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Spatial dependence in small cooperative bank risk behavior and its effects on bank competitiveness and SMEs

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Abstract

In this article we consider the effects of the inclusion of spatial dependence in the empirical model measuring small cooperative banks' risk performance. In the presence of cross-sectional dependence, spatial analysis deals with co-movement among geographical units, allowing for the evaluation of spillover effects and improving econometric models. The article makes several contributions to the literature. First, we support the hypothesis that the inclusion of spatial terms improves small bank soundness models. Second, with the *Z Score* used as a proxy for bank soundness, we indirectly test the impacts of relationship lending on small firms, which is a classic tool adopted by small banks to assess the creditworthiness of small firms. Third, since we control for banks' market power, we expand the literature on the relationship between bank risk and market competitive pressure. Finally, we find empirical evidence that bank size does affect the financial standing of small banks.

KEYWORDS

bank size, bank soundness, Lerner index, relationship lending, spatial dynamic panel data models, spatial weight matrix

1 | INTRODUCTION

Small cooperative banks differ from commercial banks both in their financial structure and in their ability to process information deriving from the local economic context. At the world level, they are more involved in traditional lending activities than non-cooperative and large cooperative banks, showing a higher net loans-to-total-assets ratio.[1] Additionally, these banks' customers are usually also shareholders (members of the cooperative). Despite the tightening of intermediation margins, lending activity remains the main business of small cooperative banks. These loans are usually granted to small and medium-sized enterprises (SMEs) operating in the same territory as the bank.[2-4] A recent review of the literature on cooperative financial institutions by McKillop et al.[5] lists the principles of self-help, identity, democracy, and cooperation among cooperatives as distinguishing them from shareholder-based banks.[1]

[1]According to the self-help principle, financial cooperatives are owned by their members who manage them in pursuit of economic and social objectives. The identity principle posits that cooperative members are locally clustered individual members, community groups, and small firms. The democracy principle is manifest in the one-head-one-vote rule at shareholders' meetings. Cooperation among cooperatives stands for the tendency of financial cooperatives to constitute network alliances to achieve economies of scale.[5]

The authors of this study contributed equally.

These characteristics imply that the performance of small cooperative banks is affected by local economic factors. Nguyen[6] clarified that the small business lending market tends to feature geographic proximity between borrower and lender. Similarly, Degryse and Ongena[7] argued that location grants rents to financial intermediaries. It is well known that the availability of local economic data is limited and that calculating the related variables is expensive. Fernandes and Artes[8] and Calabrese et al.[9] added spatial dependence effects to the traditional credit scoring models to test if this inclusion improves the discrimination capabilities of the models. In measuring local bank performance, including spatial dependence effects in econometric models might be an effective way to deal with the challenge of needing to consider local factors for which there is a lack of specific data.

The first goal of our research is to empirically verify if the inclusion of variables reflecting the spatial autocorrelation effect between small cooperative banks provides a significant contribution to estimating the *Z Score* factor, which is a measure of bank performance in terms of risk. For this purpose, we conducted an empirical analysis using a sample of Italian small cooperative banks (Banche di Credito Cooperativo; BCCs), which are the ideal laboratory to test our hypothesis.[2]

The second goal of the research is to examine the effects of the spatially and spatially temporally lagged *Z Score* variables on the *Z Score* of the BCCs, and shed new light on the impact of relationship lending practice.

Many studies have pointed out that the organizational structure of small banks exploits soft information developed by the accrual of personal interaction over time, bolstering relationship lending practices particularly with SMEs.[13-153] This mitigates the financial constraints for informationally opaque SMEs, who cannot provide adequate hard information from borrowers' balance sheets, market prices, and collateral guarantees.[17-22] Hasan et al.[23] pointed out that the local banking market, and the presence of cooperative banks, is very important for SMEs as it improves the creation of new firms, reduces financing costs, and improves access to medium- and long-term finance. They also showed that having a large quantity of foreign banks in local banking markets can worsen the banking structure from the SME perspective. Comprehensive reviews of the literature on relationship lending are provided in Udell[24] and Duqi et al.[25]

The generally accepted paradigm maintains that small banks with few managerial layers and independent decision-making autonomy have a competitive advantage over centralized nationwide banks in meeting the needs of local SMEs.[17,264]

Although small banks can finance SMEs that would be otherwise credit constrained, scholars have pointed out possible opportunistic behavior against SMEs on the part of banks adopting relationship lending due to the market power of geographically proximate banks.[32] Other studies insist on the high costs of relationship lending.[33-35] There is therefore a "darker side" identified in the literature to decentralized banks in their dealings with small firms in the absence of an adequately competitive environment (see, for instance, Canales and Nanda[36]). Relationship lending allows banks to exploit their dominant market position and spurs the cherry picking of firms and restrictions on credit.[5] In this regard, unsurprisingly, Coccorese and Santucci[38] found that large banks have less market power than small banks.

Kysucky and Norden's[39] meta-analysis attempted to sort out the large heterogeneity in the findings of the literature on relationship lending. They verified the favorable impact of relationship lending for borrowers, such as the benefits of the positive monotonic effects of bank competition and relationship lending. Finally, the authors called for future studies to consider bargaining power, on both the supply and demand sides, in examining bank-firm relationships.

Against this background, our spatial models permit the examination of the extent of the market strength held by small cooperative banks over SMEs, to indicate whether these banks exploit the relationship with their customers to increase their own profitability (and capitalization). Indeed, in the short run, the *Z Score* is sensitive to deposit and lending interest

[2]BCCs are a typical European "prevailing mutualism" bank, as their members must reside in the same area as the bank, they must apply the one-head-one-vote principle in shareholders' meetings and grant loans in the area where they operate, and a minimum of 51% of lending must be to their members.[10] Comparable non-profit financial institution around the world are, for instance, the credit union, widespread in the Anglo-Saxon countries (see, Lessambo[11]) and the Japanese shinkin banks.[12] Moreover, there is an important heterogeneous banking morphology for BCCs in Italy: the northeast, especially Trentino-Alto Adige, is rich with cooperative banks, but they are sparse in the rest of the country. Similarly, the macroeconomic conditions under which BCCs operate differs across geographical regions of the country, with Italy comprising 20 regions and 110 provinces that are generally conditioned by their different levels of economic performance (with the northern regions typically more developed and the southern regions typically less developed).

[3]Liberti and Petersen[16] surveyed the literature on soft and hard information and define the characteristics of each.

[4]Cf. De la Torre et al.,[27] who provide evidence that large banks apply specific business models for the SME niche that differ from relationship lending, and Berger and Black,[28] who argued that large banks adopting hard information technologies can gain an advantage in lending activity even toward small firms. However, despite the availability of new lending technologies, the propensity of local banks to lend to SMEs has been confirmed in the most recent studies (e.g., Meslier et al.,[29] Nguyen and Barth,[30] Mkhaiber and Werner,[31])

[5]Recently Levine et al.[37] pointed out that geographic distance is negatively associated with lending to informationally opaque borrowers.

rates and, to a lesser extent, to capital injection, which in BCCs is achieved through their members.[6] In this regard, our investigation provides some insight into customers' reactions to changes in their bank's financial strength, showing the extent of the constraints deriving from relationship lending. In short, we stress test the hypothesis that small bank borrowers have no alternative to the BCCs for credit supply.

An attempt to answer the question of whether there is spatial dependence in the risk behavior of small cooperative banks cannot disregard the effects on soundness of bank market competition. The literature presents two opposing hypotheses on the relationship between bank competition and soundness: the competition-fragility view and the competition-stability view. The first of these maintains that an increase in bank competition reduces bank margins and encourages risk-taking, which weakens banks and ultimately the whole banking system.[40,41] The second view rests on the classical adverse selection assumption. Strong market power allows for imposing a surcharge on customers, which results in higher interest rates that deter low-risk borrowers. On this view, therefore, the loan portfolio of banks enjoying strong market power will be riskier than that of banks operating in competitive markets.[42-44]

The specific effects of market competition among small cooperative banks on their solvency has been analyzed in previous studies,[4,45] but with conflicting results. Fiordelisi and Mare[45] presented evidence of a positive relationship between competition and stability (especially in the loan market), showing that lower market power is indirectly related to bank stability. Analyzing the effect of geographic bank deregulation in the US banking market, Berger et al.[46] also provided evidence in support of the competition stability hypothesis for small and medium banks. Conversely, Clark et al.[4] found a negative relationship between competition and stability, albeit with a non-linear effect. We contribute to this debate by evaluating the effect of the *Z Score* of small cooperative banks on a long-standing market competition indicator (the Lerner index) while also considering spatial dependence.

Finally, the spatial specification model enables the investigation of the connection between small-bank risk failure and bank size. Emmons et al.[47] argued that a small bank that increases its scale could benefit from portfolio diversification but, as it seeks loan opportunities in more distant markets, its relationship lending practices become less effective and thus its ability to screen borrowers based on creditworthiness is weakened. The empirical literature on this topic has returned conflicting results. Mare[48] showed a positive and statistically significant relationship between *Z Score* and bank size among a sample of Italian BCCs. Similar results can be found in Chiaramonte et al.[49] and Barra and Zotti.[50] On the contrary, Mare and Gramlich's[51] examination of the risk exposures of cooperative banks in Austria, Germany, and Italy showed that bank size directly affects credit risk, interest rates, and residual bank risk. The results of the study of Chiaramonte et al.,[52] focusing on banks operating in 27 EU member states, again differed in finding no significant relationship between the same variables in either of two sub-samples of 2972 cooperative and savings banks, and small banks.

The remainder of the article is structured as follows. Section 2 introduces the spatial econometric methodology and the data and variables adopted in the empirical specification. Section 3 presents the three steps of our empirical analysis: the test for the presence of spatial dependence and random effects in the sample, the system GMM (SYS-GMM) estimation of our equation, and the tests on the residuals of the estimation to assess the treatment-induced variation of cross-sectional dependence. Some final remarks conclude the article in Section 4.

2 | SPATIAL ECONOMETRIC METHODOLOGY AND DATA

This section introduces the spatial econometric models adopted in our analysis and the data used for our empirical research and presents the econometric specification.

2.1 | Spatial methods

The spatial econometric approach structures the relationships among the elements observed in diverse geographic areas, including the spatial interaction (spatial autocorrelation) and spatial framework (spatial heterogeneity) in econometric

[6]Capital increases in Italian small cooperative banks are carried out almost exclusively through their members, as the specific governance rules of "prevailing mutualism" discourage external investors. These rules entail the adoption of the democratic procedure, the prohibition on share ownership with a value greater than 50,000 euros, the requirement for bank members to be located in areas where the bank is headquartered or has branches, and the holding of 70% of bank profits in reserve.[15]

models.[53-55] Spatial dependence concerns the relationship of one spatial unit with a neighboring unit by exploiting Tobler's first law of geography.[56] This relationship is defined as spatial autocorrelation, which represents a weaker expression of spatial dependence.[53]

In our analysis, we consider a spatial dynamic panel data (SDPD) model,[55,57] which enables the investigation of the spatial spillovers among units. In particular, we consider the time-space simultaneous (TSS) model proposed by Anselin et al.[58] using the SYS-GMM estimator.[59-63] In detail:

$$y_{i,t} = \beta y_{i,t-1} + \rho \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{j,t} + \mathbf{x}_{i,t-1}\gamma + (\eta_i + \nu_{i,t}) \tag{1}$$
$$|\beta| < 1, \ |\rho| < 1; \quad i = 1 \ \dots \ N; \quad t = 1 \ \dots \ T$$

where $y_{i,t}$ is an observation of the dependent variable y for the ith individual at the tth time period, $y_{i,t-1}$ its lagged value, $\sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{j,t}$ represents the first-order spatial lag of y,[7] and $\mathbf{x}_{i,t}$ represents the $k \times 1$ vector of explanatory variables. Lastly, $(\eta_i + \nu_{i,t})$ is the decomposition of the error term. More precisely, η_i is the value of the individual effect correlated with $y_{i,t-1}$ and $\nu_{i,t}$ is the random error assumed to be normally distributed with zero mean and variance σ^2.

Alongside the TSS model, Anselin et al.[58] also developed the time-space dynamic (TSD) model, which includes the first-order spatial lag of the lagged dependent variable (with respect to the spatial weight matrix $\boldsymbol{W} = (w_{ij})$) in the TSS model, on the basis that the omission of the lagged term could lead to biased estimates in some cases.[64] Consequently, Equation 1 becomes:

$$y_{i,t} = \beta y_{i,t-1} + \rho \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{j,t} + \psi \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{j,t-1} + \mathbf{x}_{i,t-1}\gamma + (\eta_i + \nu_{i,t}) \tag{2}$$
$$|\beta| < 1, \ |\rho| < 1, \ |\psi| < 1; \quad i = 1 \ \dots \ N; \quad t = 1 \ \dots \ T$$

In Equation 2, the coefficient β incorporates the time dependence of the dependent variable, while ρ and ψ indicate the spatial effect and spatial-temporal effect, respectively, under the constraint $|\beta + \rho + \psi| < 1$, whose violation implies the presence of a unit root problem in the data that could bias the estimation, and suggests of differencing the dependent variable of each individual i to deal with this issue.[8]

The spatial weight matrix $\boldsymbol{W}$ is a key element for modelling spatial data. In general, $\boldsymbol{W}$ is a fixed (non-stochastic) N by N matrix, where N is the number of spatial units in the dataset, with the following properties:

- $w_{ij} = 0$ if i and j are not spatially connected and if $i = j$ by definition, that is if all elements on the principal diagonal are zero, meaning that an object is not spatially connected with itself;
- $w_{ij} \neq 0$ if i and j are spatially connected, and the values are mostly higher than zero.

More specifically, to model spatial relations between point units the matrix $\boldsymbol{W}$ is built making use of the Gaussian kernel.[66] This weight matrix is based on the distances (d_{ij}) between each pair of spatial point units i and j. The data points represent discrete locations in space that have zero area and are located through the geographical coordinates (latitude and longitude). According to a classical contiguity concept, for this study we use a modified Gaussian kernel matrix where the function for computing the weight w_{ij} is given by

$$w_{ij} = \begin{cases} \exp\left[-\frac{1}{2}(\frac{d_{ij}}{h_{ij}})^2\right], & \forall i \neq j \\ 0, & \forall i = j \end{cases} \tag{3}$$

where d_{ij} is equal to the distance between the generic point units i and j and h_{ij}(bandwidth) is a non-negative parameter that produces a decay of influence with distance. Varying the bandwidth results in different exponential decay profiles, which in turn produces weights that vary more or less rapidly over space. The weighting of other data will therefore decrease along a Gaussian curve as the distance between the spatial units i and j increases. For spatial units that are a

[7]Generally, a spatial lag operator is the average value of a random variable observed in the neighbors of a given spatial unit.
[8]See Yu and Lee[65] for further information about the estimation of the unit root of SDPD models.

long way from i, the weight w_{ij} will fall to virtually zero. This approach is a generalization of neighbors based on distance that can be used to structure dependence in behavior, leading to a model that is formally analogous to the geographical nearest neighbors. Finally, the Gaussian kernel matrix is standardized so that all rows sum to one.

Dealing with spatial dependence in panel data requires us to adjust the weighted matrix as in Anselin et al.,[67] on the assumption that the distance among the spatial units stays constant over time.

Specifically, if $\boldsymbol{W}(N \times N)$ is the spatial weight matrix for the cross-sectional context, the $NT \times NT$ spatial matrix used in spatial panel analysis is computed as follows:[9]

$$\boldsymbol{W}_{NT} = \boldsymbol{I}_T \otimes \boldsymbol{W}_N, \tag{4}$$

where $\boldsymbol{I}_T$ represents an identity matrix of size T, and $\boldsymbol{W}_n$ is the row-standardized spatial weights matrix of dimension $n \times n$.

2.2 | Data and equation

Our empirical analysis draws on a strongly balanced panel dataset for 264 active BCCs over the 2011–2017 period, with about 1848 observations. The data are collected from two sources: the Bureau van Dijk Orbis Bank Focus (BvD Orbis) database for the bank-specific characteristic[10] and *Il Sole 24 Ore* for local economic data.[11] By geocoding the address of each BCCs headquarters, we built a geospatial dataset containing geo-referenced variables (latitude, longitude) for each observation.

Both the TSS and TSD models are estimated using the SYS-GMM technique by Arellano and Bover[68] and developed by Blundell and Bond[69] to obtain consistent and unbiased estimates dealing with possible endogeneity issues. In this regard, the SYS-GMM models are estimated with Windmeijer[70] finite sample correction and with forward orthogonal deviation (FOD) transformation.[12] All of the explanatory variables are lagged.

The TSS equation is as follows:[13]

$$\begin{aligned} \text{Z Score}_{i,t} = {} & \alpha + \beta \text{Z Score}_{i,t-1} + \rho \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot \text{Z Score}_{j,t} + \gamma Lerner_{i,t-1} \\ & + \delta Cap_{i,t-1} + \zeta Size_{i,t-1} + \iota NPL_{i,t-1} + \varphi LLP_{i,t-1} \\ & + \kappa Service_{i,t-1} + \lambda Funding_{i,t-1} + \phi Branches_{i,t-1} \\ & + \omega GDP_{i,t-1} + \theta_t D_t + (\eta_i + \nu_{i,t}) \end{aligned} \tag{5}$$

The dependent variable of our spatial econometric model is the *Z Score*, which is a measure of bank soundness.[73-75] It is calculated as follows:

$$Z \quad Score_{i,t} = \frac{ROA_{i,t} + \frac{E_{i,t}}{A_{i,t}}}{\sigma_{(ROA)_{i,t}}} \tag{6}$$

where, *ROA* represents the return on assets ratio, *E/A* constitutes the equity to total assets, and $\sigma(ROA)$ indicates the standard deviation of *ROA*.[76] To account for the time change in the bank's return volatility pattern, in line with the literature adopting the *Z Score* variable, we have considered a rolling time window equal to five years.[14] The two subscripts i and t indicate the ith bank and the tth period, respectively.

[9]See Anselin et al.[58]

[10]We encountered some missing values in the Bankscope/Orbis dataset, in particular for the years 2011 and 2012, constituting a total of nineteen observations. In all of these cases the accounting data were entirely missing, and the information was entered manually after consulting the balance sheets of the respective BCCs.

[11]*Il Sole 24 Ore* publishes an annual report called Quality of Life that includes data for various environmental indexes at the Italian provincial level. It thus provides a set of provincial data corresponding to social and economic indicators. See https://lab24.ilsole24ore.com/qualita-della-vita/.

[12]In principle, SYS-GMM is usually preferred over the standard GMM estimator[71] because it performs better in cases where the variables are highly persistent over time and for possible simultaneity bias (on this point, see Blundell and Bond[69,72]).

[13]The TSD equation also includes the spatial-temporal lagged variable, that is $\varrho \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot \text{Z Score}_{j,t-1}$.

[14]In the literature a three-year rolling window is often adopted, although there are some studies that have adopted a five-year rolling window (e.g., Beck et al.,[77] Ly et al.,[78]). Unlike us, these studies usually found their estimation on an unbalanced dataset, and the described empirical strategy avoids

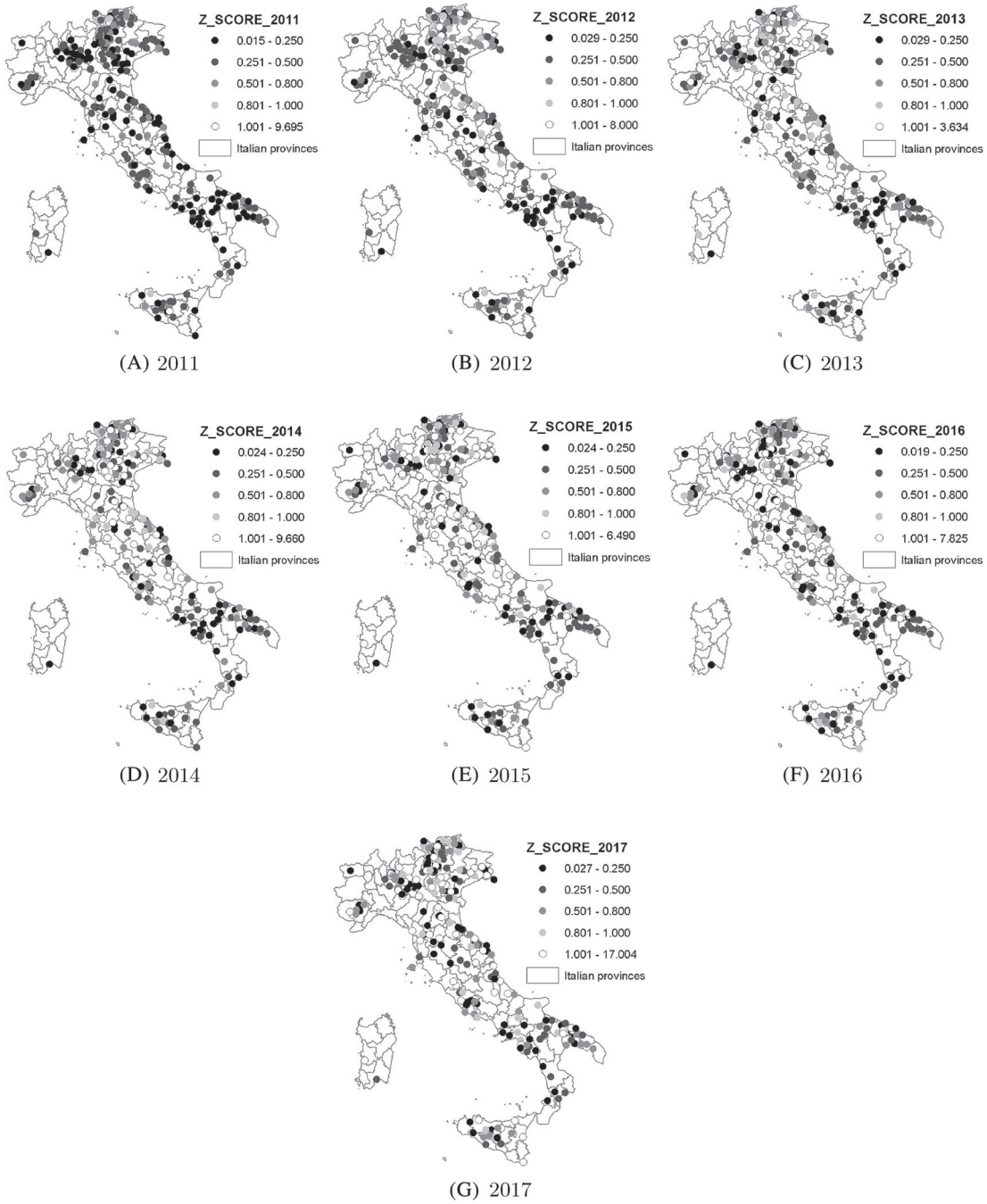

FIGURE 1 *Z Score* maps

The *Z Score* reflects the main shields against banking risk: profitability, and its volatility, and capitalization. The higher the index, the greater is the bank's stability.[49,77,79,80]

The following figure presents seven graphs for the territory of Italy, pertaining to each of the years we consider in the spanning period of the dataset (Figure 1). The scatterplots indicate banks' geographical locations and corresponding *Z Score*, classified in quintile ranges.

Our models include four different types of explicative variables. The first includes the spatial lag operator and its time-lagged value. The second is a competition measure proxied by the Lerner index and calculated at bank level.

the denominator being computed over different window lengths for different banks. Using a five-year rolling time window also considerably reduces the number of observations.

The third is a measure of bank size. The fourth is an extensive set of variables for bank-specific characteristics and the macroeconomic environment.

Our empirical specifications include spatial terms that are calculated by multiplying the dependent variable and its lagged value by three spatial weighted matrices. Specifically, we use a Gaussian kernel matrix with three different bandwidths, expressed in kilometers:[15]

(**1**) $h(d_{ij}) = \text{Minimum}(d_{ij}) = h_\alpha$
(**2**) $h(d_{ij}) = 0.01[\text{Maximum}(d_{ij})] = h_\beta$
(**3**) $h(d_{ij}) = 0.5[(h_\alpha + h_\delta)] = h_\gamma$

where h_α is equal to 3.5 km (the minimum distance necessary to ensure that each bank has at least one neighbor); h_β is equal to 12 km (1% of the maximum distance between BCCs of 1200.69 km); and h_γ is equal to 61 km (the mean between the minimum distance and the Maxmin distance of 118.5 km).[16]

The covariate chosen to capture bank market power is the Lerner index, calculated as the difference between a bank's price and marginal costs, divided by bank price: $Lerner_{i,t} = \left(P_{i,t} - mc_{i,t}\right)/P_{i,t}$. Its rationale is trivial: the greater a bank's market power, the more its prices exceed its marginal costs.

Unlike a bank's price, which can be easily calculated using accounting data (total interest income divided by total assets),[17] calculating the marginal costs requires a standard translog cost function. For this purpose, as in Fiordelisi and Mare,[45] Degl'Innocenti et al.,[82] Coccorese and Santucci,[38] and Coccorese and Ferri[15] we estimate total bank costs (sum of personnel expenses, other administrative expenses, and other operating expenses) taking into account one output Q (bank total asset) and three inputs (proxied by P_1, staff expenses over total assets, P_2, other administrative expenses over total assets, and P_3 interest expenses over bank funding). The equation to be estimated is as follows:

$$lnTC_{i,t} = \beta_0 + \beta_1 lnQ_{i,t} + \frac{1}{2}\beta_2 lnQ_{i,t}^2 + \sum_{k=1}^{3} \gamma_k lnP_{k,i,t} + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \delta_{k,j} lnP_{k,i,t} lnP_{j,i,t} + \frac{1}{2}\sum_{k=1}^{3} \zeta_k lnQ_{i,t} lnP_{k,i,t} + u_{i,t} + v_{i,t} \tag{7}$$

In Equation 7, the error term consists of two components: the usual $v_{i,t}$, which is a standard error whose distribution is i.i.d. $N(0, \sigma_v^2)$; and the actual cost inefficiency term $u_{i,t}$, modeled as a truncated non-negative random variable $N^+(0, \sigma_u^2)$. The estimated parameters of the above reported cost function allow us to determine the marginal cost at bank level and time period by calculating the partial derivatives of the above reported equation with respect to the bank output $Q_{i,t}$ as follows:[18]

$$mc_{i,t} = \frac{\partial TC_{i,t}}{\partial Q_{i,t}} = \frac{\partial lnTC_{i,t}}{\partial lnQ_{i,t}} \frac{TC_{i,t}}{Q_{i,t}} = \left(\hat{\beta}_1 + \hat{\beta}_2 lnQ_{i,t} + \sum_{k=1}^{3} \hat{\zeta}_{k,i,t} lnP_k\right) \frac{TC_{i,t}}{Q_{i,t}} \tag{8}$$

Size captures the bank size effect, proxied by the natural logarithm of total assets. Countless studies of cooperative or non-cooperative banks have used this proxy of bank size.[4,51,52] The expected effect of the coefficient to be estimated is uncertain.

In what follows, we briefly describe the control variables and their expected signs. *Cap* is the total capital ratio, calculated at bank level as regulatory capital over risk weighted assets. Highly capitalized banks are able to absorb the negative impact of shocks.[83-86] Greater capitalization might lead to lower bank risk-taking because it decreases the asset-substitution moral hazard[87] and reinforces the incentives for bank monitoring.[88] Therefore, we expect that the coefficient associated with this variable takes a positive sign.

[15]We considered a variety of bandwidths for the spatial matrices and settled on the three bandwidths providing the best results.
[16]Recalling that in the Maxmin function, h_δ, is chosen in such a way that the following relationship is satisfied: $h_\delta = max(e_1, e_2, \ldots, e_i, \ldots, e_n)$, where e_i represents the minimum distance of the generic spatial unit i with the other units j (with $i \neq j$). As a consequence, each spatial unit is connected to all of the others (for further information, see Mucciardi and Bertuccelli[81]).
[17]As specified, BCCs are focused on lending activity. Considering non-interest income provides similar results.
[18]In our case, marginal cost is: $mc_{i,t} = \left(1.2633 - 0.0214 \cdot lnQ_{i,t} + 0.1103 \cdot lnP_{1,i,t} - 0.1831 \cdot lnP_{2,i,t} + 0.0052 \cdot lnP_{3,i,t}\right)$.

TABLE 1 Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Z Score	0.754	0.868	0.019	17.01
Lerner	0.486	0.160	−3.019	0.841
Cap	0.198	0.079	0.066	0.808
Size	12.94	1.011	9.552	16.28
NPL	0.155	0.073	0	0.408
LLP	0.015	0.012	−0.009	0.097
Service	0.642	0.116	0.233	2.165
Funding	0.860	0.044	0.653	0.948
Branches	59.60	21.50	18	104
GDP	0.012	0.027	−0.201	0.212
$TC^{\S}$	11,922	14,395	228	189,899
$Q^{\S}$	698,549	945,611	14,075	11,769,238
$P_1^{\flat}$	1.153	0.281	0.185	2.866
$P_2^{\flat}$	0.901	0.235	0.209	2.359
$P_3^{\flat}$	1.080	0.510	0.142	5.999
Price	0.029	0.007	0.004	0.061

Notes: The number of observations is 1584 for all the variables.
§in thousand Euros.
$^{\flat}$in percentage terms.

We consider two different asset quality variables, namely the ratio of non-performing loans to gross loans (*NPL*) and the ratio of loan loss provision to total loans (*LLP*), capturing different aspects of a bank's credit risk policies.[89] *NPL* represents a backward-looking measure of credit quality, as it refers the ability of banks to recover their loans.[90] Greater values express poor credit decision making.[91] *LLP*, in contrast, is a forward-looking gauge of credit quality that reveals bank hedging policies against expected losses on lending activity. Banks can manage the provision for losses on loans to smooth their income.[92][19]

Service is the ratio of net interest income to operating revenue and represents a measure of both profitability and (indirectly) efficiency.[96] This ratio highlights the relative weight of the more profitable service sold by a bank with respect to the less lucrative credit service. As suggested by Lucas et al.,[97] fee-focused banks have a high loan-to-asset ratio.

Funding is a proxy of funding risk, calculated as the ratio between total funds (the sum of bank deposits, customer deposits, and debt securities) over total assets. It represents the ability to collect funds for financing illiquid asset positions under the conditions laid down at a given moment.[98]

Our equation also incorporates business cycle effects via the annual growth of real gross domestic product per capita (*GDP*) , and financial sector development via the number of bank branches per 100,000 inhabitants (*Branches*).[99,100] Both of these the variables are set at Italian NUTS-3 region (province) level.

Frame et al.[101] observed that the number of bank branches in the local market is positively correlated to the use of credit scoring. In addition, they found a positive and statistically significant relationship between share of loans to small businesses and number of branches. Annual growth rate of real GDP is used to capture cyclical movements, thus controlling for loan demand effects.[102] Specifically, more favorable economic conditions increase the amount of profitable projects as the expected net present value improves, and loan demand increases accordingly.[103] Finally, a set of year dummies variables control for the time effects.

Table 1 reports the summary statistics of the variables used in our specifications, while Table 2 shows the correlation matrix.

[19]The literature emphasizes that banks smoothed their income more intensely through loan loss provision during the economic crisis.[93,94] In addition, the level of loan loss provision can be distorted by forbearance.[95] Mergaerts and Vander Vennet[92] also highlight that greater loan loss provision is linked to lower profitability and also to higher risk in the long run. With all of this considered, the expected sign is uncertain.

TABLE 2 Correlation matrix for the data shown in Table 1

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1.	$Z\ Score_t$	1									
2.	$Lerner_{t-1}$	0.0528*	1								
3.	Cap_{t-1}	0.0984*	−0.1786*	1							
4.	$Size_{t-1}$	0.0544*	0.3301*	−0.4050*	1						
5.	NPL_{t-1}	−0.1614*	0.0060	−0.0258	0.1692*	1					
6.	LLP_{t-1}	−0.1011*	0.0947*	−0.0502*	0.2076*	0.6130*	1				
7.	$Service_{t-1}$	0.0236	0.0556*	0.0585*	−0.1165*	−0.1280*	−0.1791*	1			
8.	$Funding_{t-1}$	−0.1383*	0.3607*	−0.4521*	0.3470*	0.2521*	0.2157*	−0.0988*	1		
9.	$Branches_{t-1}$	0.1720*	0.1726*	−0.3510*	0.2570*	−0.2848*	−0.1636*	−0.0119	−0.1063*	1	
10.	GDP_{t-1}	−0.0072	−0.1452*	−0.0186	0.0140	−0.0619*	−0.1341*	−0.0246	−0.0033	0.0765*	1

Notes: *Denotes significance at the 5% level or lower.

The dynamic specification that we adopt reduces the number of observations to 1584, while retaining the 264 banks. The key variables of our analysis are *Z Score* and *Lerner*. The latter takes negative values for eight observations, equal to 0.4 percent of the sample. As in a previous study,[45] it assures the representativeness of the sample pertaining to BCCs with high fixed costs (e.g., those that needed to invest in establishing intermediation activities).

3 | EMPIRICAL RESULTS AND DISCUSSION

This section presents the results of the empirical investigation. First, we describe the diagnostic tests for the presence of spatial dependence and random individual effects. Next, we report the empirical estimates of the SYS-GMM estimators and the cross-sectional dependence test of the robustness of the models. Finally, we discuss the evidence for explaining the spillover effects between cooperative banks.

3.1 | Diagnostic tests for spatial dependence and random effects

We ran three sets of Lagrange multiplier (LM) tests to verify the existence of spatial autocorrelation and random individual effects. If there is spatial autocorrelation in the data and this were to be disregarded, the statistical inferences and estimates would be misleading.[104,105] Table 3 reports all of the spatial dependence tests.

The first group of LM tests verified the existence of spatial autocorrelation. The null hypothesis was that the spatial lag autoregressive coefficient and spatial error autoregressive coefficient are both equal to zero.[106,109] The test result strongly rejected the null hypothesis, indicating the presence of spatial correlation in the data.

The second set of tests controlled for spatial correlation and random effects, applying the joint and conditional LM tests built by Baltagi et al..[107] The hypotheses of no spatial correlation and no random individual effects were all rejected in these tests. The joint LM test rejected the null hypothesis below the 1% threshold, showing that at least one of the determinates of spatial dependence (spatial error correlation and/or random effects) is present in the residuals. Similarly, the marginal LM tests to verify the presence of no spatial autocorrelation or random effects significantly rejected the respective null hypotheses. To further confirm the presence of spatial correlation and random effects, we also ran conditional LM tests.[20] These tests again rejected the null hypotheses, confirming the presence of both spatial autocorrelation and random effects.

Finally, the last array of tests developed by Baltagi et al.[108] check jointly and conditionally for spatial correlation, serial correlation, and random effects. In addition to considering the presence of serial correlation, neglected in Baltagi et al.,[107]

[20]In detail, the presence of spatial autocorrelation was tested considering the conditional LM test for no spatial autocorrelation, allowing for the presence of random effects. In the same way, the presence of random effects was tested using the conditional LM test for no random effects, allowing for the presence of spatial autocorrelation.

TABLE 3 LM tests for spatial, serial correlation and random effects

LM test description	Statistic	*p*-value
Anselin[106]		
Conditional test for spatial error autocorrelation		
(H_0: spatial error autoregressive coefficient equal to zero)	7.403	0.000
Conditional test for spatial lag autocorrelation		
(H_0: spatial lag autoregressive coefficient equal to zero)	3.337	0.001
Baltagi et al.[107]		
Joint test		
(H_0: absence of random effects and spatial autocorrelation)	369.5	0.000
Marginal test of random effects		
(H_0: absence of random effects)	18.79	0.000
Marginal test of spatial autocorrelation		
(H_0: absence of spatial autocorrelation)	4.067	0.000
Conditional test of spatial autocorrelation		
(H_0: absence of spatial autocorrelation, assuming random effects are non null)	3.587	0.001
Conditional test of random effects		
(H_0: absence of random effects, assuming spatial autocorrelation may or may not be equal to zero)	18.89	0.000
Baltagi et al.[108]		
Joint test		
(H_0: absence of serial or spatial error correlation or random effects)	595.8	0.000
One-dimensional conditional test		
(H_0: absence of spatial error correlation, assuming the existence of both serial correlation and random effects)	13.79	0.001
One-dimensional conditional test		
(H_0: absence of serial correlation, assuming the existence of both spatial error correlation and random effects)	408.9	0.000
One-dimensional conditional test		
(H_0: absence of random effects, assuming the existence of both serial and spatial error correlation)	99.41	0.000

the latter LM tests investigated the presence of each of the three above mentioned components, assuming the presence of the other two. The test results significantly rejected the null hypothesis, indicating the presence of serial correlation, spatial correlation, and random effects.[21]

All of the above tests are sensitive to the specification of the spatial weights matrix. Therefore, following Arouri et al.,[111] Sarafidis and Wansbeek,[112] and Liddle,[113] we ran a robustness check for spatial dependence by using the two cross-sectional dependence tests proposed by Pesaran.[114,115] These tests verify the presence of strict and weak cross-sectional dependence, respectively.[22] As Chudik et al.[117] and Vega and Elhorst[118] have emphasized, unobserved common factors (strong cross-sectional dependence) or co-movement of the spatial units (weak cross-sectional dependence) can produce cross-sectional dependence. Table 4 reports the results of the tests, along with the respective *p*-values.

The results indicate the presence of both strict and weak cross-sectional dependence, confirming the evidence provided by the LM tests reported in Table 3. The presence of spatial dependence supports the appropriateness of spatial econometric techniques.

[21]We estimated all the LM tests using the splm R package developed by Millo and Piras.[110] It should be noted that the tests reported in Table 3 were estimated using the matrix $\boldsymbol{W}$ with h_α. However, the tests were also estimated using the remaining two matrices, with the other two bandwidths considered in our analysis: h_β and h_γ. The results were consistent and are not reported here for reasons of space; they can be supplied upon request.
[22]Testing for cross-sectional dependence corresponds to testing for the presence of contemporaneous correlations in the residuals. Compared to other specifications, the first test is the most suitable for samples where T is small and N is large, as in our study. In addition, under the null hypothesis, it is asymptotically normally distributed.[116]

TABLE 4 Testing for cross-sectional dependence

Test	Pesaran[114]	Pesaran[115]
CD	8.343	3.598
p-value	0.000	0.000

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

TABLE 5 Estimation results of dynamic and TSS model, using *Z Score* as dependent variable

	Dynamic model	Spatial dynamic models		
		$\boldsymbol{h}_\alpha$	$\boldsymbol{h}_\beta$	$\boldsymbol{h}_\gamma$
Variable	**(1)**	**(2)**	**(3)**	**(4)**
$Z\ Score_{t-1}$	0.5437*** (0.100)	0.5610*** (0.073)	0.5411*** (0.071)	0.5440*** (0.100)
$Lerner_{t-1}$	0.4558*** (0.136)	0.7708*** (0.159)	0.7585*** (0.165)	0.7666*** (0.156)
Cap_{t-1}	2.2541*** (0.811)	1.9188*** (0.708)	1.9273*** (0.694)	1.8656*** (0.608)
$Size_{t-1}$	0.1863** (0.075)	0.1199** (0.055)	0.1229** (0.059)	0.1651** (0.082)
NPL_{t-1}	−1.4249** (0.603)	−0.9665** (0.475)	−1.0060** (0.497)	−1.2446** (0.573)
LLP_{t-1}	−2.3928* (1.307)	−2.4658** (1.120)	−2.3149** (1.158)	−2.2664* (1.284)
$Service_{t-1}$	0.0241 (0.041)	−0.0480 (0.302)	−0.0414 (0.357)	−0.0021 (0.020)
$Fundings_{t-1}$	0.6236 (1.300)	−0.2763 (0.820)	−0.4048 (0.881)	−0.5130 (0.768)
$Branches_{t-1}$	0.0021 (0.003)	0.0017 (0.002)	0.0016 (0.002)	−0.0010 (0.002)
GDP_{t-1}	0.8782 (0.703)	−0.0727 (0.553)	−0.0651 (0.577)	1.1856 (1.183)
$\boldsymbol{W} \times Z\ Score_t$		0.1341** (0.061)	0.1592** (0.075)	0.3232** (0.149)
No. Instruments	109	112	112	112
AR(1)	0.0265	0.0142	0.0157	0.0212
AR(2)	0.4635	0.4972	0.4796	0.4025
Hansen test	0.2227	0.3820	0.4766	0.2781

Notes: Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Estimates rely on the use of the two-step system GMM estimator. In all the models, both the dependent and the explanatory variables have been considered as endogenous. Year dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and year dummies; *p*-values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 264 banks for a total of 1584 observations.

3.2 | Empirical estimation

The SYS-GMM estimates of the SDPD model specified in Equation (5) are reported in Table 5, together with the results of the dynamic panel data model.[23] Table 6 presents the estimation of the three TSD models only.

The number of instruments spans from 109 for the dynamic model to 116 for the spatial dynamic specifications, and is lower than the number of groups. The Hansen test statistic highlights the overall validity of the instruments for all specifications, and allows for the inference of unbiased estimated coefficients. Similarly, the test for first- and second-order autocorrelation of the residuals confirmed the rejection of the AR(1) hypotheses and the non-rejection of the AR(2) hypothesis.

The coefficients of variables incorporating time dependence, spatial dependence, and space-time dependence sum to less than 1, fulfilling the condition of global stationarity.

The estimation results show a positive contemporaneous spatial dependence effect for the risk profile of Italian cooperative banks, which holds along all six specifications considered. This is evidence for a simultaneous increase in neighboring bank risk leading to an increase in the *i*th bank risk and vice versa, given that a higher *Z Score* implies that

[23] All estimates are performed using the xtabond2 Stata command developed by Roodman.[119]

TABLE 6 Estimation results of TSD model for *Z Score*

	Spatial dynamic models		
	h_α	h_β	h_γ
Variable	**(5)**	**(6)**	**(7)**
$Z\ Score_{t-1}$	0.7984*** (0.194)	0.8051*** (0.191)	0.8170*** (0.190)
$Lerner_{t-1}$	1.0037*** (0.298)	0.9951*** (0.288)	0.8582*** (0.217)
Cap_{t-1}	1.9160** (0.858)	1.7552** (0.809)	2.2206** (0.874)
$Size_{t-1}$	0.1695** (0.081)	0.1422** (0.067)	0.2285** (0.094)
NPL_{t-1}	−1.3358* (0.718)	−1.1652* (0.653)	−0.8228 (0.799)
LLP_{t-1}	−3.7206** (1.884)	−3.8212** (1.868)	−6.4013** (3.084)
$Service_{t-1}$	−0.9013* (0.459)	−0.8811* (0.464)	−0.0368 (0.033)
$Fundings_{t-1}$	0.3733 (1.298)	0.6268 (1.428)	0.7884 (1.422)
$Branches_{t-1}$	−0.0005 (0.002)	−0.0005 (0.002)	−0.0017 (0.002)
GDP_{t-1}	−0.7067 (0.843)	−0.6673 (0.854)	0.1099 (0.822)
$\boldsymbol{W}\times Z\ Score_t$	0.3112** (0.130)	0.4233** (0.175)	0.5253*** (0.189)
$\boldsymbol{W}\times Z\ Score_{t-1}$	−0.2064** (0.103)	−0.2928** (0.140)	−0.3565** (0.142)
No. Instruments	116	116	116
AR(1)	0.0133	0.0158	0.0172
AR(2)	0.3797	0.3806	0.3110
Hansen test	0.3549	0.2811	0.5229

Notes: Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Estimates rely on the use of the two-step system GMM estimator. In all the models, both the dependent and the explanatory variables have been considered as endogenous. Year dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and year dummies; *p*-values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 264 banks for a total of 1584 observations.

the bank is more sound. The outcome is consistent with the clear assumption that local macroeconomic factors affect the performance of small banks, which are strongly involved in financing the community economy. While the spatial weights variables are statistically significant, the macroeconomic variables reported in our specifications are not. Bearing in mind that the local macroeconomic variables we have considered are expressed at the Italian provincial level, our result highlights the inclusion of spatial variables as a way to consider local effects regardless of the availability of specific indicators.

On the contrary, the space-time lagged coefficients take negative values for all three bandwidths. Neighboring banks having decreased their *Z Score* index in the previous year is associated with the *i*th BCC improving its *Z Score* in the current year, and vice versa. This evidence casts some light on the disputed effect of relationship lending on financing SMEs shown by Kysucky and Norden.[39] The financially constrained small firms that constitute the primary customers of BCCs have other options to finance their investments (assuming they are highly creditworthy) besides the exclusivity of a single small-bank relationship. Highly creditworthy BCC customers switch to nearby BCCs if their bank becomes less financially stable. The rationale behind this pattern lies in the assumption that a small bank's *Z Score* deterioration can imply higher interest rates on loans to improve profitability and/or can call for strengthening bank capitalization.[24] Consequently, financially sound BCC borrowers move to nearby banks, improving these banks' average credit portfolio risk and worsening the *Z Score* of the bank they leave. At the same time, riskier borrowers, whose applications for loans at nearby banks would be rejected, will remain at the original bank. This confirms Elsas's[120] insight that under certain conditions, relationship lending does not require a long duration or exclusivity in the bank-borrower relationship, and the finding of Bonini et al.[121] that relationship lending does not imply rent extraction. In addition, we take a step towards the conclusion of Wang et al.[122] that a more concentrated banking market worsens SME credit conditions, with it apparently holding only for less creditworthy firms.

[24]Recalling that small cooperative banks will require capital from their members/customers, because regulations forbid access to financial markets.

TABLE 7 Testing for cross-sectional independence

	Time-space simultaneos			Time-Space Dynamic		
Test	h_α	h_β	h_γ	h_α	h_β	h_γ
CD	0.764	0.638	0.831	−0.777	−0.742	−0.293
P-value	0.445	0.523	0.406	0.437	0.458	0.770

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

Furthermore, the estimated coefficients of our two spatial terms take the highest values for the higher bandwidth (61 km), showing that the *i*th BCC is also sensitive to the initiative of more distant competitors.

Turning to the *Lerner* variable, the estimated coefficients are statistically significant and positive along all specifications, indicating that higher market power brings less bank risk. This result is in accordance with Clark et al.[4] and in discordance with Fiordelisi and Mare,[45] supporting the competition fragility view. Interestingly, the *Lerner* coefficient of Model 1, without the spatial lagged value, is lower than the remaining values that were treated with the spatial dependence present in the data and already shown in the tests presented in Section 3.1. Therefore, the spatial econometric approach is useful for studying the relationship between small cooperative bank soundness and bank market power.

As in Mare,[48] Chiaramonte et al.,[49] and Barra and Zotti,[50] but contrary to Mare and Gramlich,[51] the coefficient of *Size* is positive in both the dynamic and SDPD models. Therefore, the larger the bank size of a bank, the more sound is its finances.

The coefficients of the control variables substantially bear the inclusion of the spatial terms. Comparing the estimated coefficients of the dynamic model with those of the SDPD models shows a general consistency in signs and significance but considerable variance in the coefficients, with very few exceptions.

The asset quality variables negatively affect small cooperative bank risk, with both the backward looking NPL and the forward looking *LLP* coefficients almost always statistically significant. The coefficients for the remaining bank-level variables take the expected sign and are statistically significant. However, the macroeconomic variables are not statistically significant.

3.3 | Testing for cross-sectional independence

As stated in Section 3.1, the presence of spatial dependence and random individual effects in the data led us to consider spatial lag operators in the model specifications. The inclusion of spatial lags allowed us to control for the weak cross-sectional dependence in the data. Common factors generating strict cross-sectional dependence could still exist[123] even after the use of spatial models.

To verify this, we ran a post-estimation test on the errors of the spatial models. We used the test proposed by Pesaran[114] to check for the existence of cross-sectional independence in the residuals of the SDPD specifications. We thereby control for whether the inclusion of the spatial lag operators explains the cross-sectional dependence that we observed through the tests already reported in Table 4. Unobserved common factors would suggest several problems of bias in the estimations.[124,125]

Table 7 reports the results of the cross-sectional dependence test, showing that the assumption of cross-sectional independence was not rejected for all the specifications. Thus provides strong evidence for the absence of correlations among panel units., with the residuals of all six SDPD models not affected by strict cross-sectional dependence. Therefore, we conclude that the spatial econometric methodology overcomes any issues deriving from co-movements among spatial panel units.

4 | CONCLUDING REMARKS

In this article we have applied spatial analysis techniques to investigate the risk performance of small cooperative banks, proxied by the *Z Score* index. We ran this empirical analysis on a large sample of Italian small cooperative banks (BCCs), with the well-known Italian regional disparities and the features of Italian banking market appealing as an ideal laboratory for testing the hypothesis that spatial autocorrelation can have an impact on the risk-taking behavior of small banks.

We calculated three Gaussian kernel matrices containing spatial weights based on three bandwidth distances (3.5, 12, and 61 km) and determined six spatial terms by multiplying the single matrices with both the dependent and lagged dependent variable. We thereby incorporated contemporaneous and time-lagged spatial dependence in the econometric models. Finally, we ran several Lagrange multiplier tests and cross-sectional dependence tests, which confirmed the existence of spatial dependence, and estimated six SDPD models for each of the above described spatial terms using SYS-GMM methods, along with a model without spatial terms. These results show possible bias in empirical estimations concerning small-bank financial soundness if spatial terms are neglected.

The results also provide evidence of a significant and positive neighbor effect for the spatial lagged variables, and a negative effect for the spatial-temporal lagged *Z Score*. Considering the composition of the dependent variable and the regulatory rules regarding the corporate governance structure of BCCs, these outcomes support the notion that the relationship lending usually adopted by small banks does not make for low demand price elasticity. The small firms that make up most of the customer base of BCCs are sensitive to deterioration in their bank's financial soundness, as the more creditworthy among them at least are prone to leave it in favor of neighboring banks in this scenario. This implies that relationship lending does not constrain borrowers to small banks if there are similar lenders in the proximate area. Considering the conflicting conclusions of the previous studies, our study represents a step forward in the body of empirical research on relationship lending effects for SMEs.

With our specification also controlling for the market competition effect through the Lerner index, the estimation results support the competition fragility view, which holds that bank monopolistic power enhances small bank soundness. Integrating the empirical models regarding the relationship between small bank soundness and small bank market power with spatial dependence operators gives definite support to the empirical question of the effects of a competitive market.

This study is the first to consider spatial analysis techniques for exploring the geographical spillover effects on the managerial choices of small cooperative banks using two specifications of spatial dependence: contemporaneous and serially lagged or non-contemporaneous. Follow-up studies are required to clarify a number of points that are not covered by our research due to lack of data, such as whether the relationship holds with consideration of the effect of unconventional monetary policies.

DATA AVAILABILITY STATEMENT

Data available on request from the authors

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