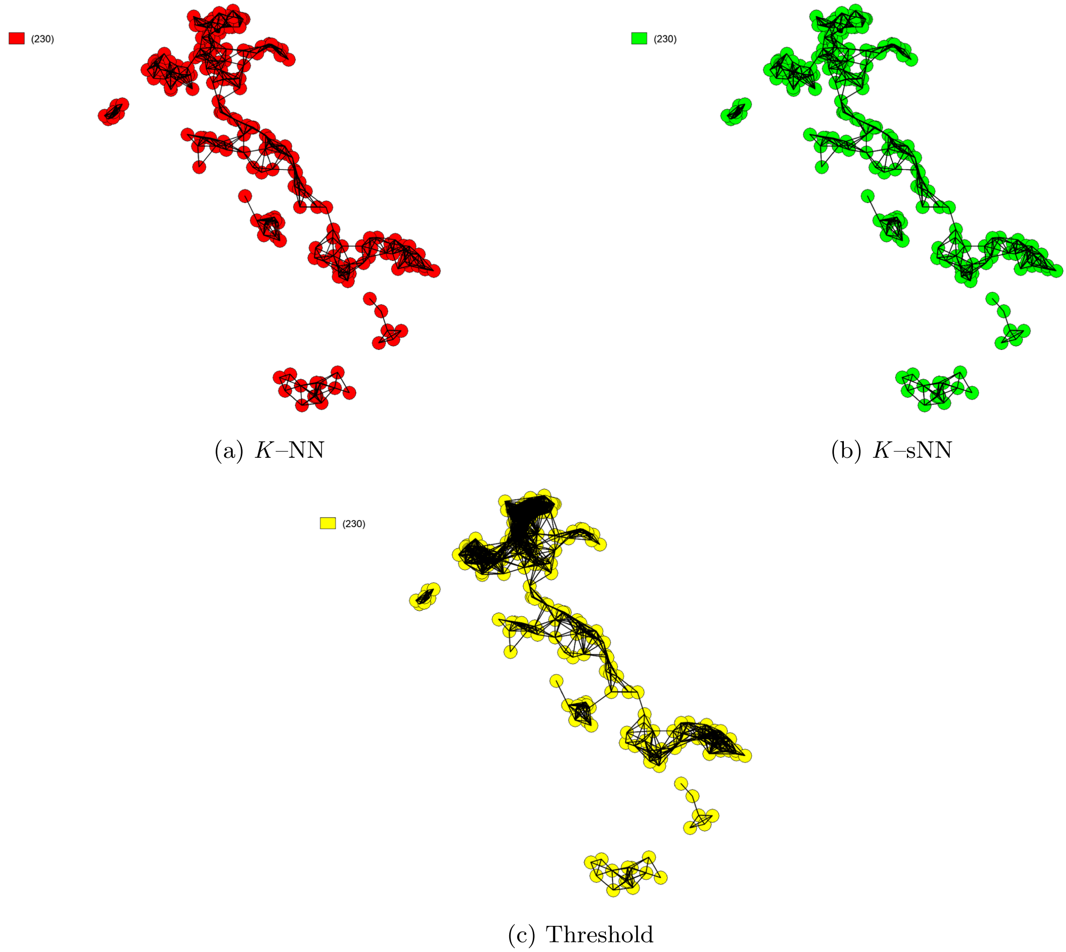


FIGURE 1 Spatial connectivity among CCBs

funds, staff expenses, fixed assets, and loan loss provisions). The last input (loan loss provisions) accounts for risk/loan quality in the model to estimate bank efficiency (Aggelopoulos & Georgopoulos, 2017; Drake et al., 2006; Fukuyama & Matousek, 2017).[16] The inputs and outputs expressed in monetary value are deflated by the *CPI*. Finally, the specification includes year dummies to control the time effect D_t. Although both efficiency orientations are estimated, as profit maximization is not the core purpose of banks pursuing mutual objectives we follow earlier studies (e.g., Coccorese & Ferri, 2020; Harimaya & Ozaki, 2021) in focusing primarily on the input-orientation findings.

Table 1 shows the descriptive statistics used to calculate the DEA efficiency score.

In our analysis, the general equation regarding efficiency presented in the previous section (Eq. 1) becomes as follows:

$$\hat{\delta}_i = \alpha + \mathbf{x}_i \beta + \varphi \sum_{j=1}^{n} w_{ij} \cdot \mathbf{x}_j + \sum_{t=2}^{6} \vartheta_t D_t + \epsilon_i \tag{6}$$

[16]Laeven and Majnoni (2003) claimed that credit risk should be embedded within the input vector by adding the loan loss provisions.

TABLE 1 Descriptive statistics of output and input variables

Variable	Mean	Std. dev.	Min	Max
Total loans	538,033,554	620,240,937	27,658,006	4,791,224,320
Other earning assets	2,287,868	5,366,132	1,000	41,857,360
Total funds	660,638,239	731,058,268	40,212,024	5,065,458,688
Staff expenses	7,568,141	7,368,868	551,274	49,152,716
Fixed assets	9,854,019	11,073,425	150,876	65,946,448
Loan loss provisions	6,829,223	7,934,419	44,176	45,818,016

Notes: The number of observations is 2,300 for all the variables.

TABLE 2 Spatial weight matrices descriptive statistics

	Number of neighbors			
Type	Mean	Median	Min	Max
K-NN	5.73	6	1	6
K-sNN	6.94	7	1	12
Threshold	18.63	12	1	52

Notes: The number of observations is 230 for all the SWMs.

$$i = 1, 2, \ldots, n.$$

The determinants of bank efficiency performance are the bank-specific variables and their spatial lag terms. We determine the spatial lag operators by multiplying each independent variable with the spatial matrices. Specifically, the three alternative SWMs are:

(1) $\boldsymbol{W}_1 = \boldsymbol{W}(6) \times \boldsymbol{W}(d)$;
(2) $\boldsymbol{W}_2 = \boldsymbol{W}(s6) \times \boldsymbol{W}(d)$;
(3) $\boldsymbol{W}_3 = \boldsymbol{W}(d)$.

Table 2 summarizes the statistics on the distribution of the number of neighbors for each of the three SWMs. The data for the distance criteria reveal that at least one cluster contains up to 45 CCBs that are close to each other.

The environmental variables included in the specification as determinants of bank TE refer to several bank profiles related to capitalization, diversification of income and funding, soundness, risk, and management quality.[17]

Although the literature focusing on gross risk bank capitalization measures (such as equity over total assets) shows a favorable association of these measures with efficiency (Barth et al., 2013; Bitar et al., 2018; Coccorese & Ferri, 2020), studies using risk-adjusted measures, such as capital adequacy ratio, report negative associations with bank efficiency (Ding & Sickles, 2018; Minviel & Ben Bouheni, 2021). Moreover, Glass and Kenjegalieva (2019) document that the capital ratios (either *Tier 1* or *Tier 2*) of a network of large banks strongly degrade the cost efficiency of large banks. Therefore, we assume that this effect is also strong among small banks. The specification includes total capital to risk-weighted assets ratio (*CAP*) as a proxy of prudential risk management, in which a higher ratio implies less banking activity and, in turn, less efficiency.

[17]The variance inflation factor (VIF) was used to test for multicollinearity. On average, the VIF values are equal to 1.96 for both efficiency models.

As in Wu et al. (2020), we examine the revenue diversification (*Income div*) and financing structure (*Funding div*) of banks, which have both been overlooked in earlier studies on bank efficiency. Although *Income div* is net interest income to operating revenue ratio and thus signifies the bank's reliance on interest income (Foos et al., 2017; Fraser et al., 2002), diversification strategies can create cost inefficiencies for retail-oriented banks, such as small cooperative banks (Bernini & Brighi, 2018). However, diversification has a variable effect on cooperative banks. Because of economies of scale and capability endowments, larger banks are urged to broaden their diversification strategy to increase their productivity (Iosifidi et al., 2021). Conversely, small local banks, and *a fortiori* cooperative banks, tend to avoid diseconomies by concentrating on conventional fields of operation rather than diversifying into non-traditional operations (McKee & Kagan, 2016; Van Cuong et al., 2020). Similarly, the literature indicates that the spatial effect is contingent on bank size: for small banks there is no indirect efficiency effect of noninterest activity from neighbor banks (Glass et al., 2020), whereas the spatial noninterest income activity of network banks dramatically affects the cost efficiency of large banks (Glass & Kenjegalieva, 2019). As a consequence, the effect of *Income div* on both efficiency measures is indefinable *a priori*. The bank funding structure shows how the financial intermediary is exposed to asset-liability mismatch risk, and we assume that the weight of deposits in total bank assets (*Funding div*) is the suitable measure to capture this effect. If a bank, including a CCB, collects financial resources mainly or only through this short-term source, it may be highly exposed to this risk up to a point that precludes bank TE. According to the above prior evidence, Coccorese and Ferri (2020) show that a larger deposit share of total funding impairs the cost efficiency of Italian CCBs. However, the literature focusing on different kind of banks (e.g., Curi et al., 2015; Iosifidi et al., 2021; Wu et al., 2020) reports the opposite effect.

The *Funding rate* indicates the interest rate offered on the collected funding, namely the interest expense divided by total funds. As CCBs face resource constraints in the financial market, bank management makes use of this price lever to capture customer share. To mitigate the rising interest expenses, we may expect these banks to increase their operational performance (Pérez-Cárceles et al., 2019; Roman & Şargu, 2013).

LIQ is liquid assets (i.e., the sum of cash and balances with other banks, money market instruments, and marketable securities) scaled on total assets. Vazquez and Federico (2015) posit that the soundness of smaller banks is to a large extent directly related to liquidity, because a low level of liquid assets may spur bank management to adopt the most efficient practices. As a consequence, the effect of liquidity on bank efficiency should be negative. Furthermore, medium and large banks magnify the maturity mismatch between loans and deposits and become less liquid, but more profit-efficient (Bitar et al., 2018; Sakouvogui, 2020). On the contrary, Altunbas et al. (2007) show that bank liquidity is positively associated with technical cost efficiency; indeed, Fernandes et al. (2018) find that liquidity risk lowers the bank efficiency performance because of the increasing funding costs and Bitar et al. (2020) verify this relationship among both traditional and Islamic banks, showing that financial intermediaries with suitable liquidity endowments achieve greater efficiency. Earlier studies in this stream focusing on developing countries argue that banks holding more liquid assets bear the opportunity cost of certain investment options that could generate high profits, thus jeopardizing bank efficiency (Brissimis et al., 2008; Kirkpatrick et al., 2008; Sufian, 2009). In the context of our analysis, the expected influence of the variables is unknown.

NPL stands for the ratio of nonperforming loans to gross loans, which is a proxy of a bank's asset quality (Berger & Mester, 1997; Podpiera & Weill, 2008). This retrospective credit quality indicator may degrade cost efficiency (Gaganis & Pasiouras, 2013; Iosifidi et al., 2021; Le et al., 2020; Luo et al., 2016; Mamatzakis, 2015). Similarly, a loan portfolio degradation level that reflects a deteriorating general economic outlook may cause a flight to quality on the part of prime clients, which will impair bank operations. As a consequence, we assume that the associated coefficient takes a negative sign.

The *Z Score* is a proxy for a bank's financial stability, defined as return on assets (*ROA*) plus equity to assets, all divided by the standard deviation of *ROA*. To adjust for the temporal shift in the bank yield dynamic trend, we use a rolling time window of 3 years, as recommended by studies using this risk variable (see, e.g., Barra & Zotti, 2019). An elevated *Z Score* is consistent with the soundness of a financial institution (Shim, 2019). However, for banks that

TABLE 3 List of variables

Variable	Description
CAP	(Tier 1 + Tier 2)/ Risk weighted assets
Income div	Net interest income/Total revenues
Funding div	Total deposits/Total assets
Funding rate	Total interest expense/Total funds
LIQ	Liquid assets/Total assets
NPL	Nonperforming loans/Total gross loans
Z Score	(Return on assets (ROA) + Equity/Assets)/ σ(ROA)
OETA	Total operating expenses/Total assets
Stochastic frontier function	
y_1	Total net loans
y_2	Other earning assets
p_1	Staff expenses/Total assets
p_2	(Other administrative expenses + Other operating expenses)/Total fixed assets
p_3	Interest expenses/Total funds

Notes: This table supplies a description of the variables used in the efficiency models.

TABLE 4 Descriptive statistics of the efficiency determinants

Variable	Mean	Std. dev.	Min	Max
CAP	0.196	0.07	0.059	0.794
Income div	0.644	0.11	0.361	0.884
Funding div	0.726	0.12	0.444	0.918
Funding rate	0.009	0.01	0.000	0.060
LIQ	0.131	0.09	0.021	0.425
NPL	0.123	0.07	0.012	0.325
Z Score	1.267	1.88	0.012	26.377
OETA	0.020	0.00	0.009	0.035

Notes: The number of observations is 2,300 for all the variables.

depend largely on depository financing, soundness may come at the expense of efficiency (Miah & Uddin, 2017); therefore, the sign is uncertain. This is especially relevant for banks that depend largely on depository financing.[18]

OETA is the ratio of operating expenses to total assets and is a measure of a bank's management effectiveness (Roman & Şargu, 2013). As the most efficient banks are more able to control their operating expenses (Saha et al., 2015), the expected effect is negative.

Table 3 describes the variables of our empirical investigation, and Table 4 presents the descriptive statistics for the variables considered in the second stage of the estimation.

As stated above, the sample comprises strongly balanced panel data containing 2300 observations for the period from 2011 to 2020. Concerning bank-specific features, we observe that the mean of all variables except for one is greater than the standard deviation, thus indicating that our sample consists of banks with fairly similar features.

[18]Inefficiency of a bank would likely affect its profits through which it would affect the *Z Score* (Delis et al., 2017). Hence, we checked for the possible endogeneity of *Z Score*, by estimating the endogenous stochastic frontier models (Karakaplan & Kutlu, 2017), with the results indicating that endogeneity correction was unnecessary. We owe this robustness check to an anonymous referee.

TABLE 5 LM tests for spatial, serial correlation, and random effects

LM test description	Input oriented model		Output oriented model	
	Statistic	*p*-value	Statistic	*p*-value
Anselin (1988)				
Conditional test for spatial error autocorrelation				
(H_0: spatial error autoregressive coefficient equal to zero)	8.97	0.000	8.87	0.000
Conditional test for spatial lag autocorrelation				
(H_0: spatial lag autoregressive coefficient equal to zero)	15.19	0.000	17.10	0.000
Baltagi et al. (2003)				
Joint test (H_0: absence of random effects and spatial autocorrelation)	2152.7	0.000	2191.4	0.000
Marginal test of random effects (H_0: absence of random effects)	44.19	0.000	44.45	0.000
Marginal test of spatial autocorrelation (H_0: absence of spatial autocorrelation)	14.15	0.000	14.69	0.000
Conditional test of spatial autocorrelation (H_0: absence of spatial autocorrelation, assuming random effects are non-null)	12.78	0.002	13.71	0.001
Conditional test of random effects (H_0: absence of random effects, assuming spatial autocorrelation may or may not be equal to 0)	44.78	0.000	45.83	0.000
Baltagi et al. (2007)				
Joint test (H_0: absence of serial or spatial error correlation or random effects)	2346.3	0.000	2428.6	0.000
One-dimensional conditional test (H_0: absence of spatial error correlation, assuming the existence of both serial correlation and random effects)	32.22	0.000	34.02	0.000
One-dimensional conditional test (H_0: absence of serial correlation, assuming the existence of both spatial error correlation and random effects)	368.47	0.000	462.97	0.000
One-dimensional conditional test (H_0: absence of random effects, assuming the existence of both serial and spatial error correlation)	120.68	0.000	119.35	0.000

5 | EMPIRICAL RESULTS

The statistical tests that are used to confirm the existence of spatial dependency are first presented. The estimates of the spatial truncated regression models are then shown and discussed. Finally, the cross-sectional independence test is calculated to corroborate the estimators' robustness.

5.1 | Check for spatial dependence

We performed many Lagrange Multiplier (LM) tests to check for geographical dependency by considering either the spatial or serial autocorrelation, as well as random effects in the data.[19] Statistical inferences and estimates will be incorrect if spatial dependence exists and is neglected, as is well known in the field (see, for instance, Kar et al., 2011; Kutlu & Nair-Reichert, 2019; Mur & Angulo, 2006).

Table 5 presents the findings of the diagnostic tests.

[19]These tests look for singular spatial autocorrelation and random effects that cannot be verified at the same time and thus are not always accurate. However, there is no test that can verify both of these issues together (we owe this observation to an anonymous referee).

TABLE 6 Testing for cross-sectional dependence

Test	Pesaran (2004)		Pesaran (2015)	
	Input oriented model	Output oriented model	Input oriented model	Output oriented model
CD	6.581	7.923	3.709	3.731
p-value	0.000	0.000	0.000	0.000

Notes: The tests measure strong and weak cross-sectional dependence under the null hypothesis of absence of it.

The first series of LM tests determines whether there is any co-movement. Both the spatial error and the lag autoregressive coefficients must be zero, according to the null hypothesis (Anselin, 1988; Breusch & Pagan, 1980). Our tests refute this hypothesis, implying the existence of spatial autocorrelation.

The second group of tests is based on the joint and conditional LM tests for spatial autocorrelation and random effects in Baltagi et al. (2003). All the diagnostic tests show the existence of these problems. In more detail, the findings of the joint LM test indicate that the error term has at least one component-spatial correlation or random individual effects. Likewise, spatial correlation and random effects are tested separately via the marginal LM tests. The tests confirm that the two issues are both present in the sample. Moreover, we conduct conditional LM tests to determine whether there is a geographical dependency.[20] These tests show that there is co-movement in the sample.

The last group of tests from Baltagi et al. (2007) controls for spatial correlation, serial autocorrelation, and random effects jointly and conditionally. The joint LM considers the question of serial correlation under the specifications of Baltagi et al. (2003), and the one-dimensional conditional tests allow testing for the presence of each individually while allowing for the existence of the other two. The findings show that serial and spatial autocorrelation occur, as well as random effects.[21]

To validate the result of the preceding spatial dependence tests, which are linked to the SWM used, we also estimate the CD tests proposed by Pesaran (2004, 2015), as also suggested by Sarafidis and Wansbeek (2012), Millo (2017), and Elhorst et al. (2020). Vega and Elhorst (2016) clarifies that these tests account for cross-sectional dependence caused by unobserved common factors, i.e., strong cross-sectional dependence, and spatial dependence, i.e., weak cross-sectional dependence. Table 6 summarizes the findings, which show that both of these types of cross-sectional dependency are present.

The results of all the tests call for the adoption of appropriate spatial econometric techniques.

5.2 | Empirical results

Table 7 shows that the efficiency scores are almost the same regardless of whether input or output oriented. Among the Italian CCBs there are top-performing intermediaries (with at least 26 banks for input and 19 banks for output realizing the maximum efficiency score in 1 year) and banks that are far from the efficiency frontier, but on average these banks operate with pockets of inefficiency. Figure A2 shows that the kernel density of the average efficiency performance presents a distribution similar to Gaussian, with some cooperative banks that realize the optimal value.

[20]More specifically, the test for the existence of spatial autocorrelation allows for the presence of random effects and the test for the existence of random effects assumes that there might also be spatial autocorrelations.

[21]All the LM tests are estimated using the *splm* package in *R* proposed by Millo and Piras (2012). The test results presented in Table 5 are those estimated using the *k*-NN weight matrix ($\boldsymbol{W}_1$). As the results of the statistical tests computed considering the other two spatial matrices present the same picture, we have not presented them here, but they can be provided on request.

TABLE 7 Summary statistics of input and output efficiency scores

Variable	Mean	Std. Dev.	Min	Max
X_{TE}	0.699	0.15	0.271	1
Y_{TE}	0.695	0.15	0.207	1

Notes: The number of observations is 2,300 for all the two technical efficiency measures.

TABLE 8 Estimates of input-oriented technical efficiency model

	Truncated regression model	Spatial truncated regression models		
		W_1	W_2	W_3
X_{TE}	(1)	(2)	(3)	(4)
CAP	−0.3836***(0.038)	−0.2162***(0.039)	−0.2142***(0.038)	−0.2023***(0.039)
Income div	0.2195***(0.028)	0.2115***(0.029)	0.2157***(0.028)	0.2228***(0.028)
Funding div	−0.1194***(0.030)	−0.0248(0.034)	−0.0154(0.034)	0.0299(0.034)
Funding rate	0.6688(0.884)	4.5963***(0.889)	5.0069***(0.884)	5.9035***(0.908)
LIQ	0.0903**(0.040)	0.1597***(0.038)	0.1621***(0.038)	0.1686***(0.038)
NPL	−0.8214***(0.041)	−0.5685***(0.046)	−0.5618***(0.044)	−0.6225***(0.042)
Z Score	0.0001(0.001)	−0.0008(0.001)	−0.0008(0.001)	−0.0004(0.001)
OETA	−0.7107(0.536)	1.3654**(0.606)	1.4532**(0.594)	1.6026***(0.575)
$\mathbf{W} \times$ *CAP*		−0.2450*** (0.066)	−0.2060***(0.070)	−0.2187***(0.084)
$\mathbf{W} \times$ *Income div*		0.0865*(0.049)	0.0724(0.050)	0.0841(0.056)
$\mathbf{W} \times$ *Funding div*		−0.2197***(0.055)	−0.2647***(0.057)	−0.3678***(0.062)
$\mathbf{W} \times$ *Funding rate*		-11.7713***(1.613)	-14.1055***(1.700)	-19.7185***(1.880)
$\mathbf{W} \times$ *LIQ*		−0.3995***(0.067)	−0.4339***(0.071)	−0.4498***(0.083)
$\mathbf{W} \times$ *NPL*		−0.4836***(0.067)	−0.4956***(0.069)	−0.3254***(0.079)
$\mathbf{W} \times$ *Z Score*		−0.0138***(0.003)	−0.0165***(0.003)	−0.0141***(0.003)
$\mathbf{W} \times$ *OETA*		−2.4253** (0.950)	−2.8585***(0.970)	−3.5484***(1.062)
Wald χ^2	1681.98***	2154.60***	2225.28***	2150.81***

Notes: Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01. Estimates rely on the usage of the truncated regression proposed by Simar and Wilson (2007) with 2,000 bootstrap replications. The number of observations is 2,300 for all the regressions. Constant and year dummies are included but not reported. Variables that are spatially lagged are indicated with a leading "***W***."

Tables 8 and 9 show the detailed empirical results and related marginal effects for the input-oriented efficiency model, and Tables 10 and 11 show the equivalent for the output-oriented efficiency model.[22]

We consider the results jointly, as the coefficients for input-oriented are broadly consistent with the output-oriented efficiency specifications.

The sign and significance of the explanatory variables are consistent across all bank profiles (bank capitalization, liquidity, credit quality, risk, and cost of funds). This regularity almost always holds, both in the three specifications that consider spatial effects and in the one specification that does not.

In line with empirical studies based on capital-risk adjusted measures, the capitalization variable (*CAP*) shows a monotonic spatial effect across all the models. Higher capital weighted risk directly (Ding & Sickles, 2018; Minviel &

[22]The truncated regression models are estimated with 2000 bootstrap replications. The joint significance of explicative variables is indicated by the Wald test results.

TABLE 9 Marginal effects of the determinants of input technical efficiency

	Truncated regression model	Spatial truncated regression models		
		W_1	W_2	W_3
X_{TE}	(5)	(6)	(7)	(8)
CAP	−0.3684***(0.036)	−0.2085***(0.036)	−0.2067***(0.038)	−0.1953***(0.038)
Income div	0.2108***(0.026)	0.2040***(0.027)	0.2081***(0.028)	0.2151***(0.027)
Funding div	−0.1147***(0.030)	−0.0239(0.033)	−0.0148(0.033)	0.0289(0.032)
Funding rate	0.6422(0.858)	4.4331***(0.855)	4.8309***(0.886)	5.6992***(0.856)
LIQ	0.0867**(0.039)	0.1540***(0.035)	0.1564***(0.037)	0.1627***(0.037)
NPL	−0.7887***(0.039)	−0.5483***(0.044)	−0.5421***(0.044)	−0.6009***(0.040)
Z Score	0.0001(0.001)	−0.0008(0.001)	−0.0008(0.001)	−0.0004(0.001)
OETA	−0.6825(0.530)	1.3170**(0.590)	1.4021**(0.573)	1.5471***(0.558)
W × *CAP*		−0.2363***(0.065)	−0.1987***(0.068)	−0.2111***(0.081)
W × *Income div*		0.0835* (0.047)	0.0699(0.048)	0.0812(0.053)
W × *Funding div*		−0.2119***(0.054)	−0.2554***(0.055)	−0.3550***(0.058)
W × *Funding rate*		-11.3532***(1.556)	-13.6096***(1.617)	-19.0360***(1.781)
W × *LIQ*		−0.3853***(0.067)	−0.4187***(0.070)	−0.4343***(0.078)
W × *NPL*		−0.4665***(0.066)	−0.4782***(0.066)	−0.3141***(0.076)
W × *Z Score*		−0.0133***(0.003)	−0.0159***(0.003)	−0.0136***(0.003)
W × *OETA*		−2.3391** (0.920)	−2.7580***(0.959)	−3.4256***(1.017)

Notes: Marginal effects for all efficiency determinants included in the input-oriented model. Variables that are spatially lagged are indicated with a leading "**W**." Standard errors in parentheses. **p* < 0.1, ***p* < 0.05, ****p* < 0.01.

Ben Bouheni, 2021) and indirectly (Glass & Kenjegalieva, 2019) determines higher inefficiency, with banks benefiting from spillover effects where competitor banks operate with a low weight of lending with respect to equity. The spatial effects also indirectly confirm Ding and Sickles's (2019) results in showing that cooperative banks operate within a bank network characterized by herd behavior. A possible alternative explanation is that cooperative banks operate within a network with a higher capital level, which implies—given the regulatory rule restricting capital raising through bank members—that bank activity is performed in a more competitive bank capital market. This competitive environment will entail greater effort in terms of expanding service offerings and/or lowering the price of the service provided to consumers to collect and maintain an adequate capital endowment, thus impairing both sides of the efficiency equation.

In this regard, a liability diversification strategy (*Funding div*) also degrades bank efficiency performance indirectly through the spillover effect. It is likely that while competitors collect funds from deposits there is less opportunity for banks to collect funds from this stable source, which ends up impairing their operational efficiency because the alternative fund channels are more resource demanding.

The proxy for revenue diversification partially confirms evidence presented by earlier studies. Indeed, *Income div* presents only a direct effect on bank efficiency and the associated spillover effects is almost never significant, which confirms that small banks are not affected by noninterest activities of neighboring banks (Glass et al., 2020). To a large extent, this would imply that Italian small cooperative banks can diversify their services with respect to the rival mutual banks of the same area. Likewise, the nonspatial effect of *Income div* follows a clear pattern, as less diversified banks can avoid the additional operating costs associated with nontraditional bank activities, which reduce cost efficiency (Bernini & Brighi, 2018; McKee & Kagan, 2016; Van Cuong et al., 2020).

Funding rate and *LIQ* coefficients directly and indirectly affect bank efficiency in the same way. More specifically, the direct effects are positive, whereas the spatial spillovers are negative. The positive direct effect of *Funding rate*

TABLE 10 Estimates of output-oriented technical efficiency model

Y_{TE}	Truncated regression model (9)	Spatial truncated regression models W_1 (10)	W_2 (11)	W_3 (12)
CAP	−0.5112***(0.038)	−0.3138***(0.040)	−0.3139***(0.039)	−0.2958***(0.039)
Income div	0.1965***(0.029)	0.1868***(0.029)	0.1907***(0.029)	0.2051***(0.029)
Funding div	−0.1406***(0.032)	−0.0321(0.035)	−0.0173(0.035)	0.0404(0.034)
Funding rate	−0.9475(0.924)	3.9368***(0.900)	4.4275***(0.924)	5.4327***(0.916)
LIQ	0.0499(0.040)	0.1285***(0.040)	0.1346***(0.038)	0.1450***(0.038)
NPL	−0.8399***(0.043)	−0.5142***(0.046)	−0.5102***(0.046)	−0.5864***(0.043)
Z Score	−0.0004(0.001)	−0.0014(0.001)	−0.0013(0.001)	−0.0010(0.001)
OETA	−2.0190***(0.574)	0.1158(0.629)	0.2917(0.608)	0.5820(0.599)
W × *CAP*		−0.2125***(0.070)	−0.1517**(0.074)	−0.2330***(0.087)
W × *Income div*		0.0395(0.049)	0.0337(0.051)	0.0634(0.057)
W × *Funding div*		−0.2551***(0.058)	−0.3184***(0.058)	−0.4658***(0.063)
W × *Funding rate*		-13.7312***(1.672)	-16.5051***(1.676)	-23.0568***(1.860)
W × *LIQ*		−0.4495***(0.070)	−0.5191***(0.076)	−0.5186***(0.085)
W × *NPL*		−0.6405***(0.069)	−0.6463***(0.070)	−0.4368***(0.079)
W × *Z Score*		−0.0122***(0.003)	−0.0143***(0.003)	−0.0122***(0.003)
W × *OETA*		−2.3498**(0.974)	−2.9280***(1.023)	−3.5951***(1.088)
Wald χ^2	1598.07***	2092.22***	2149.36***	2182.80***

Notes: Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01. Estimates rely on the usage of the truncated regression proposed by Simar and Wilson (2007) with 2,000 bootstrap replications. The number of observations is 2,300 for all the regressions. Constant and year dummies are included but not reported. Variables that are spatially lagged are indicated with a leading "***W***."

shows that as the CCB raises the funding interest rate offered, it is forced to improve its efficiency because of the implied balance sheet constraints (Pérez-Cárceles et al., 2019; Roman & Şargu, 2013). The negative coefficients of the spatial lagged terms indicate that as interest rates rise, competition increases to the point where bank operability deteriorates, thereby supporting the "banking specificities" hypothesis (Pruteanu-Podpiera et al., 2016). That is, market competition weakens long-term credit relationships, thereby increasing the information asymmetry between banks and customers. To a large extent, increased funding costs imply increased lending interest rates.

The estimated coefficients for *LIQ* confirm the finding from the literature on bank efficiency (Fernandes et al., 2018; Bitar et al., 2020) that a high liquidity edge necessitates good efficiency performance, because liquid assets generate lower profits for a given level of risk. Furthermore, a more liquid asset strategy allows for a reduction in both monitoring and screening costs, resulting in an increase in cost efficiency. Banks that belong to a network that holds more liquidity, on the contrary, suffer from greater inefficiency. It is reasonable to assume that bank activity is less exposed to the loan market as a result of credit rationing, which is common in riskier areas.[23] As a result, banks' maturity transformation is not fully implemented, resulting in technical inefficiency.

Credit risk (*NPL*) and the proxy for bank soundness (*Z Score*) both exhibit a negative spatial dependence on efficiency. A riskier environment necessitates more rigorous and costly monitoring and screening activities to assess the creditworthiness of those who face adverse selection and moral hazard issues, which ultimately affect bank operational activity. Similarly, a riskier network may result in a contagion effect in CCB banks. Finally, in times of

[23] In this regard, the liquidity risk is measured as the ratio of total loans over total assets (see for instance Casu et al., 2016; Fernandes et al., 2018).

TABLE 11 Marginal effects of the determinants of output technical efficiency

Y_{TE}	Truncated regression model (13)	Spatial truncated regression models W_1 (14)	W_2 (15)	W_3 (16)
CAP	−0.4829***(0.035)	−0.2986***(0.036)	−0.2988***(0.038)	−0.2818***(0.036)
Income div	0.1856***(0.027)	0.1777***(0.028)	0.1815***(0.027)	0.1954***(0.028)
Funding div	−0.1328***(0.030)	−0.0306(0.034)	−0.0165(0.033)	0.0385(0.033)
Funding rate	−0.8951(0.884)	3.7451***(0.883)	4.2141***(0.892)	5.1758***(0.874)
LIQ	0.0472(0.039)	0.1223***(0.036)	0.1281***(0.037)	0.1382***(0.038)
NPL	−0.7935***(0.039)	−0.4892***(0.045)	−0.4856***(0.044)	−0.5587***(0.041)
Z Score	−0.0004(0.001)	−0.0013(0.001)	−0.0013(0.001)	−0.0009(0.001)
OETA	−1.9074***(0.530)	0.1102(0.592)	0.2776(0.592)	0.5544(0.560)
W × *CAP*		−0.2022***(0.066)	−0.1443**(0.069)	−0.2220***(0.083)
W × *Income div*		0.0376(0.047)	0.0321(0.050)	0.0604(0.055)
W × *Funding div*		−0.2427***(0.053)	−0.3031***(0.056)	−0.4437***(0.060)
W × *Funding rate*		-13.0627***(1.546)	-15.7094***(1.691)	-21.9664***(1.843)
W × *LIQ*		−0.4277***(0.067)	−0.4941***(0.069)	−0.4940***(0.082)
W × *NPL*		−0.6093***(0.066)	−0.6152***(0.067)	−0.4161***(0.079)
W × *Z Score*		−0.0116***(0.003)	−0.0136***(0.003)	−0.0117***(0.003)
W × *OETA*		−2.2354**(0.946)	−2.7868***(0.967)	−3.4250***(1.049)

Notes: Marginal effects for all efficiency determinants included in the output-oriented model. Variables that are spatially lagged are indicated with a leading "***W***." Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

crisis, loan recovery procedures may exacerbate the weaknesses of backward areas. For example, a stringent loan collection procedure can depress real estate market prices and increase homeowner defaults (Frame, 2010; Campbell et al., 2011). Furthermore, in line with the literature, banks face a negative shock from impaired loans, which results in an increase in loan loss provisioning, lowering the bank's operational efficiency and thus productivity (Gaganis & Pasiouras, 2013; Iosifidi et al., 2021; Le et al., 2020; Luo et al., 2016; Mamatzakis, 2015). The *Z Score* has a negligible direct effect on bank efficiency.

Finally, poor management that brings about larger operating expenses (*OETA*) and a barely efficient environment (***W***× *OETA*) are indicators of nonoptimal use of resources. This finding largely confirms the evidence of Saha et al. (2015).

5.3 | Diagnostic test for cross-sectional independence

The presence of spatial interdependence identified and discussed in Section 5.1 suggests that the two-stage econometric estimator should incorporate spatial terms. This procedure enables us to control for co-movement among the spatial units. However, common factors could persist after the use of the spatial model specification.

To check for cross-sectional independence in the spatial model errors, we use Pesaran's (2004) CD test on the residuals of the spatial truncated estimators. The results are biased if the test rejects this hypothesis (Andrews, 2005; Bai & Ng, 2010).

The CD test findings in Table 12 reveal that all spatial specifications present cross-sectional independence, thus spatial unit co-movement is no longer present. Equally, the strong cross-sectional dependence does not affect all

TABLE 12 Testing for cross-sectional independence

	Input oriented model			Output oriented model		
Test	W_1	W_2	W_3	W_1	W_2	W_3
CD	0.902	0.725	0.566	0.069	−0.528	−0.881
P-value	0.3670	0.4684	0.5715	0.9451	0.5973	0.3781

Notes: The test measures strong cross-sectional dependence under the null hypothesis of absence of it.

truncated regressions. Therefore, the spatial econometric methodologies used allow us to address the problem of panel unit correlations.

6 | ROBUSTNESS CHECK: PARAMETRIC ESTIMATES

To bolster our empirical findings on spatial spillover effects in the TE of small cooperative banks, we apply the alternative SFA technique, which is based on nonparametric estimation. There is a body of literature on SFA that allows for the assessment of TE in the presence of geographical spillovers (Glass et al., 2014; 2016; Kutlu, 2018; Kutlu et al., 2020; Orea & Álvarez, 2019).

Indeed, the literature cited in Section 2 on the spatial effects of bank efficiency is mainly based on the use of SFA. It is well known that this methodology allows us to consider the efficiency performance as a result of both stochastic and deterministic shocks, but the SFA needs to specify the appropriate cost or production function. Therefore, we have estimated this model using either the translog production or cost function, which represents the second-order Taylor expansion of any given function.

In detail, the translog cost function specification is similar to that commonly used in the literature (Casu & Girardone, 2006; Casu & Molyneux, 2003; Degl'Innocenti et al., 2020; Fiordelisi & Mare, 2014; Maudos et al., 2002; Srairi, 2010), in which the total cost (personnel expenses, other administrative expenses, and other operating expenses) is related to three inputs (staff expenses over total assets, other administrative expenses and other operating expenses to total fixed assets, and interest expenses divided by bank funding) and two outputs (total loans and other earning assets).

The translog cost function is therefore as follows:

$$\begin{aligned} lnTC_i &= \alpha + \sum_{i=1}^{2}\beta_i lnQ_i + \sum_{j=1}^{3}\gamma_j lnP_j + \frac{1}{2}\sum_{i=1}^{2}\sum_{j=1}^{2}\delta_{ij}Q_{ij} + \frac{1}{2}\sum_{i=1}^{3}\sum_{j=1}^{3}\zeta_{ij} lnP_{ij} \\ &\sum_{i=1}^{2}\sum_{j=1}^{3}\eta_{i,j} lnQ_{ii} lnP_j + \tau t + u_i + \nu_i. \end{aligned} \tag{7}$$

We imposed homogeneous conditions to ensure that the model is consistent with the cost function's theoretical properties, such as standard symmetry that is $\delta_{ij} = \delta_{ji}$ and $\zeta_{ij} = \zeta_{ji}$, and the linear restriction $\Sigma_{j=1}^{3} = 1;\ \zeta = 0\ \Sigma_{j=1}^{3}\eta_{ij}$.

The production function relates the same three inputs to the bank output (i.e., total loans), which is the primary goal of the mutualistic banks, as in Zhao et al. (2020).

The ratio of observed output for each bank (y_i) to the matching stochastic frontier output is the most popular output-oriented metric of TE. Coelli et al. (2005) defines the technical inefficiency as follows:

$$TE_i = \frac{y_i}{exp(\mathbf{x}',\beta + \nu_i)} = \frac{exp(\mathbf{x}'\beta + \nu_i - u_i)}{exp(\mathbf{x}'\beta + \nu_i)} = exp(-u_i.)$$

TABLE 13 One-step stochastic cost frontier estimates

Cost function	Nonspatial model (17)	Spatial models W_1 (18)	W_2 (19)	W_3 (20)
lny_1	0.9592***(0.009)	0.9795***(0.007)	0.9802***(0.007)	0.9799***(0.007)
lny_2	0.0332***(0.005)	0.0225***(0.004)	0.0216***(0.004)	0.0238***(0.004)
lnp_1	0.7710***(0.044)	0.8012***(0.017)	0.8003***(0.017)	0.7954***(0.017)
lnp_2	0.1811***(0.042)	0.1623***(0.020)	0.1609***(0.020)	0.1730***(0.020)
lnp_3	0.0479***(0.019)	0.0365***(0.012)	0.0388***(0.012)	0.0317***(0.012)
$1/2\ lny_1 \times lny_2$	0.0074(0.009)	0.0105**(0.004)	0.0107***(0.004)	0.0115*** (0.004)
$1/2\ lny_1 \times lnp_1$	0.1272(0.097)	0.1247***(0.042)	0.1225***(0.042)	0.1104***(0.042)
$1/2\ lny_1 \times lnp_2$	0.0954(0.080)	0.0197(0.062)	0.0239(0.062)	−0.0045(0.063)
$1/2\ lny_1 \times lnp_3$	−0.0180(0.025)	−0.0208(0.014)	−0.0229(0.014)	−0.0195(0.014)
$1/2\ lny_2 \times lnp_1$	−0.0511(0.034)	−0.0301***(0.012)	−0.0311***(0.012)	−0.0337***(0.012)
$1/2\ lny_2 \times lnp_2$	0.0882***(0.028)	0.0858***(0.017)	0.0860***(0.017)	0.0871***(0.017)
$1/2\ lny_2 \times lnp_3$	0.0036(0.008)	0.0104**(0.005)	0.0115**(0.005)	0.0099**(0.005)
$1/2\ lnp_1 \times lnp_2$	−0.7602**(0.384)	−0.4315***(0.113)	−0.4412***(0.113)	−0.3815***(0.114)
$1/2\ lnp_1 \times lnp_3$	−0.1763(0.129)	−0.0750*(0.038)	−0.0759**(0.038)	−0.0768**(0.039)
$1/2\ lnp_2 \times lnp_3$	0.2305(0.149)	0.0798(0.062)	0.0807(0.062)	0.0888(0.062)
$1/2\ (lny_1)^2$	0.0241(0.020)	0.0195*(0.011)	0.0197*(0.011)	0.0151(0.011)
$1/2\ (lny_2)^2$	0.0064***(0.001)	0.0036***(0.001)	0.0034***(0.001)	0.0037***(0.001)
$1/2\ (lnp_1)^2$	0.1213(0.189)	0.0302(0.072)	0.0312(0.072)	−0.0243(0.073)
$1/2\ (lnp_2)^2$	0.6138**(0.238)	0.4362***(0.092)	0.4425***(0.092)	0.4388***(0.093)
$1/2\ (lnp_3)^2$	−0.0291(0.018)	−0.0398***(0.012)	−0.0373***(0.012)	−0.0450***(0.012)
τ	0.0127***(0.003)	0.0115***(0.002)	0.0118***(0.002)	0.0123***(0.002)
Inefficiency determinants				
CAP	0.1226***(0.015)	0.0847***(0.010)	0.0901***(0.011)	0.0892***(0.011)
Income div	−0.0187**(0.008)	−0.0461***(0.008)	−0.0475***(0.008)	−0.0500*** (0.008)
Funding div	0.0614***(0.008)	0.0675***(0.010)	0.0674***(0.010)	0.0638***(0.010)
LIQ	−0.0454***(0.015)	−0.0260**(0.012)	−0.0240**(0.011)	−0.0285** (0.013)
NPL	0.1127***(0.010)	0.0284** (0.012)	0.0377***(0.012)	0.0510***(0.011)
Z Score	0.0004(0.000)	0.0008**(0.000)	0.0007**(0.000)	0.0006*(0.000)
$\boldsymbol{W} \times$ *CAP*		0.0816***(0.018)	0.0653***(0.018)	0.1486***(0.022)
$\boldsymbol{W} \times$ *Income div*		−0.0088(0.012)	−0.0113(0.013)	−0.0156(0.014)
$\boldsymbol{W} \times$ *Funding div*		0.0972***(0.017)	0.1105***(0.018)	0.0911***(0.019)
$\boldsymbol{W} \times$ *LIQ*		0.0548***(0.016)	0.0596***(0.016)	0.0557***(0.017)
$\boldsymbol{W} \times$ *NPL*		0.1665***(0.017)	0.1577***(0.017)	0.1130***(0.019)
$\boldsymbol{W} \times$ *Z Score*		0.0026***(0.001)	0.0041***(0.001)	0.0057***(0.001)

Notes: The number of observations is 2,299. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Time effects are included in the specification. Variables that are spatially lagged are indicated with a leading "***W***."

TABLE 14 One-step stochastic profit frontier estimates

Profit function	Nonspatial model (21)	Spatial models W_1 (22)	W_2 (23)	W_3 (24)
lnp$_1$	0.5579***(0.025)	0.5197***(0.025)	0.5227***(0.025)	0.5270***(0.025)
lnp$_2$	0.1052***(0.022)	0.1370***(0.023)	0.1332***(0.023)	0.1272***(0.022)
lnp$_3$	0.3370***(0.015)	0.3433***(0.014)	0.3441***(0.014)	0.3458***(0.015)
$1/2\ lnp_1 \times lnp_2$	0.5586***(0.106)	0.4414***(0.120)	0.4399***(0.118)	0.4270***(0.121)
$1/2\ lnp_1 \times lnp_3$	−0.4503***(0.070)	−0.4818***(0.068)	−0.4772***(0.067)	−0.4685***(0.068)
$1/2\ lnp_2 \times lnp_3$	−0.1315**(0.062)	−0.0668(0.062)	−0.0676(0.062)	−0.0731(0.061)
$1/2\ (lnp_1)^2$	0.0331(0.077)	0.0914(0.079)	0.0895(0.078)	0.0963(0.080)
$1/2\ (lnp_2)^2$	−0.2661***(0.053)	−0.2273***(0.063)	−0.2259***(0.062)	−0.2221***(0.062)
$1/2\ (lnp_3)^2$	0.2563***(0.016)	0.2431***(0.015)	0.2414***(0.015)	0.2404***(0.015)
τ	0.0845***(0.003)	0.0864***(0.003)	0.0867***(0.003)	0.0869***(0.003)
Inefficiency Determinants				
CAP	0.1658***(0.009)	0.0868***(0.010)	0.0864***(0.010)	0.0820***(0.009)
Income div	−0.0531***(0.007)	−0.0405***(0.007)	−0.0415***(0.007)	−0.0392***(0.007)
Funding div	0.0422***(0.008)	0.0044(0.008)	0.0033(0.008)	0.0020(0.008)
LIQ	−0.0507***(0.013)	−0.0425***(0.013)	−0.0420***(0.012)	−0.0456***(0.013)
NPL	0.1747***(0.008)	0.0729***(0.010)	0.0758***(0.009)	0.0827***(0.009)
Z Score	−0.0001(0.000)	0.0003(0.000)	0.0003(0.000)	0.0003(0.000)
W × *CAP*		0.1080***(0.013)	0.1068***(0.013)	0.1204***(0.016)
W × *Income div*		−0.0382***(0.010)	−0.0455***(0.011)	−0.0461***(0.012)
W × *Funding div*		0.0933***(0.012)	0.1091***(0.013)	0.1009***(0.014)
W × *LIQ*		0.0490***(0.014)	0.0537***(0.014)	0.0600***(0.015)
W × *NPL*		0.1827***(0.013)	0.1855***(0.013)	0.1942***(0.014)
W × *Z Score*		0.0015**(0.001)	0.0024***(0.001)	0.0027***(0.001)

Notes: Number of obs 2,294. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Time effects are included in the specification. Variables that are spatially lagged are indicated with a leading "**W**".

As in the DEA technique, this efficiency metric ranges from a value of 0 to 1, where 1 represents a fully efficient bank with optimal utilization of inputs, whereas an efficiency score of 0 indicates the maximum distance from the best performers.

The one-step method (detailed in Schmidt, 2011) is used, in which the inefficiency determinants are regressed to the variance of the bank's inefficiency term (σ_u). Except for the variables used in the production or cost frontier, the inefficiency function relates the determinants already used in the DEA models. Indeed, our SLX specification allows for the inclusion of the spatial terms associated with these inefficiency determinants, as in Adetutu et al. (2015).[24]

Given the difference in the two econometric techniques and that the coefficients in the SFA model represent the impact of inefficiency on a bank, and therefore a negative sign implies an inefficiency reduction (and vice versa),

[24]Other studies based on SFA consider alternative spatial specifications: for instance, Gude et al. (2018) adopts an efficiency Durbin model, Glass et al. (2016) consider an SAR model, and Fusco and Vidoli (2013) consider an SER.

the results of the parametric estimates confirm the robustness of our benchmark models. Indeed, the findings of the two methodologies provide similar effects in terms of sign and statistical significance. The only exceptions are the direct effect of *Funding div* for the cost side model, which confirms Coccorese and Shaffer's (2020) findings that a less diversified fund strategy increases the cost inefficiency of Italian CCBs, and the indirect effect of *Income div* on the production side. Tables 13 and 14 report the estimated results.

7 | CONCLUDING REMARKS

In this article, we use a spatial two-stage bootstrap DEA approach to investigate the impact of spillover effects on the TE performance of small and local cooperative banks. It focuses on small Italian cooperative banks, which present a heterogeneous geographical distribution across Italian regions. These banks dominate the bank market in certain areas while they have a negligible presence in others. The characteristics of CCBs make them a suitable sample for testing the hypothesis that spatial dependence is a crucial determinant of efficiency scores in both of the DEA models. In this regard, the set of spatial dependence tests supports the presence of bank co-movements. Overall, regardless of the spatial matrix type considered, the findings show strong evidence of spatial spillover effects: the CCBs' network negatively conditions either input or output operational efficiency. This implies that small cooperative banks, as specialized intermediaries that compete in a niche financial market, interact with other mutual banks operating in the same area to the point that their efficiency is sensitive to bank network effects, and that a cascade effect can arise among these financial institutions.

Bank authorities should be aware that bank liquidity and bank capital endowment policy indications may condition the operation of local banks. Our evidence highlights nonperforming loans as the Achilles' heel of mutual banks, not only directly harming bank efficiency but also triggering a vicious cycle from contagion among neighbors.

Overall, all bank stakeholders should be aware that although being a local and mutual bank provides significant benefits in terms of regulation and fiscal incentives, operating in small local economies exposes these institutions to negative externalities in terms of inefficiency.

This is a pioneering study of the impact of geographical dependency on local bank efficiency, but the findings need to be viewed with some caution and could be challenged in future studies. The study blurs the line between local banks that are more focused on households and those that are more focused on small and micro businesses. The demand elasticity of these various types of bank customers varies and, as a result, banks' loan portfolios should be weighted to control this effect on efficiency performance. However, this issue could not be overcome because of a lack of data.

Furthermore, additional research could be conducted to link local bank efficiency to spatial dependence within branch networks. It would also be interesting to examine if the findings hold in other countries where small cooperative banks are prevalent and in countries where they are not.

ACKNOWLEDGMENTS

We thank three anonymous referees and the Editor for constructive comments and criticism. The authors would like to thank Professor Theodor Skivas and Professor Pasquale De Meo for their support. Usual disclaimer applies. Open Access Funding provided by Universita degli Studi di Messina within the CRUI-CARE Agreement.

ORCID

Carmelo Algeri https://orcid.org/0000-0001-7122-4376
Luc Anselin https://orcid.org/0000-0003-1076-2220
Antonio Fabio Forgione https://orcid.org/0000-0003-4015-4939
Carlo Migliardo https://orcid.org/0000-0002-4055-0782

REFERENCES

Adetutu, M., Glass, A. J., Kenjegalieva, K., & Sickles, R. C. (2015). The effects of efficiency and TFP growth on pollution in europe: a multistage spatial analysis. *Journal of Productivity Analysis*, *43*(3), 307–326.

Agarwal, S., Chang, Y., & Yavas, A. (2012). Adverse selection in mortgage securitization. *Journal of Financial Economics*, *105*(3), 640–660.

Agarwal, S., Chomsisengphet, S., Liu, C., Song, C., & Souleles, N. S. (2018). Benefits of relationship banking: Evidence from consumer credit markets. *Journal of Monetary Economics*, *96*, 16–32.

Aggelopoulos, E., & Georgopoulos, A. (2017). Bank branch efficiency under environmental change: A bootstrap DEA on monthly profit and loss accounting statements of greek retail branches. *European Journal of Operational Research*, *261*(3), 1170–1188.

Ahmad, N., Naveed, A., Ahmad, S., & Butt, I. (2020). Banking sector performance, profitability, and efficiency: a citation-based systematic literature review. *Journal of Economic Surveys*, *34*(1), 185–218.

Aiello, F., & Bonanno, G. (2018a). Multilevel empirics for small banks in local markets. *Papers in Regional Science*, *97*(4), 1017–1037.

Aiello, F., & Bonanno, G. (2018b). On the sources of heterogeneity in banking efficiency literature. *Journal of Economic Surveys*, *32*(1), 194–225.

Almazan, A. (2002). A model of competition in banking: Bank capital vs expertise. *Journal of Financial Intermediation*, *11*(1), 87–121.

Altunbas, Y., Carbo, S., Gardener, E. P. M., & Molyneux, P. (2007). Examining the relationships between capital, risk and efficiency in european banking. *European Financial Management*, *13*(1), 49–70.

Aly, H. Y., Grabowski, R., Pasurka, C., & Rangan, N. (1990). Technical, scale, and allocative efficiencies in US banking: An empirical investigation. *The review of Economics and Statistics*, 211–218.

Andrews, D. W. K. (2005). Cross-section regression with common shocks. *Econometrica*, *73*(5), 1551–1585.

Anselin, L. (1988). *Spatial econometrics: Methods and models*, Vol. 4. Springer Science & Business Media.

Anselin, L. (1995). Local indicators of spatial association—lisa. *Geographical Analysis*, *27*(2), 93–115.

Anselin, L. (2002). Under the hood issues in the specification and interpretation of spatial regression models. *Agricultural Economics*, *27*(3), 247–267.

Anselin, L. (2003). Spatial externalities, spatial multipliers, and spatial econometrics. *International Regional Science Review*, *26*(2), 153–166.

Anselin, L., Le Gallo, L., & Jayet, H. (2007). *Spatial panel econometrics. in matyas, l. & sevestre, p.(eds.) the econometrics of panel data fundamentals and recents developments in theory and practice*: Springer Berlin Heidelberg.

Asimakopoulos, G., Chortareas, G., & Xanthopoulos, M. (2018). The eurozone financial crisis and bank efficiency asymmetries: Peripheral versus core economies. *The Journal of Economic Asymmetries*, *18*(C), 1.

Baas, T., & Schrooten, M. (2006). Relationship banking and smes: A theoretical analysis. *Small Business Economics*, *27*(2-3), 127–137.

Bai, J., & Ng, S. (2010). Panel unit root tests with cross-section dependence: a further investigation. *Econometric Theory*, *26*(4), 1088–1114.

Baltagi, B. H., Song, S. H., & Koh, W. (2003). Testing panel data regression models with spatial error correlation. *Journal of Econometrics*, *117*(1), 123–150.

Baltagi, B. H., Song, S. H., Jung, B., & Koh, W. (2007). Testing panel data regression models with spatial and serial error correlation. *Journal of Econometrics*, *140*, 5–51.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9), 1078–1092.

Barra, C., & Zotti, R. (2019). Bank performance, financial stability and market concentration: Evidence from cooperative and non-cooperative banks. *Annals of Public and Cooperative Economics*, *90*(1), 103–139.

Barth, J. R., Lin, C., Ma, Y., Seade, J., & Song, F. M. (2013). Do bank regulation, supervision and monitoring enhance or impede bank efficiency? *Journal of Banking & Finance*, *37*(8), 2879–2892.

Baumont, C., Ertur, C., & Le Gallo, J. (2004). Spatial analysis of employment and population density: the case of the agglomeration of dijon 1999. *Geographical Analysis*, *36*(2), 146–176.

Berger, A. N., Bouwman, C. H. S., & Kim, D. (2017). Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance over time. *The Review of Financial Studies*, *30*(10), 3416–3454.

Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, *21*(6), 849–870.

Berger, A. N., & Mester, L. J. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking & Finance*, *21*(7), 895–947.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? evidence from the lending practices of large and small banks. *Journal of Financial Economics*, *76*(2), 237–269.

Berger, A. N., & Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business*, 351–381.

Berger, A. N., & Udell, G. F. (2002). Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal*, *112*(477), F32–F53.

Bernini, C., & Brighi, P. (2018). Bank branches expansion, efficiency and local economic growth. *Regional Studies*, *52*(10), 1332–1345.

Bhatia, V., Basu, S., Mitra, S. K., & Dash, P. (2018). A review of bank efficiency and productivity. *Opsearch*, *55*(3-4), 557–600.

Binam, J. N., Sylla, K., Diarra, I., & Nyambi, G. (2003). Factors affecting technical efficiency among coffee farmers in cote d'ivoire: Evidence from the centre west region. *African Development Review*, *15*(1), 66–76.

Bitar, M., Pukthuanthong, K., & Walker, T. (2018). The effect of capital ratios on the risk, efficiency and profitability of banks: Evidence from OECD countries. *Journal of International Financial Markets, Institutions and Money*, *53*, 227–262.

Bitar, M., Pukthuanthong, K., & Walker, T. (2020). Efficiency in islamic vs. conventional banking: The role of capital and liquidity. *Global Finance Journal*, *46*, 100487.

Breusch, T. S., & Pagan, A. R. (1980). The lagrange multiplier test and its applications to model specification in econometrics. *The review of Economic Studies*, *47*(1), 239–253.

Brissimis, S. N., Delis, M. D., & Papanikolaou, N. I. (2008). Exploring the nexus between banking sector reform and performance: Evidence from newly acceded EU countries. *Journal of Banking & Finance*, *32*(12), 2674–2683.

Burgstaller, J. (2020). Retail-bank efficiency: Nonstandard goals and environmental determinants. *Annals of Public and Cooperative Economics*, *91*(2), 269–301.

Campbell, J. Y., Giglio, S., & Pathak, P. (2011). Forced sales and house prices. *American Economic Review*, *101*(5), 2108–31.

Cassar, G., Ittner, C. D., & Cavalluzzo, K. S. (2015). Alternative information sources and information asymmetry reduction: Evidence from small business debt. *Journal of Accounting and Economics*, *59*(2-3), 242–263.

Casu, B., Ferrari, A., Girardone, C., & Wilson, J. O. S. (2016). Integration, productivity and technological spillovers: Evidence for eurozone banking industries. *European Journal of Operational Research*, *255*(3), 971–983.

Casu, B., & Girardone, C. (2004). Financial conglomeration: efficiency, productivity and strategic drive. *Applied Financial Economics*, *14*(10), 687–696.

Casu, B., & Girardone, C. (2006). Bank competition, concentration and efficiency in the single european market. *The Manchester School*, *74*(4), 441–468.

Casu, B., Girardone, C., & Molyneux, P. (2004). Productivity change in european banking: A comparison of parametric and non-parametric approaches. *Journal of Banking & Finance*, *28*(10), 2521–2540.

Casu, B., & Molyneux, P. (2003). A comparative study of efficiency in european banking. *Applied Economics*, *35*(17), 1865–1876.

Cerqueiro, G., Degryse, H., & Ongena, S. (2009). Distance, bank organizational structure, and lending decisions, *The Changing Geography of Banking and Finance*: Springer, pp. 57–74.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444.

Chiappori, P.-A., Perez-Castrillo, D., & Verdier, T. (1995). Spatial competition in the banking system: Localization, cross subsidies and the regulation of deposit rates. *European Economic Review*, *39*(5), 889–918.

Cliff, A. D., & Ord, J. K. (1968). The problem of spatial autocorrelation. In: Scott, A.J. (ed.). *london papers in regional science* (Vol. 1, pp. 25-55). Pion, London.

Coccorese, P., & Ferri, G. (2020). Are mergers among cooperative banks worth a dime? evidence on efficiency effects of m&as in italy. *Economic Modelling*, *84*, 147–164.

Coccorese, P., & Santucci, L. (2019). Banking competition and bank size: Some evidence from italy. *Journal of Economics and Finance*, 1–22.

Coccorese, P., & Shaffer, S. (2020). Cooperative banks and local economic growth. *Regional Studies*, 1–15.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*: Springer Science & Business Media.

Cook, W. D., Tone, K., & Zhu, J. (2014). Data envelopment analysis: Prior to choosing a model. *Omega*, *44*, 1–4.

Cooper, W. W., Seiford, L. M., & Tone, K. (2006). *Introduction to data envelopment analysis and its uses: with dea-solver software and references*: Springer Science & Business Media.

Curi, C., Lozano-Vivas, A., & Zelenyuk, V. (2015). Foreign bank diversification and efficiency prior to and during the financial crisis: Does one business model fit all? *Journal of Banking & Finance*, *61*, S22–S35.

D'Aurizio, L., Oliviero, T., & Romano, L. (2015). Family firms, soft information and bank lending in a financial crisis. *Journal of Corporate Finance*, *33*, 279–292.

Degl'Innocenti, M., Fiordelisi, F., & Trinugroho, I. (2020). Competition and stability in the credit industry: Banking vs. factoring industries. *The British Accounting Review*, *52*(1), 100831.

Degl'Innocenti, M., Mishra, T., & Wolfe, S. (2018). Branching, lending and competition in italian banking. *The European Journal of Finance*, *24*(3), 208–230.

Delis, M., Iosifidi, M., & Tsionas, M. G. (2017). Endogenous bank risk and efficiency. *European Journal of Operational Research*, *260*(1), 376–387.

Diallo, B. (2018). Bank efficiency and industry growth during financial crises. *Economic Modelling*, *68*, 11–22.

Ding, C., & He, X. (2004). K-nearest-neighbor consistency in data clustering: incorporating local information into global optimization. In *Proceedings of the 2004 ACM symposium on Applied computing*, pp. 584–589.

Ding, D., & Sickles, R. C. (2018). Frontier efficiency, capital structure, and portfolio risk: An empirical analysis of US banks. *BRQ Business Research Quarterly*, *21*(4), 262–277.

Ding, D., & Sickles, R. C. (2019). Capital regulation, efficiency, and risk taking: A spatial panel analysis of US banks, *Panel data econometrics*: Elsevier, pp. 405–466.

Drake, L., Hall, M. J. B., & Simper, R. (2006). The impact of macroeconomic and regulatory factors on bank efficiency: A non-parametric analysis of hong kong's banking system. *Journal of Banking & Finance*, *30*(5), 1443–1466.

Elhorst, J. P. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*, Vol. 479: Springer.

Elhorst, J. P., Madre, J.-L., & Pirotte, A. (2020). Car traffic, habit persistence, cross-sectional dependence, and spatial heterogeneity: New insights using french departmental data. *Transportation Research Part A: Policy and Practice*, *132*, 614–632.

Elsas, R. (2005). Empirical determinants of relationship lending. *Journal of Financial Intermediation*, *14*(1), 32–57.

Ergungor, O. E., & Moulton, S. (2014). Beyond the transaction: Banks and mortgage default of low-income homebuyers. *Journal of Money, Credit and Banking*, *46*(8), 1721–1752.

Ertur, C., & Koch, W. (2006). Regional disparities in the european union and the enlargement process: an exploratory spatial data analysis, 1995–2000. *The Annals of Regional Science*, *40*(4), 723–765.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, *120*(3), 253–281.

Fernandes, F. D. S., Stasinakis, C., & Bardarova, V. (2018). Two-stage dea-truncated regression: Application in banking efficiency and financial development. *Expert Systems with Applications*, *96*, 284–301.

Fiordelisi, F., & Mare, D. S. (2014). Competition and financial stability in european cooperative banks. *Journal of International Money and Finance*, *45*, 1–16.

Florax, R., & Folmer, H. (1992). Specification and estimation of spatial linear regression models: Monte carlo evaluation of pre-test estimators. *Regional Science and Urban Economics*, *22*(3), 405–432.

Foos, D., Lütkebohmert, E., Markovych, M., & Pliszka, K. (2017). Euro area banks' interest rate risk exposure to level, slope and curvature swings in the yield curve. *Bundesbank Discussion Paper*, *24/2017*.

Frame, W. S. (2010). Estimating the effect of mortgage foreclosures on nearby property values: A critical review of the literature. *Economic Review*, *95*.

Fraser, D. R., Madura, J., & Weigand, R. A. (2002). Sources of bank interest rate risk. *Financial Review*, *37*(3), 351–367.

Fukuyama, H., & Matousek, R. (2017). Modelling bank performance: A network DEA approach. *European Journal of Operational Research*, *259*(2), 721–732.

Fusco, E., & Vidoli, F. (2013). Spatial stochastic frontier models: controlling spatial global and local heterogeneity. *International Review of Applied Economics*, *27*(5), 679–694.

Fusco, E., Vidoli, F., & Rogge, N. (2020). Spatial directional robust benefit of the doubt approach in presence of undesirable output: An application to italian waste sector. *Omega*, *94*, 102053.

Fusco, E., Vidoli, F., & Sahoo, B. K. (2018). Spatial heterogeneity in composite indicator: A methodological proposal. *Omega*, *77*, 1–14.

Gaganis, C., & Pasiouras, F. (2013). Financial supervision regimes and bank efficiency: International evidence. *Journal of Banking & Finance*, *37*(12), 5463–5475.

Garcia-Appendini, E. (2011). Lending to small businesses: The value of soft information. Available at SSRN 1750056.

Gehrig, T. (1998). Screening, cross-border banking, and the allocation of credit. *Research in Economics*, *52*(4), 387–407.

Gibbons, S., & Overman, H. G. (2012). Mostly pointless spatial econometrics? *Journal of Regional Science*, *52*(2), 172–191.

Glass, A., Kenjegalieva, K., & Sickles, R. C. (2014). Estimating efficiency spillovers with state level evidence for manufacturing in the us. *Economics Letters*, *123*(2), 154–159.

Glass, A. J., Kenjegaliev, A., & Kenjegalieva, K. (2020). Spatial scale and product mix economies in US banking with simultaneous spillover regimes. *European Journal of Operational Research*, *284*(2), 693–711.

Glass, A. J., & Kenjegalieva, K. (2019). A spatial productivity index in the presence of efficiency spillovers: Evidence for US banks, 1992–2015. *European Journal of Operational Research*, *273*(3), 1165–1179.

Glass, A. J., Kenjegalieva, K., & Sickles, R. C. (2016). A spatial autoregressive stochastic frontier model for panel data with asymmetric efficiency spillovers. *Journal of Econometrics*, *190*(2), 289–300.

Gude, A., Álvarez, I., & Orea, L. (2018). Heterogeneous spillovers among spanish provinces: a generalized spatial stochastic frontier model. *Journal of Productivity Analysis*, *50*(3), 155–173.

Halleck Vega, S., & Elhorst, J. P. (2015). The SLX model. *Journal of Regional Science*, *55*(3), 339–363.

Harimaya, K., & Ozaki, Y. (2021). Effects of diversification on bank efficiency: Evidence from shinkin banks in japan. *International Review of Economics & Finance*, *71*, 700–717.

Hasan, I., Jackowicz, K., Jagiełło, R., Kowalewski, O., & Kozłowski, L. (2021). Local banks as difficult-to-replace SME lenders: Evidence from bank corrective programs. *Journal of Banking & Finance*, *123*, 106029.

Hasan, I., Jackowicz, K., Kowalewski, O., & Kozłowski, L. (2017). Do local banking market structures matter for SME financing and performance? new evidence from an emerging economy. *Journal of Banking & Finance*, *79*, 142–158.

Hauswald, R., & Marquez, R. (2003). Information technology and financial services competition. *The Review of Financial Studies*, *16*(3), 921–948.

Iosifidi, M., Panopoulou, E., & Tsoumas, C. (2021). Mortgage loan demand and banks' operational efficiency. *Journal of Financial Stability*, 100851.

Kar, M., Nazlıoğlu, S., & Ağır, H. (2011). Financial development and economic growth nexus in the MENA countries: Bootstrap panel granger causality analysis. *Economic Modelling*, *28*(1-2), 685–693.

Karakaplan, M. U., & Kutlu, L. (2017). Endogeneity in panel stochastic frontier models: an application to the japanese cotton spinning industry. *Applied Economics*, *49*(59), 5935–5939.

Kelejian, H. H., & Prucha, I. R. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics*, *157*(1), 53–67.

Kirkpatrick, C. O. L. I. N., Murinde, V., & Tefula, M. O. S. E. S. (2008). The measurement and determinants of x-inefficiency in commercial banks in sub-saharan africa. *The European Journal of Finance*, *14*(7), 625–639.

Kulasekaran, S., & Shaffer, S. (2002). Cost efficiency among credit card banks. *Journal of Economics and Business*, *54*(6), 595–614.

Kutlu, L. (2018). Estimating efficiency in a spatial autoregressive stochastic frontier model. *Economics Letters*, *163*, 155–157.

Kutlu, L., & Nair-Reichert, U. (2019). Agglomeration effects and spatial spillovers in efficiency analysis: a distribution-free methodology. *Regional Studies*, *53*(11), 1565–1574.

Kutlu, L., Tran, K. C., & Tsionas, M. G. (2020). A spatial stochastic frontier model with endogenous frontier and environmental variables. *European Journal of Operational Research*, *286*(1), 389–399.

Kysucky, V., & Norden, L. (2015). The benefits of relationship lending in a cross-country context: A meta-analysis. *Management Science*, *62*(1), 90–110.

Laeven, L., & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: too much, too late? *Journal of Financial Intermediation*, *12*(2), 178–197.

Le Gallo, J., & Ertur, C. (2003). Exploratory spatial data analysis of the distribution of regional per capita GDP in europe, 1980–1995. *Papers in Regional Science*, *82*(2), 175–201.

Le, M., Hoang, V.-N., Wilson, C., & Managi, S. (2020). Net stable funding ratio and profit efficiency of commercial banks in the us. *Economic Analysis and Policy*, *67*, 55–66.

LeSage, J. (2014). What regional scientists need to know about spatial econometrics. *The Review of Regional Studies*, *44*(1), 13–32.

LeSage, J. P., & Fischer, M. M. (2008). Spatial growth regressions: model specification, estimation and interpretation. *Spatial Economic Analysis*, *3*(3), 275–304.

Liberti, J. M., & Mian, A. R. (2008). Estimating the effect of hierarchies on information use. *The Review of Financial Studies*, *22*(10), 4057–4090.

Liberti, J. M. (2018). Initiative, incentives, and soft information. *Management Science*, *64*(8), 3714–3734.

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies*, *8*(1), 1–41.

Luo, Y., Tanna, S., & De Vita, G. (2016). Financial openness, risk and bank efficiency: Cross-country evidence. *Journal of Financial Stability*, *24*, 132–148.

Mamatzakis, E. (2015). Risk and efficiency in the central and eastern european banking industry under quantile analysis. *Quantitative Finance*, *15*(3), 553–567.

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*(1), 33–58.

McKee, G., & Kagan, A. (2016). Determinants of recent structural change for small asset US credit unions. *Review of Quantitative Finance and Accounting*, *47*(3), 775–795.

Miah, M. D., & Uddin, H. (2017). Efficiency and stability: A comparative study between islamic and conventional banks in GCC countries. *Future Business Journal*, *3*(2), 172–185.

Millo, G. (2017). A simple randomization test for spatial correlation in the presence of common factors and serial correlation. *Regional Science and Urban Economics*, *66*, 28–38.

Millo, G., & Piras, G. (2012). splm: Spatial panel data models in R. *Journal of Statistical Software*, *47*(1), 1–38.

Minviel, J. J., & Ben Bouheni, F. (2021). Technical and managerial efficiency assessment of european banks using a conditional nonparametric approach. *International Transactions in Operational Research*, *28*(2), 560–597.

Mur, J., & Angulo, A. (2006). The spatial durbin model and the common factor tests. *Spatial Economic Analysis*, *1*(2), 207–226.

Okeahalam, C. C. (2004). Foreign ownership, performance and efficiency in the banking sector in uganda and botswana. *Studies in Economics and Econometrics*, *28*(1), 89–118.

Ongena, S., & Smith, D. C. (2001). The duration of bank relationships. *Journal of Financial Economics*, *61*(3), 449–475.

Orea, L., & Álvarez, I. C. (2019). A new stochastic frontier model with cross-sectional effects in both noise and inefficiency terms. *Journal of Econometrics*, *213*(2), 556–577.

Pérez-Cárceles, M. C., Gómez-García, J., & Gallego, J. C. G. (2019). Goodness of governance effect on european banking efficiency. *International Review of Economics & Finance*, *64*, 29–40.

Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels*. Working Paper 435, Cambridge Working Papers in Economics.

Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, *34*(6-10), 1089–1117.

Petersen, M. A. (2004). Information: Hard and soft Working paper, Kellogg School of Management, Northwestern University, Evanston, IL, and NBER, Cambridge, MA.

Petersen, M. A., & Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance*, *49*(1), 3–37.

Podpiera, J., & Weill, L. (2008). Bad luck or bad management? emerging banking market experience. *Journal of Financial Stability*, *4*(2), 135–148.

Pruteanu-Podpiera, A., Weill, L., & Schobert, F. (2016). Banking competition and efficiency: A micro-data analysis on the czech banking industry, *Global banking crises and emerging markets*: Springer, pp. 52–74.

Roman, A., & Şargu, A. C. (2013). Analysing the financial soundness of the commercial banks in romania: an approach based on the camels framework. *Procedia Economics and Finance*, *6*, 703–712.

Saha, A., Ahmad, N. H., & Dash, U. (2015). Drivers of technical efficiency in M alaysian banking: a new empirical insight. *Asian-Pacific Economic Literature*, *29*(1), 161–173.

Sakouvogui, K. (2020). Impact of liquidity and solvency risk factors on variations in efficiency of US banks. *Managerial Finance*.

Sarafidis, V., & Wansbeek, T. (2012). Cross-sectional dependence in panel data analysis. *Econometric Reviews*, *31*(5), 483–531.

Schenone, C. (2010). Lending relationships and information rents: Do banks exploit their information advantages? *The Review of Financial Studies*, *23*(3), 1149–1199.

Schmidt, P. (2011). One-step and two-step estimation in SFA models. *Journal of Productivity Analysis*, *36*(2), 201–203.

Sealey Jr, C. W., & Lindley, J. T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *The Journal of Finance*, *32*(4), 1251–1266.

Shim, J. (2019). Loan portfolio diversification, market structure and bank stability. *Journal of Banking & Finance*, *104*, 103–115.

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31–64.

Skevas, I., & Oude Lansink, A. (2020). Dynamic inefficiency and spatial spillovers in dutch dairy farming. *Journal of Agricultural Economics*, *71*(3), 742–759.

Skevas, T., & Grashuis, J. (2020). Technical efficiency and spatial spillovers: Evidence from grain marketing cooperatives in the US midwest. *Agribusiness*, *36*(1), 111–126.

Speelman, S., D'Haese, M., Buysse, J., & D'Haese, L. (2008). A measure for the efficiency of water use and its determinants, a case study of small-scale irrigation schemes in north-west province, south africa. *Agricultural Systems*, *98*(1), 31–39.

Srairi, S. A. (2010). Cost and profit efficiency of conventional and islamic banks in GCC countries. *Journal of Productivity Analysis*, *34*(1), 45–62.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The Journal of Finance*, *57*(5), 1891–1921.

Stein, J. C. (2003). Agency, information and corporate investment, *Handbook of the Economics of Finance*, Vol. 1: Elsevier, pp. 111–165.

Sufian, F. (2009). Determinants of bank efficiency during unstable macroeconomic environment: Empirical evidence from malaysia. *Research in International Business and Finance*, *23*(1), 54–77.

Sussman, O., & Zeira, J. (1995). Banking and development. *CEPR Discussion Papers*, *1127*.

Tabak, B. M., Miranda, R. B., & Fazio, D. M. (2013). A geographically weighted approach to measuring efficiency in panel data: The case of US saving banks. *Journal of Banking & Finance*, *37*(10), 3747–3756.

Tobler, W. R. (1970). A computer movie simulating urban growth in the detroit region. *Economic Geography*, *46*(sup1), 234–240.

Van Cuong, H., Luu, H. N., Nguyen, L. Q. T., & Chu, V. T. (2020). Income structure, diversification strategy and owners' benefit in cooperative financial institutions. *International Journal of Managerial Finance*.

Vazquez, F., & Federico, P. (2015). Bank funding structures and risk: Evidence from the global financial crisis. *Journal of Banking & Finance*, *61*, 1–14.
Vega, S. H., & Elhorst, J. P. (2016). A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors. *Regional Science and Urban Economics*, *60*, 85–95.
Wu, J., Chen, L., Chen, M., & Jeon, B. N. (2020). Diversification, efficiency and risk of banks: Evidence from emerging economies. *Emerging Markets Review*, *45*, 100720.
Yosano, T., & Nakaoka, T. (2019). *Utilization of soft information on bank performance: The roles of relationship lending in competitive local markets*. Springer.
Zhao, B., Kenjegalieva, K., Wood, J., & Glass, A. (2020). A spatial production analysis of chinese regional banks: case of urban commercial banks. *International Transactions in Operational Research*, *27*(4), 2021–2044.

How to cite this article: Algeri, C., Anselin, L., Forgione, A. F., & Migliardo, C. (2022). Spatial dependence in the technical efficiency of local banks. *Papers in Regional Science*, *101*(3), 685–716. https://doi.org/10.1111/pirs.12669

APPENDIX A

A.1 | TECHNICAL APPENDIX

A.1.1 | The DEA method

Several alternative approaches have been applied to calculate the technical efficiency score of DMUs. Basically, the econometric approaches can be parametric (SFA) or non–parametric (DEA). SFA requires specifying the functional form for either a production or cost function. The main advantage of this technique is that it assumes a deviation from optimality can also result from stochastic shocks. DEA uses mathematical programming to measure efficiency scores for multiple DMUs that are either input– or output–oriented. An input orientation aims to achieve the greatest proportional reduction in inputs remaining inside the production frontier. Accordingly, an entity is inefficient when it is possible to reduce the quantity of inputs without changing the output levels. An output orientation, in contrast, aims at expanding the output levels without modifying the input vector, provided that the output vector stays within the frontier of achievable production. The DEA approach identifies the best practice frontier under a specific assumption of constant (CRS) or variable (VRS) returns to scale (Cook et al., 2014).[25] The most significant advantage of the non–parametric technique is that it does not require an *ex ante* specification of the production or cost function (Cooper et al., 2006).

In our investigation, the bank efficiency measure is estimated by applying a two–stage DEA approach. In the first stage, we estimate a DEA–BCC model, which is the appropriate method when the inputs and outputs are large or the input–output relationships are nonlinear. The DEA–BCC model is estimated as pooled across time. In detail, given a set of k inputs and m outputs for each n bank, we define $x_i = (x_{1i}, x_{2i}, \ldots, x_{ki})$ as a $k \times 1$ input vector for the i_{th} bank, and $X = (x_1, x_2, \ldots, x_n)$ as a $k \times n$ input matrix; and we define $y_i = (y_{1i}, y_{2i}, \ldots, y_{ki})$ as a $m \times 1$ output vector for the i_{th} bank, and $Y = (y_1, y_2, \ldots, y_n)$ as an $m \times n$ output matrix. The technical efficiency score for each DMU is then obtained by dividing the weighted sum of its outputs divided by a weighted sum of its inputs, that is:

$$TE = \frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{s=1}^{k} v_s x_{sj}} \tag{A1}$$

[25]The first non–parametric analysis regarding technical efficiency was introduced by Farrell (1957). Subsequently, Charnes et al. (1978) and Banker et al. (1984) developed the two main DEA models: DEA–CCR under the hypothesis of CRS, and DEA–BCC under the hypothesis of VRS.

where y_i and x_i represent the output and input, while u and v are the output r and input s weights, respectively.

The best weights are identified using a linear programming methodology that maximizes the ratio of weighted outputs to weighted inputs for the DMU (TE), subject to the constraint that the ratio is bounded in the interval between 0 and 1. In more detail, the true TE_i scores from the Farrell–Debreu measure range from 1 to ∞, with 1 being the optimal level and a higher value indicating greater technical inefficiency. As a result, the reciprocal of TE falls within the $[0, 1]$ interval, in which the best performing DMU achieves the maximum value (1) and the totally inefficient DMU operates with a technical efficiency score of 0.

Following Banker et al. (1984), the DEA methodology faces an optimization problem related to input or output. In more detail, the input–oriented BCC model is designed to minimize inefficiency, and is defined as follows:

$$\begin{aligned} &\kappa^* = \mathrm{Min}\,\kappa \\ &\text{subject to} \\ &\sum\nolimits_{j=1}^{n} \lambda_j x_{ij} \le \kappa x_{i0}, \quad i = 1, 2, \ldots, k \\ &\sum\nolimits_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0}, \quad r = 1, 2, \ldots, m \\ &\sum\nolimits_{j=1}^{n} \lambda_j = 1,\ \lambda_j \ge 0, \quad j = 1, 2, \ldots, n \end{aligned} \tag{A2}$$

where κ^* is the input–oriented efficiency score, x_i and y_i are the input and output vectors, and λ is an $n \times 1$ vector of constants.

The output–oriented BCC model, which is designed to maximize TE, relies on the following linear programming problem:

$$\begin{aligned} &\theta^* = \mathrm{Max}\ \theta \\ &\text{subject to} \\ &\sum\nolimits_{j=1}^{n} \lambda_j x_{ij} \le x_{i0}, \quad i = 1, 2, \ldots, k \\ &\sum\nolimits_{j=1}^{n} \lambda_j y_{rj} \ge \theta y_{r0}, \quad r = 1, 2, \ldots, m \\ &\sum\nolimits_{j=1}^{n} \lambda_j = 1,\ \lambda_j \ge 0, \quad j = 1, 2, \ldots, n \end{aligned} \tag{A3}$$

in which x_i, y_i and λ are equal to the specification in A2, and θ^* represents the output–oriented TE score.

According to the assumption of constant return to scale proposed by Charnes et al. (1978), the programming models (A2) and (A3) do not consider the convexity constraint. As a consequence, the VRS assumption guarantees that each inefficient DMU is only compared to DMUs that are similar in size, which in turn allows the measurement of economies of scale.

APPENDIX FIGURES

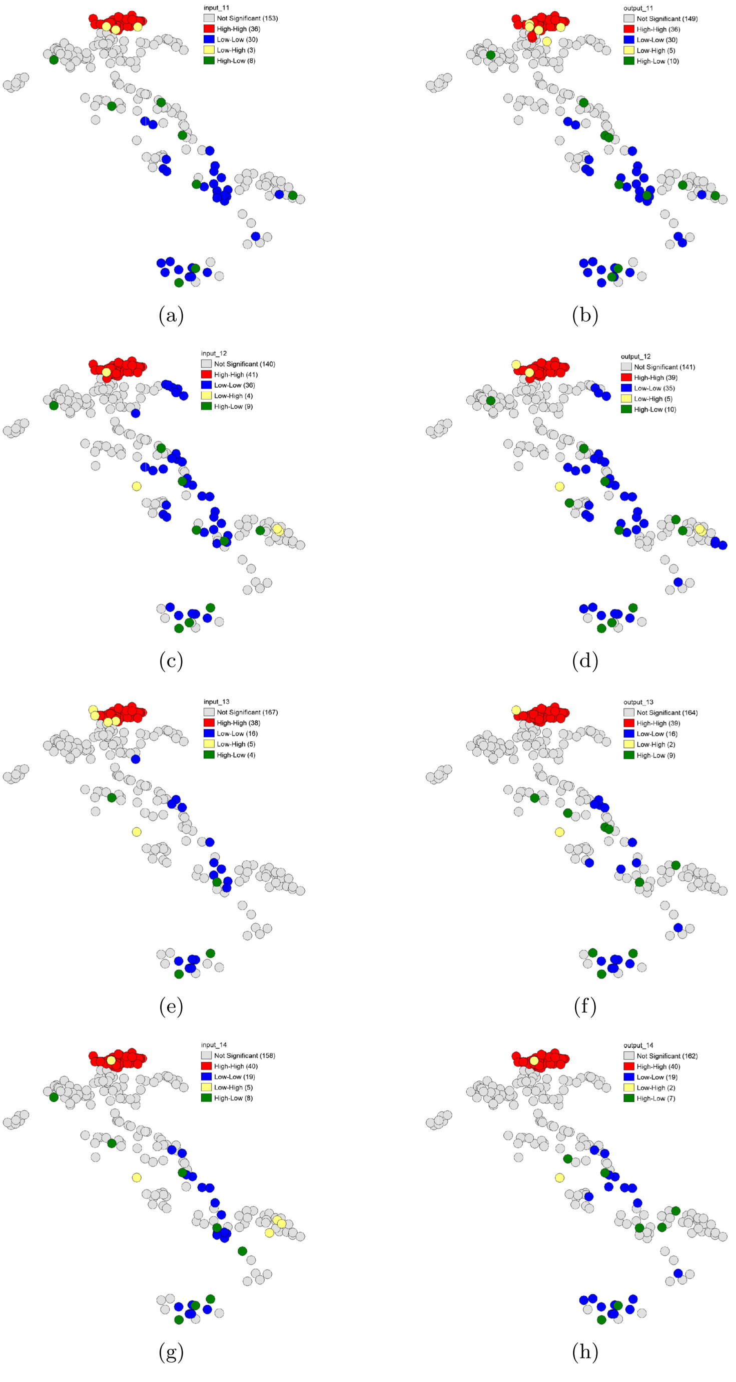


FIGURE A1 LISA cluster map of Input and Output TE. (a) Input TE scores (2011), (b) Output TE scores (2011), (c) Input TE scores (2012), (d) Output TE scores (2012), (e) Input TE scores (2013), (f) Output TE scores (2013), (g) Input TE scores (2014), (h) Output TE scores (2014), (i) Input TE scores (2015), (j) Output TE scores (2015), (k) Input TE scores (2016), (l) Output TE scores (2016), (m) Input TE scores (2017), (n) Output TE scores (2017), (o) Input TE scores (2018), (p) Output TE scores (2018), (q) Input TE scores (2019), (r) Output TE scores (2019), (s) Input TE scores (2020), (t) Output TE scores (2020)

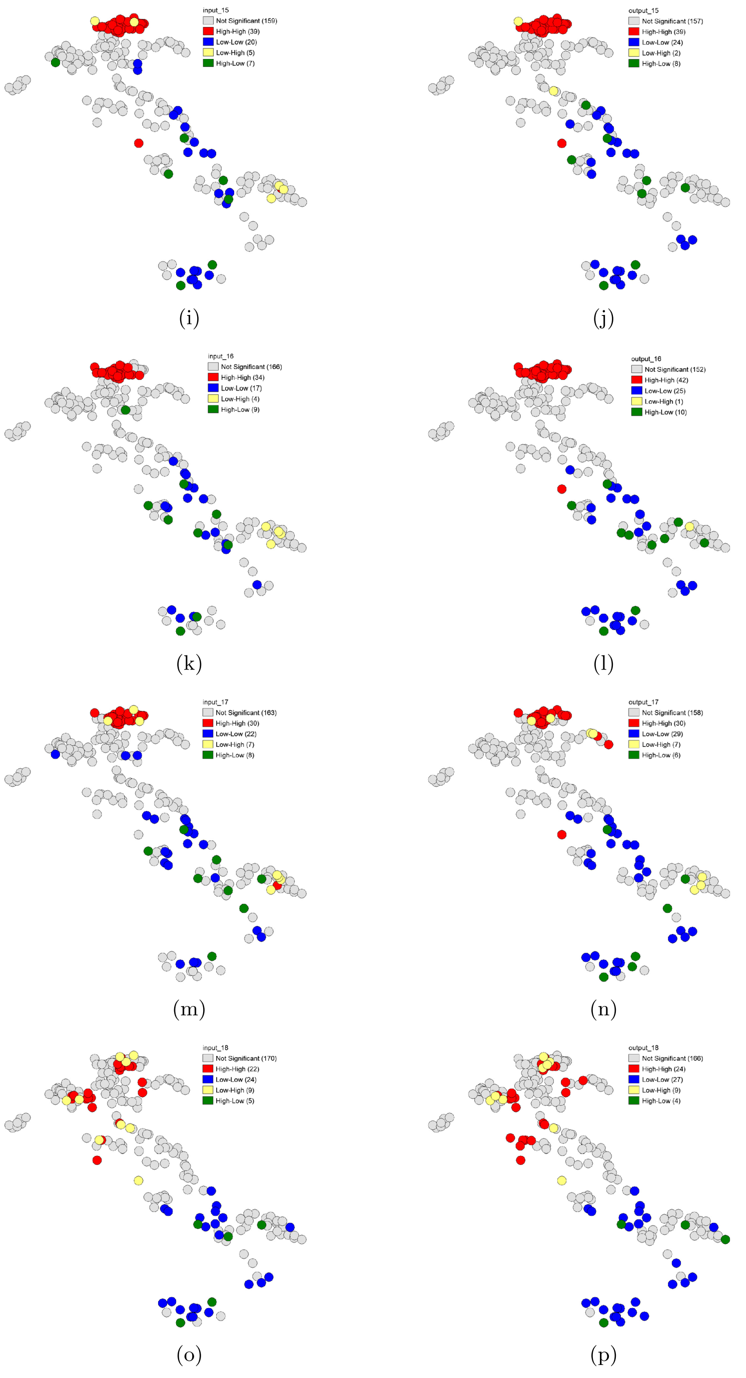
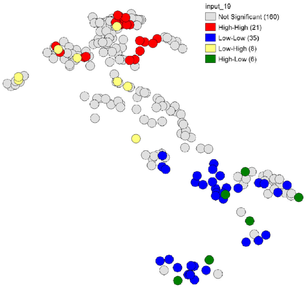
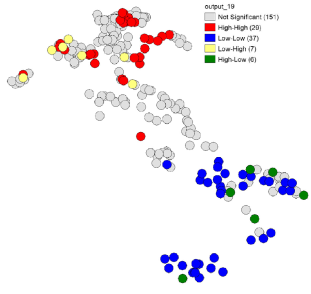


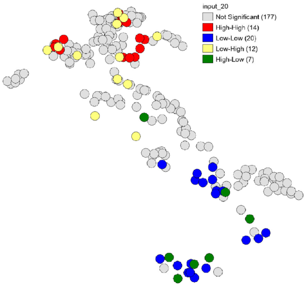
FIGURE A1 (Continued)



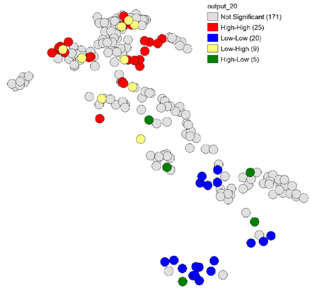
(q)



(r)

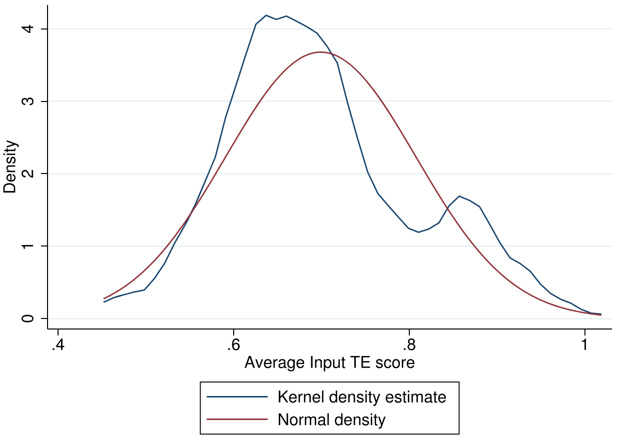


(s)

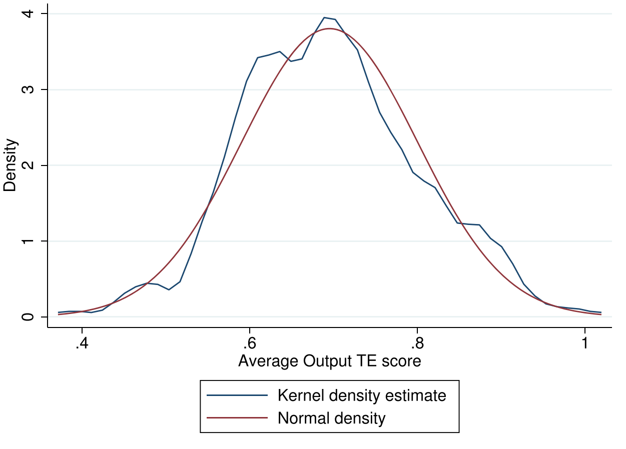


(t)

FIGURE A1 (Continued)



(a)



(b)

FIGURE A2 Kdensity of Input and Output TE scores. (a) Average Input TE score, (b) Average Output TE score

DOI: 10.1111/pirs.12669

Resumen. Los bancos cooperativos compiten principalmente entre sí porque se dirigen a nichos de mercado que los grandes bancos suelen ignorar. El presente estudio muestra que, en este entorno competitivo, la conexión entre los intermediarios financieros afecta a la eficiencia operativa de los bancos pequeños. Los resultados indican que la capitalización, las estrategias de diversificación, los costos de financiación, la liquidez, la calidad del crédito y el riesgo de los vecinos de los bancos tienen efectos indirectos sobre la eficiencia técnica. Así, las redes bancarias desencadenan un efecto en cascada que exige la atención de los inversores de los bancos.

抄録: 協同組合銀行(cooperative bank)が同業者同士で競合するのは、大手銀行が大抵は取引をしないニッチな市場をターゲットにしているためである。今回の研究から、このような競争環境では、金融仲介業の結びつきが小規模銀行の業務効率性に影響を与えることが示された。知見から、資本化、多角化戦略、資金調達コスト、流動性、信用の質、近隣の銀行のリスク、以上が技術効率に波及効果を及ぼすことが示される。銀行ネットワークは、このようにして、銀行のステークホルダーの注意を促すカスケード効果を引き起こす。