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Do spatial dependence and market power matter in the diversification of cooperative banks?

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Abstract

This study examines the determinants of cooperative banks' diversification proclivity, with consideration of the spatial dependence effect. The empirical analysis demonstrates that Italian cooperative banks operate as a network with significant spillover effects that should not be ignored. Indeed, local banks compete in the same market segment, and any shift in their diversification strategy has a cascading effect on neighbouring cooperative banks as a result of customer migration. Finally, we observe that an increase in bank market power results in a decline in local bank lending activity.

KEYWORDS

bank diversification, Lerner index, SDPD models, spatial dependence, spatial weights matrix

1 | INTRODUCTION

Since the late 1970s, the combined effect of technological progress and financial innovation has induced bank regulators to encourage less involvement of banks in traditional lending activities, causing financial disintermediation and leading banks to hold a more diversified portfolio. On account of this process, even those banks that focus on traditional lending and deposit-taking activities are increasingly diversifying their assets.[1]

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[1]The global financial crisis challenged this tendency, as policymakers became more aware of the systematic risk involved with more diversified banks (see, Battiston et al., 2012; Wagner, 2010).

The theoretical literature hypothesises two contrasting effects of diversification on bank performance and stability. The standard portfolio theory emphasises the benefits accruing from the ability of diversification to lower nonsystemic risks. Conversely, another vein of studies predict detrimental effects arising from an increase in agency issues and failure to exploit management skills in so far as a bank is less focused on its main business (Winton, 1999).

The empirical literature considers several proxies of bank diversification. Some studies mainly rely on the ratio of loans over total assets (Abedifar et al., 2018; Chiorazzo et al., 2008; DeYoung & Roland, 2001; Stiroh & Rumble, 2006), and other studies use noninterest income over total bank income, accounting, respectively, for asset and income bank diversification (Abedifar et al., 2018; DeYoung & Rice, 2004; Nguyen, 2012; Stiroh, 2004).[2] However, despite these two measures being frequently used as key or control variables in many empirical analyses in the fields of bank management, and despite the frequently contradictory results, very few studies have been undertaken to identify the factors determining these proxies of bank involvement in nontraditional activities.

The goal of the present analysis is to thoroughly examine the determinants at the balance sheet level that affect the diversification strategy of cooperative banks, considering both of the aforementioned proxies. Given that these intermediaries are focused on deposit-taking from and loan provision to households, microfirms, and local SMEs (Lang et al., 2016), we assume that both variables are valid benchmarks of bank asset diversification.

Specifically, the loans-to-assets ratio is a measure of bank specialisation but also of bank risk (Goddard et al., 2013). Loans are certainly illiquid and risky assets that increase both the average of the bank portfolio risk (see, for instance, Baselga-Pascual et al., 2015) and the overall bank risk in terms of *Z* score (e.g., Ghosh, 2020; Tran et al., 2019). However, many studies document an indirect effect of this ratio on the failure risk of commercial banks (e.g., Alali & Romero, 2013) and small cooperative banks, pinpointing a negative effect led by the inability to generate a satisfactory return (Goddard et al., 2014, 2016). In addition, Altunbas et al. (2007) find a direct relationship between efficiency and bank lending aptitude, and Cucinelli et al. (2020) highlight that the higher the ratio is, the more ability the bank has to avoid its doubtful loans from becoming nonperforming loans. Goddard et al. (2013) document simultaneously that lending activity makes banks—particularly savings and cooperative banks—more profitable and that banks with a wider range of services are more profitable.[3]

The literature assessing the effect of diversification on bank risk exposure by means of the noninterest income, pointing out the significance of bank size, likewise provides conflicting results. For instance, Köhler (2014) shows that retail-oriented banks, which are less involved in nontraditional activities, become less risky as they increase the share of noninterest income, whereas the reverse is true for investment-oriented banks. In contrast, De Jonghe et al. (2015) underline that the diversification process reduces the systemic risk exposure of large banks, and increases that of small banks. Mercieca et al. (2007) do not find evidence of a significant effect of diversification on the risk-adjusted performance of small European banks. Brunnermeier et al. (2020), examining the impact of noninterest income on the systematic risk component of US banks, underline that small banks are more exposed to macroprudential risk per unit of microprudential risk. These results conform to the assumption that bank diversification implies higher risk, particularly for smaller banks (Lepetit et al., 2008). In addition, unlike large banks, small and medium banks tend to expand operations generating noninterest income during phases of elevated economic policy uncertainty (Tran et al., 2021). Interestingly, Chiorazzo et al. (2008) find that the positive relationship between noninterest income and the risk-adjusted profits of small banks reverts as the size of the banks increases.

A possible explanation for these conflicting results is spatial dependence in the diversification propensity of local banks. The existence of spatial interactions calls for the adoption of an adequate methodology for dealing with

[2]Alternatively, some authors adopt the Hirschman–Herfindahl Index (HHI) to evaluate the extent to which banks' assets are focused or diversified, adding the squares of each percentage of the asset component as a percentage of overall assets (e.g., Francis et al., 2018). Other authors (for recent examples, see Paltrinieri et al., 2020; Wang & Lin, 2021) use the HHI to account for the level of income diversification.

[3]The authors explain this inconsistency by observing that banks can achieve diversification without necessarily diverting their assets away from their loan portfolios (for instance, through investment banking, securitisation, and fee-generating activities).

them, otherwise, the econometric models relying on the related data could suffer from severe bias. In relation to this concern, several scholars demonstrate that cooperative banks compete primarily among themselves because they tend to serve niche markets comprised of small firms and households (Coccorese et al., 2016; Ferri et al., 2014). To compete in such market segments a bank should use the relationship lending technique in evaluating the creditworthiness of borrowers, which small banks are proficient in exploiting (see, for instance, Berger et al., 2017; Coccorese & Ferri, 2020; for a literature review on relationship lending, see Duqi et al., 2018).

In light of this, we conduct an empirical study to test the presence of spatial comovement in a large sample of local Italian cooperative banks (Banche di Credito Cooperativo, CCBs) and, because our tests indicate the existence of spatial interaction in our sample, we use two spatial dynamic panel data (SDPD) models to assess the strength of the spatial association. The specifications provide valuable information about the direction and magnitude of the neighbouring effects on local banks' diversification ability. Finally, we perform a series of postestimation tests, the results of which confirm that the SDPD models treat the spatial association found in the data.

An empirical investigation into the determinants of bank diversification requires the inclusion of a measure of bank market power. Indeed, the literature has identified the level of market competition as a factor related to bank diversification, albeit with contradictory results. A first strand maintains the assumption that market strength discourages banks from diversifying their assets and sources of profits. In this regard, Nguyen et al. (2012b) conduct an empirical experiment with a sample of commercial banks operating in four South Asian countries, and Căpraru et al. (2020) take a similar approach to European Union banks, with both discovering that increased market strength leads to a greater emphasis on traditional interest income-generating activities. However, another stream of the literature reveals that monopolistic rents in traditional activities can encourage banks to diversify their activities (e.g., Nguyen et al., 2016; Ovi et al., 2014).[4] In further contrast, other authors reveal that competition encourages bank diversification in ASEAN countries (Ovi et al., 2014). Interestingly, using a sample of MENA countries' commercial banks, Zouaoui and Zoghlami (2020) perform a panel vector auto-regression and also adopt an impulse response function tool to claim that bank market power has a favourable influence on revenue diversification. Looking at reverse causality, their study shows that revenue diversification has a negative influence on bank market power, highlighting the possible threats involved in a diversification strategy.

Innovating on the literature, we study the effect of bank market power on diversification in the context of cooperative intermediaries while also taking the asset quality diversification proxy into account. Our study also considers asset quality, funding diversification, and size as potential drivers of bank diversification, all at the bank level. Consistent with our expectations, these factors are significant determinants of the diversification strategy of cooperative banks.

The remainder of the paper is arranged as follows. The following Section 2 describes the features of Italian bank cooperatives, and Section 3 details the spatial econometric approach. Section 4 discusses the data and variables used throughout the specification. Section 5 details the three stages of our empirical investigation: the test for spatial mutual dependence in the sample data, the empirical estimation of our models, and the tests on the estimation residuals, which are critical for determining cross-sectional independence following the treatment. Finally, Section 6 offers some concluding remarks.

2 | ITALIAN COOPERATIVE BANKS

In the bank-centric economy of Italy, in which many micro and small firms make up the productive system, cooperative banks play an important role in the credit channel because they use savings for mutualistic purposes and are subject to special regulations, including stringent capital subscription requirements on their

[4]Some research focusing on developing countries has also found a nonlinear relationship between the two factors (Nguyen et al., 2012a; Yildirim & Kasman, 2015).

shareholders. Italian law distinguishes two types of cooperative bank, namely the CCBs and the Banche Popolari (BPs)[5] Because BPs are a type of cooperative bank that have a nonprevailing mutual purpose, are less focused on the local area, and are frequently large in size, the current study only focuses on CCBs. The CCBs are particular in that the allocation of shares must prioritise micro or small firms, or households located within the bank's operational area, and the face value of the shares cannot exceed 50,000 euros. At least 95% of the credit services of CCBs must be granted to customers who reside in the same municipality as the bank branch or in surrounding municipalities. Moreover, there is a one-head-one-vote principle coupled with a requirement that at least 70% of bank profits be carried forward and a requirement that bank activity be focused on bank shareholders and geographically limited. CCBs must operate under the mutualistic concept, which means that is at least 51% of the risk activity must be channelled to bank member institutions.

These distinguishing characteristics establish these financial intermediaries as the paradigm for community banks, which are perfectly integrated into their socioeconomic context and possess more comprehensive information set for establishing and monitoring the bank's activity. This competitive advantage is frequently used in relationship lending, which is highly profitable when the bank's market power is strong (Petersen & Rajan, 1995). Italian CCBs are able to establish a market presence in areas with low population density and little competition, and eventually smooth monetary policy tightening to preserve a long-term relationship with customers (Ferri et al., 2014). Similarly, relationship lending and soft information production enable small borrowers, who might not meet the requirements of traditional creditworthiness analysis commonly used by national banks, to avoid credit rationing (Bartoli et al., 2013; Ferri et al., 2019). Throughout and following the financial crisis, cooperative banks around the world did not increase lending activity; rather, loan intensity gradually converged toward that of commercial banks, reducing their traditional lending activity (Becchetti et al., 2016). Several studies extend the “peer monitoring” hypothesis[6] to co-operative banks, demonstrating that local mutual banks perform better in terms of distress ratio (Ferri, 2008) or face financial distress conditions of their loans more efficiently (Coccorese & Shaffer, 2021; Mazzoli, 2016).

Over the last decade, Italy has responded to the financial crisis with a reform aimed at enhancing the financial stability of the cooperative banking system (Law 49/2016).[7] Although this reform has induced a consolidation process to enhance overall bank efficiency, a set of pitfalls have been identified by the banking literature. Indeed, Mazzoli (2016) argues that the reform fails to address some long-standing governance issues in bank cooperatives, including bank management's opportunistic behaviour in capturing bank members' consensus and a lack of incentives for an efficient leadership change. Moreover, this process has weakened the network economies (Coccorese et al., 2016) and relationship lending, with an overall effect of reducing or offsetting the efficiency gain of the reform (Coccorese & Ferri, 2020). As this new landscape may affect the behaviour of CCBs in terms of bank diversification strategy, we stress test this condition according to a set of empirical considerations, despite cooperative banks that have been merged or acquired by other banks not being included in the data set because the econometric methodology adopted requires a strongly balanced panel.

[5]As cooperatives, BPs must also conform to the one-head-one-vote principle, and their corporate statute must state that no member may own more than 1% of the company's stock and include an approval clause for new members. Unlike CCBs, however, BPs have a nonprevailing mutual purpose and can operate without regard to operating areas or customer categories.

[6]Small credit institutions based on membership can rely on monitoring activity among members as moral suasion to repay loans (Stiglitz, 1990).

[7]The European Association of co-operative Banks (EACB), summarises the reform as follows: Italian CCBs must create a banking group with significance under the Single Supervisory Mechanism, with a stock company as a holding. The holding has the authority to develop strategic guidelines for the CCBs and to intervene to guarantee conformity with the group operating objectives, but the CCBs maintain their full cooperative status and banking license. Contractual agreements, which must be authorised by the Bank of Italy, will establish the holding company's intervention power over CCBs, but CCBs will retain their autonomy in their commercial activities as long as they remain financially sound. http://www.eacb.coop/en/news/members-news/bcc-the-reform-of-the-co-operative-banks-in-italy-is-now-law.html.

3 | SPATIAL ECONOMETRIC METHODOLOGY

In our study, we use a Spatial Dynamic Panel Data (SDPD) model (Elhorst, 2005, 2010, 2014; Ho et al., 2013; Hory, 2018; Jeong & Lee, 2020; Lee & Yu, 2010a, 2010b; Shi & Lee, 2017; Taşpinar et al., 2017; Yu & De Jong, 2008), which permits the examination of the spatial dependence effects among economic units. Specifically, we make use of the Time-Space Simultaneous (TSS) model proposed by Anselin et al. (2007), using the generalised method of moments (GMM) dynamic estimator (Bouayad-Agha et al., 2013; Cainelli et al., 2014; Donfouet et al., 2018; Kukenova et al., 2009; Segura, 2017; Yu & De Jong, 2008). Our model is given by the following equation:

$$y_{i,t} = \lambda y_{i,t-1} + \kappa \sum_{j \neq i} \mathbf{w}_{ij} \cdot y_{j,t} + \mathbf{x}_{i,t}\beta + (\mu_i + \epsilon_{i,t}), \tag{1}$$

$$|\lambda| < 1, |\kappa| < 1; i = 1 \ldots N; t = 1 \ldots T,$$

where $y_{i,t}$ is an observation of the dependent variable y for individual i in period t, $y_{i,t-1}$ is its lagged value, $\sum_{j \neq i} \mathbf{w}_{ij} \cdot y_{j,t}$ represents the spatial lag of the dependent variable with w_{ij} being the observable nonstochastic spatial weights, $\mathbf{x}_{i,t}$ is a $q \times 1$ vector of control variables, and μ_i and $\epsilon_{i,t}$ are the two components forming the residual.[8] Lastly, λ, κ, and β are unknown parameters to estimate.

In the TSS model, Anselin et al. (2007) add the space-time lagged dependent variable and define this specification as the Time-Space Dynamic (TSD) model. Since the omission of the latter term could potentially lead to invalid and biased estimates (Tao & Yu, 2012), we also take this refined spatial model into consideration. Therefore, the regression model (1) becomes as follows:

$$y_{i,t} = \varphi y_{i,t-1} + \gamma \sum_{j \neq i} \mathbf{w}_{ij} \cdot y_{j,t} + \phi \sum_{j \neq i} \mathbf{w}_{ij} \cdot y_{j,t-1} + \mathbf{x}_{i,t}\vartheta + (\mu_i + \epsilon_{i,t}), \tag{2}$$

$$|\varphi| < 1, |\gamma| < 1, |\phi| < 1; i = 1 \ldots N; t = 1 \ldots T,$$

In Equation (2), the coefficient φ catches the serial (time) dependence of the dependent variable, the coefficient γ denotes the intensity of simultaneous spatial effects and ϕ captures the space-time interdependence, under the following constraint: $|\varphi + \gamma + \phi| < 1$.[9]

The geographical models entail a spatial weight matrix ($\boldsymbol{W}$) indicating the interdependence of the variables, and the panel must be strongly balanced (Elhorst, 2014; Millo, 2014).

Letting n be the number of cross-section units, $\boldsymbol{W}$ is a fixed and nonnegative matrix of spatial elements (weights) with zero on the main diagonal (Cliff & Ord, 1969; Kelejian & Prucha, 2010),[10] where each weight ($w_{ij} : i, j = 1, \ldots, n$) for each pair of spatial units takes the following properties:

(i) $w_{ij} = 0$, if i and j are spatially uncorrelated;
(ii) $w_{ij} \neq 0$, if i and j are spatially correlated.

To model the correlations among economic units, we build the spatial weighting matrix $\boldsymbol{W}$ making use of a Gaussian kernel matrix (Lu et al., 2014), in which the element w_{ij} represents a continuous and monotonic decreasing function of the Euclidean distance between i and j (Fotheringham et al., 2003).

[8]In the erratic component of the regression equation, μ_i indicates the individual effect and $\epsilon_{i,t}$ is the random error, normally distributed with zero mean and unit variance.

[9]This condition implies that the data are stationary, otherwise, the estimates require a different specification. See Yu and Lee (2010) for further details about the estimation of unit root in the SDPD model.

[10]The weights on the principal diagonal of $\boldsymbol{W}$ are equal to zero by definition since no economic unit is spatially related with itself; hence, $w_{ii} = 0$ for all $i = 1, \ldots, n$.

Formally, according to the classical contiguity concept, the Gaussian distance decay-based weighting function for calculating the spatial weights w_{ij} is defined as follows:

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

where d_{ij} corresponds to the physical distance between the generic spatial units i and j, and δ is nonnegative bandwidth (a dispersion or kernel parameter) that generates a decay of influence with distance. Changing the kernel parameter produces a diverse exponential decay profile, which in turn generates spatial weights that vary more or less rapidly over space. Thus, as the distance between the generic units i and j increases, the weighting of other data will decrease along a Gaussian curve (Fotheringham et al., 1998). For units far away from i the spatial element w_{ij} will fall to virtually zero.[11] The Gaussian kernel function is particularly useful as the distance decay parameter (δ) provides a check for the circular area of influence for each spatial observation. Lastly, the Gaussian kernel matrix is row standardised in a manner the sum of the weights in each row is equal to 1.

Under the assumption of constant distance, the $nt \times nt$ kernel matrix in a panel data context is computed as follows (see Anselin et al., 2007):

$$\boldsymbol{W}_{nt} = \boldsymbol{I}_t \otimes \boldsymbol{W}_n, \quad (4)$$

where $\boldsymbol{I}_t$ is an identity matrix of dimension t, and $\boldsymbol{W}_n$ is the $n \times n$ row-normalised spatial weight matrix.

4 | DATA AND EQUATION

To build our empirical analysis, we use a panel data set of 259 Italian CCBs over the 2011–2018 period, for 2072 observations. Since our SDPD specification requires a balanced panel data set, we drop those banks that do not report data over the whole time interval of interest.

The banks' balance sheet information[12] is provided by the Bureau van Dijk Orbis Bank Focus (BvD Orbis) database, while macroeconomic control variables at the provincial level have been provided by ISTAT[13] and Bank of Italy.[14]

Finally, to construct the geospatial data set we geocode the address of each CCB's headquarters using the geographic coordinates (latitude and longitude). Figure 1 shows the spatial location of the CCBs' headquarters.

Figure 1 shows the presence of many areas in Italy with a high concentration of CCBs that should be investigated more closely. Therefore, we concentrated on two proxies for bank diversification and the market power indicator to ascertain the extent of clustering observed in the map.[15] To this end, we used the Local Indicators of Spatial Association (LISA) test (Anselin, 1995) to rank CCBs according to a range of variables and to identify statistically significant local clusters of highly diversified banks (or banks with significant market power) and/or low-diversified banks (or banks with a low Lerner index). Figure 2 represents the LISA statistics across Italy.

[11] This procedure represents a generalisation of neighbours based on distance that can be used to structure dependence in behaviour, bringing about a model that is formally similar to the spatial nearest neighbours (LeSage, 2008).

[12] There are missing values in the original data set, which are furnished by consulting balance sheets published on the websites of the respective CCBs.

[13] See http://dati.istat.it/index.aspx?lang=en%26SubSessionId=a9642c15-9337-4a9b-8088-914ee0947dfd.

[14] For 2011–2015, see https://infostat.bancaditalia.it/inquiry/home?spyglass/taxo:CUBESET=%26ITEMSELEZ=%26OPEN=/%26ep:LC=IT%26COMM=BANKITALIA%26ENV=LIVE%26CTX=DIFF%26IDX=1%26/view:CUBEIDS=TDB10207_30990009; for 2016–2018, see https://infostat.bancaditalia.it/inquiry/home?spyglass/taxo:CUBESET=/PUBBL_00/PUBBL_00_05/TDB20220%26ITEMSELEZ=TDB20220_30990011:true%26OPEN=false/%26ep:LC=EN%26COMM=BANKITALIA%26ENV=LIVE%26CTX=DIFF%26IDX=2%26/view:CUBEIDS=.

[15] We owe this deepening of our analysis to an anonymous referee.

FIGURE 1 Geographical dislocation of BCCs

Figure 2 supports the existence of a statistically significant network of Italian mutual banks in northeastern Italy and in Sicily, both in terms of bank diversification and the Lerner index. There is also evidence of CCB networks in two additional southern Italian regions (Apulia and Campania) for the *LOANS* and *SERVICES* variables, but the evidence is weaker than that established for other Italian regions. Finally, comparing the CCBs clusters for the two proxies of bank diversification, it emerges that *SERVICES* presents a more widespread density throughout Italian regions than *LOANS*.

To provide correct and unbiased estimates and address possible endogeneity issues, we employ the System Generalised Method of Moments (SYS-GMM) approach proposed by Arellano and Bover (1995) and Blundell and Bond (1998).[16] All the explanatory variables have been lagged one period.

The empirical equation of the TSS model is as follows:[17]

[16]SYS-GMM is chosen over the difference GMM estimator (Arellano & Bond, 1991) because it has better performance when the variables are highly persistent over time and in dealing with possible simultaneity bias (for details, see Blundell & Bond, 1998, 2000), as in our case. The GMM models are estimated with Windmeijer (2005) finite sample correction and with forward orthogonal deviation (FOD) transformation.

[17]The TSD equation model also incorporates the space-time lagged dependent variable, $\psi\sum_{j\neq i} w_{ij} \cdot DIV_{j,t-1}$.

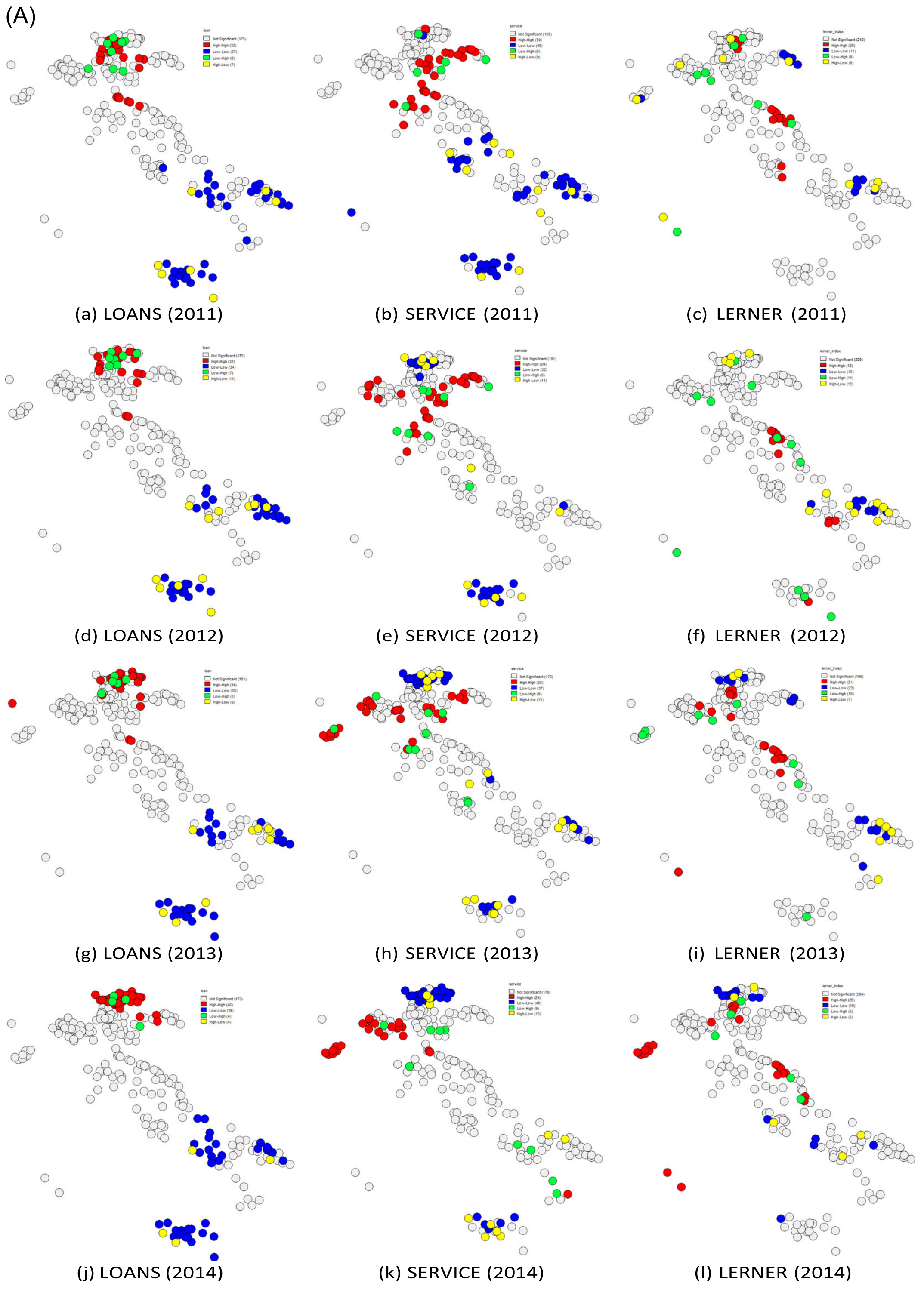

FIGURE 2 LISA cluster map of the LOANS, SERVICE, and LERNER variables

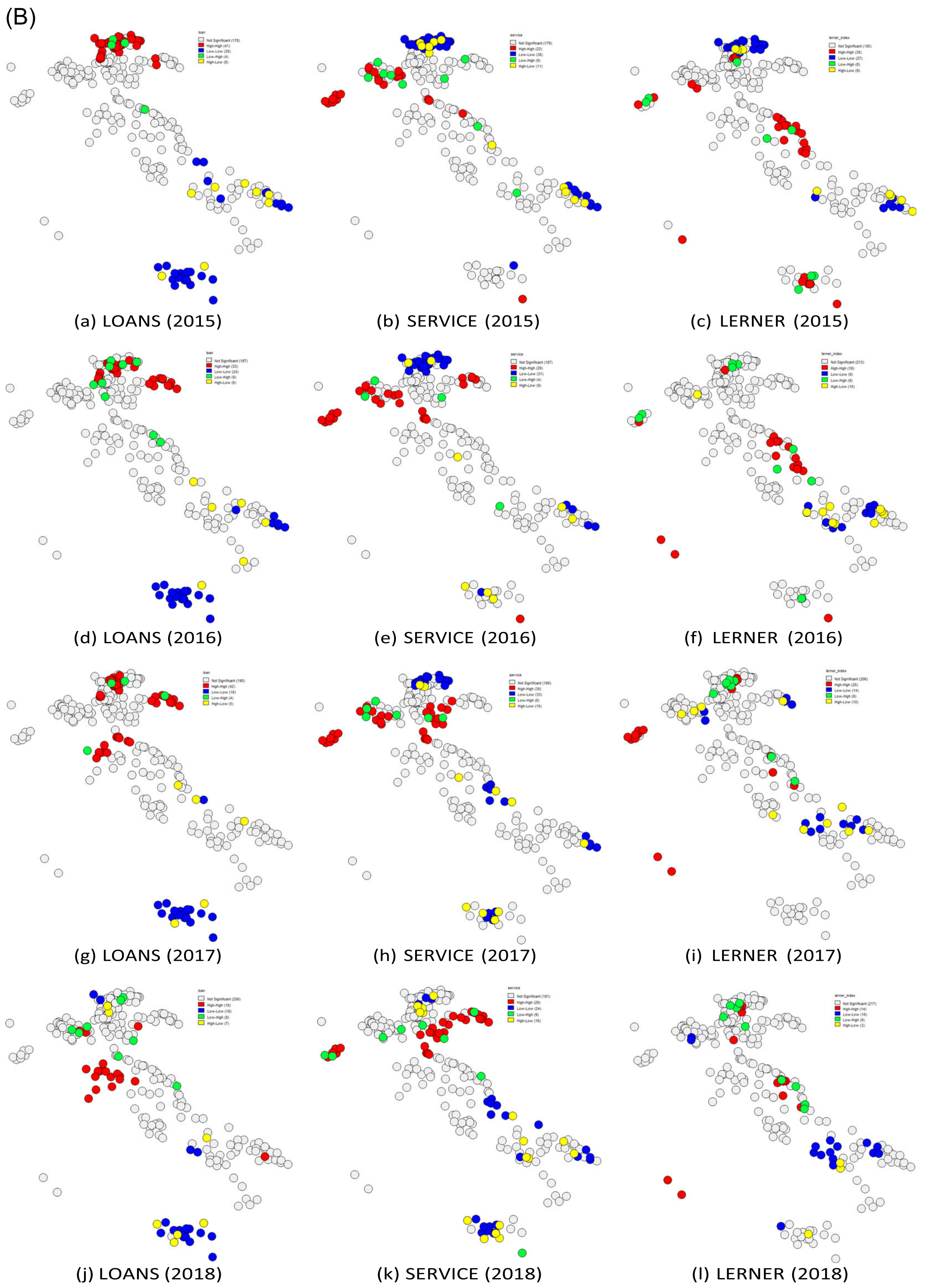

FIGURE 2 Continued

$$DIV_{i,t} = \alpha + \theta DIV_{i,t-1} + \phi\sum_{j\neq i} \mathbf{w}_{ij} \cdot DIV_{j,t} + \varsigma LERNER_{i,t-1} + \eta NPL_{i,t-1} + \zeta CAP_{i,t-1} + \lambda LN[SIZE]_{i,t-1} + \psi \Delta GDP_{k,t-1} + \omega DENSITY_{k,t-1} + (\mu_i + \varepsilon_{i,t}) \quad (5)$$

The dependent variables of our spatial regression models are *LOANS* and *SERVICES*, that is the ratio of total loans to total assets and of noninterest income over total revenues, respectively. The first depicts a specific financial ratio that measures the relationship between a bank's loan portfolio and its total assets, and serves as a proxy measure of the bank's asset risk and liquidity (Abedifar et al., 2018; Chiorazzo et al., 2008; DeYoung & Roland, 2001; Stiroh & Rumble, 2006). The higher this ratio, the lower the bank's liquidity and the more the bank is tied up in lending. Moreover, because mutual banks, unlike commercial banks, have low involvement in unconventional branches of activity, the loan-to-asset ratio is a more appropriate variable to assess the aforementioned relationship. Noninterest income is a source of revenue that integrates traditional banks' intermediation activities; in fact, they have become more strongly correlated over the last few years (Abedifar et al., 2018; DeYoung & Rice, 2004; Nguyen, 2012; Stiroh, 2004). However, *SERVICES* measures the share of bank revenue diversification, whereas *LOANS* supplies a picture of bank asset diversification.

Our spatial empirical models incorporate the spatial lag of the dependent variable and its time-lagged value in the TSD specification, the Lerner index as a commonly used measure of market power, and three bank-specific determinants. In addition, we control for the general economic conditions at the local level.

The spatial terms, which capture the effects of the neighbourhood, are calculated by multiplying the dependent variables *LOANS* and *SERVICES* by four elements of spatial weighting matrix $\boldsymbol{W}$. More specifically, we consider a Gaussian kernel matrix with four distance/decay parameters expressed in kilometres (km):

(1) $\delta = \text{Minimum}(d_{ij}) = \delta_1$,
(2) $\delta = 0.01[\text{Maximum}(d_{ij})] = \delta_2$,
(3) $\delta = 0.02[\text{Maximum}(d_{ij})] = \delta_3$,
(4) $\delta = 0.5[(\delta_1 + \delta_5)] = \delta_4$,

where δ_1 is equal to 3.6 km, corresponding to the minimum distance so that each bank has at least one neighbour; δ_2 is equal to 13.37 km, constituting 1% of the maximum distance between two CCBs (1336.6 km); δ_3 is equal to 26.73 km, representing 2% of the maximum distance; and δ_4 is equal to 68.63 km, constituting the average between δ_1 and δ_5 (i.e., 10% of the maximum distance).

The *LERNER* variable measures the market power at bank-level as proxied by the Lerner index (Lerner, 1934), which is a standard gauge adopted in the bank literature (e.g., Ahamed & Mallick, 2017; Ariss, 2010; Cipollini & Fiordelisi, 2012; Clark et al., 2018; Coccorese & Ferri, 2020; Degl'Innocenti et al., 2020; Leroy & Lucotte, 2019; de Ramon & Straughan, 2020; Spierdijka & Zaourasa, 2018). It captures the capability of a CCB to increase its marginal price beyond its marginal cost (Berger et al., 2009). The greater (lower) the index value is, the more (less) the bank's market power is; and the higher the market power, the greater the price compared to the marginal cost.

The Lerner index is calculated as follows:

$$LERNER_{i,t} = \frac{P_{i,t} - MC_{i,t}}{P_{i,t}}, \quad (6)$$

where $P_{i,t}$ represents the output price of bank i at period t and $MC_{i,t}$ is the total marginal cost. A value of *LERNER* equal to zero indicates a condition in which a bank has no market power (i.e., perfect competition); a value equal to one denotes a monopoly.[18]

[18]Indeed, the *LERNER* takes negative values for six observations, which we set to zero. As a result, those banks lack market power.

According to the literature (e.g., Carbó et al., 2009; Coccorese & Ferri, 2020; Coccorese & Santucci, 2019; Degl'Innocenti et al., 2020; Fiordelisi & Mare, 2014), the bank price $P_{i,t}$ is computed by the ratio of the sum of interest and noninterest income (total revenue) to total assets, while the marginal cost $MC_{i,t}$ is obtained from a translog cost function with a single output (total assets) and three input prices (labour, physical capital, and deposits), of which technical details are reported in the appendix.

Even though Italian cooperative banks have distinct characteristics, they provide services in markets where other banks also operate and competitive forces from noncooperative banks could have a significant impact on CCBs' behaviour; therefore, the Lerner index was calculated using a sample of all Italian banks.[19] The nexus between bank market power and bank diversification is uncertain, as seen in the conflicting results of the literature regarding this topic reviewed in Section 2 above. Moreover, some research focusing on developing countries has also found a nonlinear relationship between the two factors (Nguyen et al., 2012a; Yildirim & Kasman, 2015), but in a preliminary analysis all the nonmonotonic coefficients were nonsignificant.

NPL is the ratio of nonperforming loans to total loans and represents a proxy for a bank's asset quality. It is a backward-looking measure of credit quality, the worsening of which can hinder lending activity and encourage a bank to adopt a diversification strategy. One strand of literature has highlighted the "dark sides" of adopting a diversification strategy, as engaging in new types of business may lead to higher risk-taking due to a lack of expertise (BenLahouel et al., 2022; Louzis et al., 2012; Stiroh & Rumble, 2006). However, another strand of the literature has found no significant relationship between nonperforming loans and bank diversification (Khan et al., 2020; Naili & Lahrichi, 2022). Therefore, although it is necessary to account for the effects of bad loans, we cannot make robust predictions about the relationship between *NPL* and the bank diversification proxy.

CAP is the ratio of bank equity to total assets and indicates the bank's capitalisation (Fischer et al., 1989; Tasca et al., 2014). It indicates how much of a bank's assets are financed through equity, and as a consequence the higher the ratio is, the lower is the bank risk (Sucipto & Hasibuan, 2020). It is fair to assume that a higher capitalisation promotes lending (see Bassett & Berrospide, 2018; Bernanke et al., 1991; Berrospide & Edge, 2010; Carlson et al., 2013; Francis & Osborne, 2009)[20] and consequently the estimated coefficient should take a positive sign. The Italian banking laws make the CCB a particular type of bank and partially mitigate the central role played by capital in the management of a bank. In this regard, the smallest CCBs, with less capital, may be able to strengthen their role as cooperative banks by using lending policy as a competitive tool. In particular, these CCBs may grant relatively more loans to attract members/customers, accepting the latter to subscribe with the bare minimum of capital, and so on. At the same time, smaller CCBs may be more likely to finance their shareholders.[21] Furthermore, smaller banks are restricted almost exclusively to lending, whereas larger CCBs can, within the limits set by the bank supervisor, engage in trading and more proactive cash management, and thus increase the share of financial activities other than loans over total assets. As a consequence, a position cannot be taken regarding the sign of the coefficient.

A bank's size affects its loan portfolio dimension for several reasons (for more detail, see Koch & MacDonald, 2015; Rose & Hudgins, 2006). In particular, lending policy depends on funding characteristics, in terms of customer segments, average volume of single relationship, and fund technical forms and maturity, all of which vary as the bank size increases. Besides, a larger bank dimension allows for a larger diversified lending portfolio with less risk concentration and, in a broad sense, traditional intermediaries can achieve economies of scale and scope as they grow in size. Finally, as a larger dimension reduces the liquidity risk of loans for the bank's management, a direct relationship between the two dependent variables and bank size could arise. However, because CCBs are

[19]The Lerner index was initially estimated using only the CCB market, but an anonymous referee correctly suggested re-estimating the Lerner index using all Italian banks as a robustness check. The results of the two estimations were almost identical overall, and to prevent redundancy, we report only the Lerner index results for the entire Italian banking system. We thank the referee for suggesting this robustness check.

[20]Banks with adequate capital are better able to absorb shocks and their possible consequences, such as bankruptcy and/or restructuring (Schwert, 2018).

[21]Indeed, previous studies have shown that small banks require more collateral than large banks to mitigate the credit risk (see, for instance, Berger & Udell, 1995; Carter et al., 2004).

relatively "small" in relation to the banking sector, their size can have a marked effect on bank diversification. In detail, smaller CCBs lack the necessary scale to produce and distribute nontraditional services and must therefore sell them at a premium, resulting in a higher fee share that weighs more heavily on the bank's total revenues. Many indicators are commonly used to control for bank size, such as revenues, capitalisation, total assets, employees, and so on (see Schildbach & Schneider, 2017). Following the literature, we control for bank size by using the log of bank total assets (*LN [SIZE]*) and, as a robustness check, the log of number of employees.

Δ*GDP* is the real growth rate of gross domestic product (GDP) *per capita* and is used to control for business cyclical effects and macroeconomic shocks at provincial level (Micco & Panizza, 2006; Zheng, 2020). In particular, it checks for loan demand effects, as stated in Gambacorta (2005), Constant and Ngomsi (2012), Hu and Gong (2019), and many other authors. Favourable economic conditions and prospects stimulate loan demands (Kashyap et al., 1992). However, the effects of this variable on loan supply are challenging to establish a priori, given the impact that changes in the economic environment have on borrowers. Indeed, a favourable economic climate ameliorates creditworthiness issues for credit applicants (Bernanke et al., 1999), including the most vulnerable who previously could only be financed through relationship lending practices but can now be financed by large banks using transaction lending, and also thanks to the increasing value of collateral. Therefore, CCBs may suffer from the competitive pressure of large banks in favourable economic conditions.

Given that CCBs' customers must be small or micro-businesses or households, which are only slightly affected by business trends and for which specific factors prevail in determining their performance, and in line with the other explanatory variables of our model, we use a lagged term value.

Furthermore, in local banking markets there are also other categories of banks, and as the weight of CCBs are relatively small their bank activity could be affected by the presence of other banks. Hence, *DENSITY* accounts for the relative weight of CCBs on total bank branches operating in each Italian province to account for the role of the density of other banks by reflecting the presence of other noncooperative banks in the province where CCBs operate.[22]

Table 1 presents descriptive statistics of the covariates used in our model specifications, and Table 2 reports the correlations among the variables in our models. Both specifications incorporate a set of year dummies to account for time effects.

The sample is a balanced panel of annual data that spans the years 2011 to 2018. Among the bank-specific determinants, we notice that the mean of each variable is greater than the standard deviation, implying that our data set is made up of cooperative banks with very similar characteristics, even if there are observations with values that deviate significantly from the mean. Surprisingly, the *LERNER* distribution denotes the CCBs' ability to carve out market power within a highly contested bank industry in which many multinational banking groups operate. The correlation between the two target variables is equal to 28%, confirming previous research findings that the two dependent variables can be viewed as complementary proxies of bank revenue diversification (e.g., Abedifar et al., 2018; DeYoung & Rice, 2004; Nguyen, 2012; Stiroh, 2004). The correlation matrix does not report coefficients indicating the presence of potential multicollinearity issues, and the variance inflation factor (VIFs) values calculated for both diversification models (on average equal to 1.12) support our hypothesis.

5 | EMPIRICAL RESULTS AND DISCUSSION

To validate the adoption of a spatial econometric methodology, we first execute several diagnostic tests to control for the presence of spatial dependence. In more detail, we run three sets of Lagrange Multiplier (LM) tests to highlight the existence of spatial and serial correlation, and the random effects in our observations. Neglecting

[22]We really thank an anonymous referee for this insight.

TABLE 1 Summary statistics

Variable	Description	Mean	SD	Min	Max
LOANS	Net loans to total assets	0.651	0.12	0.216	0.963
SERVICES	Noninterest revenue to total revenue	0.335	0.11	0.070	0.646
LERNER	Lerner index	0.371	0.12	0.000	0.826
NPL	Nonperforming loans to gross loans	0.141	0.07	0.015	0.329
LLP	Loan loss provision to total loans	0.014	0.01	−0.009	0.097
CAP	Equity to total assets	0.107	0.04	0.044	0.225
DEBT	Total liabilities to total assets	0.893	0.04	0.751	0.985
SIZE[a]	Total assets	701,050	944,380	3,491	11,769,238
EMPLOYEES	Number of employees	101	119.93	5	1452
ΔGDP[b]	Real growth rate of GDP	0.017	0.05	−0.283	0.339
DENSITY[b]	CCBs branches to total bank branches	0.266	0.17	0.004	0.641

Note: The number of observations is 2072 for all the variables.
[a]In thousands euro.
[b]At provincial level.

spatial comovement leads to biased and imprecise estimates (see Anselin & Florax, 1995; Bai & Kao, 2006; Kutlu & Nair-Reichert, 2019; Moscone et al., 2014; Zhang et al., 2017).

The first group of LM tests (reported in Table 3) checks for the existence of spatial correlation. The results of these tests reject the null hypothesis that both the parameter of spatial error autocorrelation and the parameter of spatial lag autoregressive are equal to zero (Anselin, 2013; Breusch & Pagan, 1980). The second set of tests controls via the joint and conditional LM tests proposed by Baltagi et al. (2003) for the presence of spatial correlation and random effects. Both the joint and conditional LM tests reject the null hypothesis, indicating that at least one component (spatial error autocorrelation and/or random effects) exists in the residual term.[23]

The third and final group of LM tests, proposed by Baltagi et al. (2007), checks for spatial correlation, serial correlation, and random individual effects, jointly and conditionally.[24] The results confirm the presence of serial autocorrelation, spatial correlation, and random individual effects.[25]

The spatial dependence tests described thus far are linked to the spatial weighting matrix considered. Therefore, according to several studies (e.g., Elhorst et al., 2020; Kar et al., 2011; Millo, 2017; Sarafidis & Wansbeek, 2012; Yang, 2020), we ran the cross-sectional Dependence (CD) tests proposed by Pesaran (2004, 2015) as a robustness check for the presence of spatial connections among panel units. CD tests check for strong and weak cross-sectional dependence: as emphasised by Chudik et al. (2011) and Vega and Elhorst (2016), they test for unobserved common factors (strong cross-sectional dependence) and spatial dependence (weak cross-sectional dependence). The tests results reported in Table 4 indicate the presence of both strong and weak cross-sectional dependence.

[23]More specifically, spatial autocorrelation is checked allowing for the existence of random effects, and random individual effects are checked allowing for the presence of spatial correlation.
[24]The joint test takes into account the serial autocorrelation disregarded in Baltagi et al. (2003), whereas the conditional tests enable us to consider the existence of each separately, assuming the presence of the other two components.
[25]The outcomes of the tests illustrated in Table 3 are estimated by making use of the spatial weighting matrix ***W*** with the minimum distance as bandwidth. The tests are also estimated employing the other three spatial matrices; as the results exhibit the same framework we do not present them here for reasons of space. They can be provided on request.

TABLE 2 Correlation matrix for the data shown in Table 1

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1.	$LOANS_t$	1										
2.	$SERVICES_t$	0.139[a]	1									
3.	$LERNER_{t-1}$	−0.214[a]	−0.211[a]	1								
4.	NPL_{t-1}	−0.241[a]	−0.204[a]	0.093[a]	1							
5.	LLP_{t-1}	−0.294[a]	−0.360[a]	0.358[a]	0.582[a]	1						
6.	CAP_{t-1}	−0.035	0.331[a]	−0.043	−0.280[a]	−0.260[a]	1					
7.	$DEBT_{t-1}$	0.053[a]	−0.258[a]	0.067[a]	0.265[a]	0.239[a]	−0.909[a]	1				
8.	$LN[SIZE]_{t-1}$	0.142[a]	−0.312[a]	0.264[a]	0.183[a]	0.192[a]	−0.441[a]	0.435[a]	1			
9.	$LN[EMPLOYEES]_{t-1}$	0.156[a]	−0.339[a]	0.146[a]	0.218[a]	0.200[a]	−0.482[a]	0.451[a]	0.965[a]	1		
10.	ΔGDP_{t-1}	−0.005	−0.077[a]	0.107[a]	0.118[a]	0.118[a]	0.054[a]	−0.039	0.059[a]	0.011	1	
11.	$DENSITY_{t-1}$	0.216[a]	0.150[a]	0.019	−0.154[a]	−0.162[a]	0.330[a]	−0.283[a]	−0.081[a]	−0.199[a]	0.093[a]	1

[a]Significance at the 5% level or lower.

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

	LOANS		SERVICES	
LM test description	**Statistic**	***p* value**	**Statistic**	***p* value**
Anselin (1988)				
Conditional test for spatial error autocorrelation (H_0: spatial error autoregressive coefficient equal to zero)	9.12	0.000	3.96	0.000
Conditional test for spatial lag autocorrelation (H_0: spatial lag autoregressive coefficient equal to zero)	18.62	0.000	2.64	0.008
Baltagi et al., (2003)				
Joint test (H_0: absence of random effects and spatial autocorrelation)	1866.5	0.000	35.77	0.000
Marginal test of random effects (H_0: absence of random effects)	41.86	0.000	5.75	0.000
Marginal test of spatial autocorrelation (H_0: absence of spatial autocorrelation)	10.71	0.000	10.47	0.000
Conditional test of spatial autocorrelation (H_0: absence of spatial autocorrelation, assuming random effects are nonnull)	11.71	0.000	10.06	0.000
Conditional test of random effects (H_0: absence of random effects, assuming spatial autocorrelation may or may not be equal to 0)	42.77	0.000	5.63	0.000
Baltagi et al. (2007)				
Joint test (H_0: absence of serial or spatial error correlation or random effects)	1964.2	0.000	44.51	0.000
One-dimensional conditional test (H_0: absence of spatial error correlation, assuming the existence of both serial correlation and random effects)	25.42	0.000	10.55	0.001
One-dimensional conditional test (H_0: absence of serial correlation, assuming the existence of both spatial error correlation and random effects)	254.22	0.000	23.62	0.000
One-dimensional conditional test (H_0: absence of random effects, assuming the existence of both serial and spatial error correlation)	128.14	0.000	130.74	0.000

Thus, all of the test results confirm the existence of spatial comovements among the diversification proxies of CCBs across all of the dispersion parameters considered. This indicates that empirical studies should not ignore the strong strategic interaction of local banks targeting the same customers within the same geographical area.

The empirical GMM estimates of the SDPD models specified in equation (5) are summarised in Tables 5 and 7 for the *LOANS* and Tables 6 and 8 for the *SERVICES* variable, along all the four distances we consider. Tables 5 and 6 reports the estimates of the TSS specification together with the outcomes of the dynamic panel data model, while Tables 7 and 8 provide the results of the TSD specification.

Interestingly, the estimated coefficients have consistent algebraical signs along all the four distances we consider and also for the dynamic model. The magnitude and statistical significance are mostly the same for each space range, especially for the asset variable.

Unsurprisingly, our estimates show positive and strong persistence in the diversification measures of cooperative banks. The results hold true for both of the proxies we consider and confirm the critical role played by the lending market segment for such banks, which primarily operate with their owners/members. Furthermore, changing the asset structure of a cooperative is a challenging strategy that can be implemented only with the bank supervisor's consent.

TABLE 4 Testing for cross-sectional dependence

Test	Pesaran (2004) *LOANS*	Pesaran (2004) *SERVICES*	Pesaran (2015) *LOANS*	Pesaran (2015) *SERVICES*
CD	43.199	48.920	20.827	30.362
p value	0.000	0.000	0.000	0.000

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

Although all of the spatial coefficients are statistically significant, for both the measures of bank diversification the effect of the contemporaneous and yearly lagged factors are opposite. The spatial lagged dependent variables, in particular, have a positive impact on bank diversification, indicating that CCBs operate as a network that behaves similarly when it comes to increasing or decreasing their involvement in nontraditional operations. The common pattern appears to reflect shocks in the business cycle, as CCBs are likely to adjust their diversification strategy in response to macroeconomic shocks. As a result, in the very short run, CCBs' asset diversification does not differ from that of the cooperative bank cluster as a whole, indicating a limited ability to implement instantaneous alternative policies in response to market condition changes.

The space-time lagged variables in the TDS models, on the contrary, take a negative sign, indicating that if a nearby cooperative bank increases/decreases its loans-to-assets or service ratio, the *i*th bank acts in the opposite direction, and vice versa. The regularity of this effect is intriguing and, in contrast to the contemporaneous spatial term, necessitates an interpretation in light of competitive interaction within the bank cluster, which targets specific niche markets. Indeed, CCBs implement relationship lending practices and offer individual and personalised terms to their customers, that is, micro and small businesses as well as households (Berger et al., 2017; Coccorese & Ferri, 2020; Duqi et al., 2018). Meanwhile, the hierarchical structure of national banks precludes them from establishing long-term lending relationships based on the collection and exploitation of soft data about small borrowers. Indeed, large banks evaluate credit applicants primarily on the basis of "hard data," such as financial statements, market prices for shares or bonds, and so on (Berger et al., 2001; Stein, 2002).

In this competitive environment, any change in a CCB's asset portfolio implies a loss or gain in loan supply market share, which has a cascading effect on nearby co-operative banks because typical CCBs customers migrate to other mutual banks. This effect is strong because local banks operate in the same niche market, target the same customers, and face the same shocks.

The *LERNER* coefficients of the TSS and TSD models calculated for the two proxy variables of bank diversification are negative and statistically significant, except for the *SERVICES* models. Specifically, and consistent with recent studies (Căpraru et al., 2020; Zouaoui & Zoghlami, 2020), market power is associated with less credit exposure, reflecting the general lower quantity of output under all monopolistic market conditions. Similarly, mutual banks with a higher market power are less diversified because their share of income from services is lower.

In summary, the CCBs' monopolistic power within their niches is a Pareto inefficient market condition, because bank management is likely to pursue some form of credit rationing and, by the same token, lower revenue diversification based primarily on interest-bearing assets, which implies increased bank risk (see, among many others, Chiorazzo et al., 2008; Lee et al., 2014; Li et al., 2021). Moreover, this effect is even more socially detrimental in light of the fact that local co-operative banks may constitute the last resort credit opportunity for marginal borrowers.

Turning to the *NPL* variable, it has an indirect effect on the loans-to-asset ratio, confirming the insight that poor credit quality necessitates banks maintaining more liquid assets and lightening their credit portfolios, as a result of two complementary effects. On the one hand, an increase in *NPL* signals a deterioration in the local credit market in which the co-operative operates; on the other hand, increased bad loans would hinder bank intermediation activity given the CCBs' capital-raising constraints. However, the effect is statistically significant only in the TSD models for

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

		Spatial dynamic models			
	Dynamic model	δ_1	δ_2	δ_3	δ_4
LOANS	(1)	(2)	(3)	(4)	(5)
$LOANS_{t-1}$	0.7964*** (0.080)	0.5319*** (0.121)	0.4327*** (0.121)	0.4066*** (0.114)	0.6215*** (0.105)
$\mathbf{W} \times LOANS_t$		0.3798*** (0.084)	0.5518*** (0.138)	0.5895*** (0.135)	0.3515** (0.161)
$LERNER_{t-1}$	−0.2286*** (0.079)	−0.3718*** (0.080)	−0.3607*** (0.069)	−0.3354*** (0.070)	−0.1912*** (0.067)
NPL_{t-1}	−0.0463 (0.121)	−0.3130* (0.165)	−0.2942* (0.164)	−0.2068 (0.133)	0.0974 (0.092)
CAP_{t-1}	−0.8919** (0.395)	−1.4029*** (0.454)	−1.3857*** (0.417)	−1.1216** (0.458)	−0.6390** (0.301)
$LN[SIZE]_{t-1}$	−0.0004 (0.014)	−0.0300 (0.021)	−0.0307 (0.019)	−0.0258 (0.018)	−0.0118 (0.009)
ΔGDP_{t-1}	−0.3140*** (0.106)	−0.2471** (0.100)	−0.1882** (0.093)	−0.1796** (0.088)	−0.1980** (0.096)
$DENSITY_{t-1}$	−0.0926 (0.058)	−0.0813 (0.076)	−0.0922 (0.069)	−0.0725 (0.055)	−0.0387 (0.043)
No. Instruments	53	52	52	52	52
Years dummies	Yes	Yes	Yes	Yes	Yes
AR(1)	0.0000	0.0000	0.0000	0.0000	0.0000
AR(2)	0.8272	0.4197	0.2362	0.1839	0.6932
Hansen test	0.2453	0.6926	0.7412	0.6202	0.1812

Note: Robust standard errors in parentheses. Estimates rely on the use of the two-step system GMM estimator. All the models instrument as endogenous the dependent variable and all the explanatory variables. Time dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and time dummies; *p* values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 259 banks for a total of 1813 observations.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 6 Estimation results of dynamic and TSS model, using *SERVICES* as dependent variable

	Dynamic model	Spatial dynamic model			
		δ_1	δ_2	δ_3	δ_4
SERVICES	(1)	(2)	(3)	(4)	(5)
$SERVICES_{t-1}$	0.4833*** (0.119)	0.3632** (0.166)	0.3157** (0.138)	0.3197** (0.128)	0.2465** (0.123)
$\mathbf{W} \times SERVICES_t$		0.5649*** (0.162)	0.6607*** (0.100)	0.6777*** (0.099)	0.7477*** (0.101)
$LERNER_{t-1}$	−0.3482*** (0.057)	−0.2973*** (0.077)	−0.2629*** (0.064)	−0.2638*** (0.057)	−0.2446*** (0.055)
NPL_{t-1}	−0.3009 (0.193)	−0.0247 (0.182)	−0.0126 (0.147)	0.0670 (0.132)	0.0585 (0.155)
CAP_{t-1}	−2.4032*** (0.586)	−2.0681*** (0.558)	−1.8479*** (0.454)	−1.9648*** (0.406)	−2.0971*** (0.444)
$LN[SIZE]_{t-1}$	−0.0570** (0.023)	−0.0527* (0.027)	−0.0536** (0.023)	−0.0616*** (0.022)	−0.0576*** (0.021)
ΔGDP_{t-1}	−0.2544*** (0.091)	−0.1968* (0.114)	−0.2662* (0.146)	−0.2358* (0.124)	−0.3637* (0.198)
$DENSITY_{t-1}$	0.1084 (0.078)	0.1664* (0.093)	0.0995 (0.071)	0.1153* (0.060)	0.0806 (0.086)
No. instruments	55	56	56	56	56
Years dummies	Yes	Yes	Yes	Yes	Yes
AR(1)	0.0000	0.0001	0.0000	0.0000	0.0001
AR(2)	0.7420	0.5593	0.5112	0.4323	0.3111
Hansen test	0.2312	0.1651	0.2178	0.1650	0.1176

Note: Robust standard errors in parentheses. Estimates rely on the use of the two-step system GMM estimator. All the models instrument as endogenous the dependent variable and all the explanatory variables. Time dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and time dummies; *p* values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 259 banks for a total of 1813 observations.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

TABLE 7 Estimation results of TSD model for *LOANS*

LOANS	Spatial dynamic models δ_1 (6)	δ_2 (7)	δ_3 (8)	δ_4 (9)
$LOANS_{t-1}$	0.6927*** (0.103)	0.7052*** (0.097)	0.7043*** (0.102)	0.7868*** (0.099)
$\mathbf{W} \times LOANS_t$	0.6360*** (0.116)	0.8250*** (0.122)	0.9540*** (0.135)	0.9650*** (0.185)
$\mathbf{W} \times LOANS_{t-1}$	−0.4700*** (0.140)	−0.5636*** (0.144)	−0.6620*** (0.165)	−0.7763*** (0.253)
$LERNER_{t-1}$	−0.2811*** (0.078)	−0.2690*** (0.072)	−0.2399*** (0.068)	−0.2228*** (0.068)
NPL_{t-1}	−0.2695** (0.126)	−0.2542** (0.116)	−0.2441** (0.107)	−0.2876** (0.111)
CAP_{t-1}	−1.1744** (0.471)	−1.2237** (0.500)	−1.1262** (0.500)	−0.9806** (0.417)
$LN\,[SIZE]_{t-1}$	−0.0131 (0.019)	−0.0159 (0.018)	−0.0134 (0.016)	−0.0003 (0.012)
ΔGDP_{t-1}	−0.2834*** (0.108)	−0.2722** (0.106)	−0.2737*** (0.104)	−0.1774** (0.080)
$DENSITY_{t-1}$	−0.0558 (0.082)	−0.0467 (0.075)	−0.0233 (0.069)	−0.0785 (0.056)
No. instruments	56	56	56	56
Years dummies	Yes	Yes	Yes	Yes
AR(1)	0.0000	0.0000	0.0000	0.0000
AR(2)	0.8998	0.9401	0.8418	0.7102
Hansen test	0.8878	0.9278	0.9014	0.6157

Note: Robust standard errors in parentheses. Estimates rely on the use of the two-step system GMM estimator. All the models instrument as endogenous the dependent variable and all the explanatory variables. Time dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and time dummies; *p* values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 259 banks for a total of 1813 observations.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

LOANS, with the ex post credit quality measure (i.e., *NPL*) never affecting *SERVICES*, in line with Khan et al. (2020) and Naili and Lahrichi (2022).

The sign of the estimated coefficients of our measure of bank capitalisation (*CAP*) is not straightforward and should be interpreted in view of the distinctive features of CCBs. In a macroeconomic environment marked by historically low interest rates, the findings indicate that less capitalised CCBs earn more from services and make more loans. It is likely that less capitalised mutual banks try to compete in the market by increasing the proportion of loans in their assets; however, such banks charge expensive fees for their bouquet of services. Conversely, only the well-capitalised CCBs can depart from the constraints in lending activity typical of community banks and, in the context of the strict prudential controls under which banks operate, carry out broader management of banking investments. The findings also underline that CCBs implement lending activity regardless of their size but larger CCBs seem to be able to achieve economies of scale that allow them to charge lower bank fees. Given that, as is well known, all CCBs in Italy are essentially "small banks," their size is insufficient to have an impact on lending operations, but it is nonetheless appropriate to capitalise on economies of scale to produce and distribute nontraditional services at competitive prices, with the result of higher prices charged on services.

Interestingly, Δ*GDP* reduces CCB lending activity, corroborating the above finding that economic growth reshuffles credit market conditions, diminishing the importance of relationship lending for financing vulnerable borrowers. In light of the credit view theory (e.g., Bernanke et al., 1999, 1991), this effect results in a reduction in the lending share of CCBs that rebalance their portfolios toward financial market opportunity. This effect has no impact on the weighting of noninterest income over bank revenue.

TABLE 8 Estimation results of TSD model for *SERVICES*

SERVICES	Spatial dynamic models δ_1 (6)	δ_2 (7)	δ_3 (8)	δ_4 (9)
$SERVICES_{t-1}$	0.3089*** (0.112)	0.3549*** (0.106)	0.3888*** (0.110)	0.4231*** (0.135)
$\mathbf{W} \times SERVICES_t$	0.7961*** (0.119)	0.8692*** (0.103)	0.8846*** (0.094)	0.8264*** (0.088)
$\mathbf{W} \times SERVICES_{t-1}$	−0.4897*** (0.107)	−0.5343*** (0.108)	−0.5793*** (0.117)	−0.6783*** (0.160)
$LERNER_{t-1}$	−0.2665*** (0.060)	−0.2729*** (0.053)	−0.2743*** (0.051)	−0.2907*** (0.059)
NPL_{t-1}	0.0054 (0.147)	0.0098 (0.126)	0.0454 (0.121)	0.0804 (0.138)
CAP_{t-1}	−2.1373*** (0.580)	−1.9588*** (0.490)	−1.9553*** (0.454)	−2.1597*** (0.448)
$LN\,[SIZE]_{t-1}$	−0.0530* (0.027)	−0.0502** (0.023)	−0.0529** (0.022)	−0.0540** (0.022)
ΔGDP_{t-1}	−0.3116* (0.166)	−0.2387* (0.143)	−0.2318* (0.134)	−0.2715** (0.123)
$DENSITY_{t-1}$	0.0534 (0.075)	0.0484 (0.065)	0.0546 (0.059)	0.0753 (0.059)
No. instruments	58	58	58	58
Years dummies	Yes	Yes	Yes	Yes
AR(1)	0.0000	0.0000	0.0000	0.0000
AR(2)	0.2671	0.5690	0.7565	0.8384
Hansen test	0.5403	0.4858	0.3715	0.1285

Note: Robust standard errors in parentheses. Estimates rely on the use of the two-step system GMM estimator. All the models instrument as endogenous the dependent variable and all the explanatory variables. Time dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and time dummies; *p* values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 259 banks for a total of 1813 observations.

*p < 0.1; **p < 0.05; ***p < 0.01.

Finally, the density of CCBs has no impact on the diversification strategies of Italian mutual banks, whereas the temporal dummies (not reported) indicate an increasing effect for *LOANS* over time, particularly in the last 2 years, which is most likely a result of the Italian CCBs reform introduced by law 49/2016.

Several outputs confirm the overall goodness of the estimates. The number of SDPD model instruments (about 50) is smaller than the number of groups (259). The Hansen test confirms the validity of the instrumental variables used in all the specifications. Moreover, the AR(1) and AR(2) tests, which represent Arellano–Bond first- and second-order autocorrelation tests, indicate the rejection of the AR(1) null hypothesis and nonrejection of AR(2), thus providing evidence for the consistency of the GMM estimator. In addition, the coefficients of the variables of time dependence, spatial dependence, and space-time dependence sum to less than one, satisfying the constraint of global stationarity and thus indicating the absence of a unit root problem.

Even though our econometric models address the spatial dependence of cooperative banks, unobserved common factors may still bias the estimate. To validate this, we run a postestimation test on the residuals of the SPDP models using the Pesaran (2004) CD test to confirm the existence of cross-sectional independence in the spatial model errors. Tables 9 and 10 show the CD test results. Both specifications incorporate a set of year dummies to account for time effects.

The outcomes of these tests demonstrate that the hypothesis of cross-sectional independence is not rejected for any spatial specifications, indicating the absence of strong cross-sectional dependence.

TABLE 9 Cross-sectional independence test for *LOANS* models

Test	Time-space simultaneous				Time-space dynamic			
	δ_1	δ_2	δ_3	δ_4	δ_1	δ_2	δ_3	δ_4
CD	−1.192	−1.565	−1.584	−1.347	−1.485	−1.540	−1.487	−1.216
p value	0.233	0.118	0.113	0.178	0.137	0.124	0.137	0.224

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

TABLE 10 Cross-sectional independence test for *SERVICES* models

Test	Time-space simultaneous				Time-space dynamic			
	δ_1	δ_2	δ_3	δ_4	δ_1	δ_2	δ_3	δ_4
CD	−1.118	−0.990	−1.065	−0.639	−0.275	−1.010	−1.370	−1.124
p value	0.263	0.322	0.287	0.523	0.784	0.313	0.171	0.261

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

Finally, we have conducted a robustness check of our models by adopting some alternative covariates commonly used in the literature.[26] Specifically, we use a different proxy of credit quality, replacing the ratio of nonperforming loans to total loans with the ratio of loan loss provision to total loans (*LLP*), using funding-to-assets ratio (*DEBT*) instead of the equity-to-assets ratio as a bank capitalisation proxy, and the log of number of employees rather than the total assets as a size proxy. *LLP* represents an alternative proxy for banks' asset quality (Dietrich & Wanzenried, 2011). It is a forward-looking measure of credit quality and depicts the hedging strategies against (expected) losses on loan activity (Mergaerts & Vander Vennet, 2016; Mourouzidou-Damtsa et al., 2019). An increase in *LLP* could reflect a decline in loan portfolio quality, which in turn causes banks to invest in less risky assets (Pennathur et al., 2012). An empirical study of the Indian banking market, Ahamed (2017) concluded that banks with a smaller percentage of *LLP* over total assets may enjoy more revenue diversification advantages than banks with higher asset quality.

DEBT is the ratio of the total bank funding (both short- and long-term) to total assets. As a proxy for a bank's capitalisation (Fischer et al., 1989; Tasca et al., 2014) it depicts the amount of bank funding used to finance bank assets and it is direct measure of bank risk.

Tables 11 and 12 detail the estimates for the nonspatial and TSS models' robustness checks, respectively, for *LOANS* and *SERVICES*. While Tables 13 and 14 present the empirical results for the same two specifications using TSD models.

The stress tests validate the stability of the main relationships between the benchmark models, even the ex ante credit quality measure (loan loss provision) is more robust across all the empirical models than *NPL*. Because provisions have been accrued and the ascertained credit loss would not change the current decision on bank asset diversification, it is reasonable to assume that nonperforming loans have a minor impact on the bank diversification strategy. On the contrary, *LLP* is positively associated with *SERVICES*, indicating that accruing more reserves for loan losses is associated with increased bank earnings from nontraditional intermediation activity, corroborating the hypothesis that higher credit risk incentivizes banks to diversify their earnings. In other words, as their loan portfolio deteriorates, mutual banks appear to follow a diversification strategy similar to that of other barks.

[26]We owe this improvement to an anonymous referee. The test results for these robustness check specifications (reported in appendix, Table A1, A2, A3, and A4) suggest that a spatial model should be used again because it controls for cross-sectional dependence.

TABLE 11 Estimation results of dynamic and TSS model, using *LOANS* as dependent variable

		Spatial dynamic models			
	Dynamic model	δ_1	δ_2	δ_3	δ_4
LOANS	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$LOANS_{t-1}$	0.7256*** (0.111)	0.5704*** (0.093)	0.5382*** (0.088)	0.4790*** (0.092)	0.4910*** (0.107)
$\mathbf{W} \times LOANS_t$		0.3210*** (0.074)	0.4369*** (0.088)	0.5193*** (0.102)	0.4893*** (0.138)
$LERNER_{t-1}$	−0.1564** (0.078)	−0.1664** (0.066)	−0.1565** (0.062)	−0.1869** (0.073)	−0.2054** (0.098)
LLP_{t-1}	−2.3515** (1.186)	−3.3144*** (0.902)	−3.0351*** (0.865)	−3.2128*** (0.941)	−3.3518*** (0.866)
$DEBT_{t-1}$	0.5140** (0.252)	0.7086*** (0.201)	0.7211*** (0.222)	0.8925*** (0.260)	0.8354** (0.349)
$LN[EMPLOYEES]_{t-1}$	0.0086 (0.011)	−0.0023 (0.008)	−0.0054 (0.008)	−0.0101 (0.010)	−0.0176 (0.011)
ΔGDP_{t-1}	−0.1505** (0.075)	−0.3675*** (0.139)	−0.3298** (0.133)	−0.2442** (0.118)	−0.2848** (0.122)
$DENSITY_{t-1}$	−0.0012 (0.060)	−0.0669 (0.059)	−0.0728 (0.060)	−0.0589 (0.058)	−0.0606 (0.049)
No. instruments	53	52	52	52	52
Years dummies	Yes	Yes	Yes	Yes	Yes
AR(1)	0.0000	0.0000	0.0000	0.0000	0.0000
AR(2)	0.5900	0.5494	0.5042	0.3553	0.3761
Hansen test	0.1549	0.4118	0.5086	0.7576	0.4705

Note: Robust standard errors in parentheses. Estimates rely on the use of the two-step system GMM estimator. All the models instrument as endogenous the dependent variable and all the explanatory variables. Time dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and time dummies; *p* values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 259 banks for a total of 1813 observations.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 12 Estimation results of dynamic and TSS model, using *SERVICES* as dependent variable

	Dynamic model	Spatial dynamic models			
		δ_1	δ_2	δ_3	δ_4
SERVICES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$SERVICES_{t-1}$	0.2392** (0.111)	0.2732** (0.110)	0.2753** (0.109)	0.2597** (0.112)	0.3182*** (0.086)
$\mathbf{W} \times SERVICES_t$		0.6223*** (0.201)	0.7174*** (0.204)	0.7351*** (0.186)	0.6692*** (0.189)
$LERNER_{t-1}$	−0.0973** (0.045)	−0.0647 (0.140)	−0.1030 (0.139)	−0.0453 (0.116)	−0.0508 (0.122)
LLP_{t-1}	3.5010*** (1.130)	1.7455** (0.874)	1.6635** (0.810)	1.8631** (0.816)	2.5594*** (0.954)
$DEBT_{t-1}$	1.0037*** (0.342)	0.6574** (0.296)	0.6288** (0.311)	0.4571 (0.299)	0.5647** (0.285)
$LN\,[EMPLOYEES]_{t-1}$	−0.0143 (0.013)	−0.0398** (0.019)	−0.0389** (0.018)	−0.0395** (0.016)	−0.0335** (0.015)
ΔGDP_{t-1}	−0.2863** (0.124)	−0.0775 (0.063)	−0.1708 (0.140)	−0.0261 (0.123)	0.0993 (0.082)
$DENSITY_{t-1}$	0.0347 (0.023)	0.0158 (0.073)	0.0297 (0.029)	−0.0198 (0.063)	0.0713* (0.040)
No. Instruments	55	56	56	56	56
Years dummies	Yes	Yes	Yes	Yes	Yes
AR(1)	0.0000	0.0000	0.0000	0.0000	0.0000
AR(2)	0.1372	0.1934	0.2322	0.1330	0.1425
Hansen test	0.1963	0.8361	0.7965	0.7415	0.5963

Note: Robust standard errors in parentheses. Estimates rely on the use of the two-step system GMM estimator. All the models instrument as endogenous the dependent variable and all the explanatory variables. Time dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and time dummies; p values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 259 banks for a total of 1813 observations.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

TABLE 13 Estimation results of TSD model for *LOANS*

LOANS	Spatial dynamic models δ_1 (6)	δ_2 (7)	δ_3 (8)	δ_4 (9)
$LOANS_{t-1}$	0.6332*** (0.090)	0.6386*** (0.085)	0.6287*** (0.083)	0.6046*** (0.089)
$\mathbf{W} \times LOANS_t$	0.5564*** (0.122)	0.7124*** (0.145)	0.7497*** (0.163)	0.9720*** (0.219)
$\mathbf{W} \times LOANS_{t-1}$	−0.4200** (0.167)	−0.4964** (0.197)	−0.4970** (0.228)	−0.6903*** (0.245)
$LERNER_{t-1}$	−0.1649** (0.081)	−0.1474** (0.074)	−0.1453** (0.069)	−0.1794*** (0.062)
LLP_{t-1}	−2.4532** (1.057)	−2.1231** (1.032)	−2.4854*** (0.949)	−2.3940** (0.991)
$DEBT_{t-1}$	0.8249*** (0.225)	0.8100*** (0.275)	0.7735*** (0.235)	0.5325*** (0.193)
$LN\,[EMPLOYEES]_{t-1}$	−0.0129 (0.012)	−0.0167 (0.014)	−0.0137 (0.011)	0.0073 (0.011)
ΔGDP_{t-1}	−0.2473** (0.113)	−0.2142** (0.101)	−0.1881** (0.091)	−0.1603** (0.079)
$DENSITY_{t-1}$	−0.0475 (0.068)	−0.0581 (0.065)	−0.0500 (0.061)	0.0506 (0.038)
No. Instruments	56	56	56	56
Years dummies	Yes	Yes	Yes	Yes
AR(1)	0.0000	0.0000	0.0000	0.0000
AR(2)	0.9627	0.9706	0.8139	0.5804
Hansen test	0.6703	0.7314	0.6668	0.3892

Note: Robust standard in parentheses. Estimates rely on the use of the two-step system GMM estimator. All the models instrument as endogenous the dependent variable and all the explanatory variables. Time dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and time dummies; *p* values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 259 banks for a total of 1813 observations.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

6 | CONCLUSIONS

In this study, we looked at factors that influence cooperative banks' diversification strategies using two complementary proxies. The scarcity of studies on local bank diversification strategies, and the inconsistent findings in the literature regarding the impact of diversification on bank performance and stability motivated the present analysis. Because CCBs compete in a specific geographical area and business segment, we believe that there are spatial spillover effects influencing their business decisions; thus, we used spatial econometric tools to control the impact of neighbours on local bank diversification.

Spatial dependence is confirmed by a set of econometric tests and the results show that the neighbourhood has different effects on cooperative banks depending on the year considered: the contemporaneous spatial effects on the two bank diversification proxies are positive, whereas the 1-year lagged spatial effect is indirect. The former result seems to reflect the effect of macroeconomic policies that affect all CCBs similarly, whereas the latter result confirms that cooperative banks tend to target similar consumers, forming a distinct market category. As a result, market strategies that direct the adjustment of the bank investment portfolio composition are influenced by/have an impact on proximate banks.

Our models show that monopolistic rents induce social losses, because the CCBs' market power determine a reduced willingness to grant loans, which can induce a kind of credit rationing for fragile local borrowers. Likewise, the diversification strategy is less oriented toward service and, as the literature has shown, this can expose the

TABLE 14 Estimation results of TSD model for *SERVICES*

SERVICES	Spatial dynamic models δ_1 (6)	δ_2 (7)	δ_3 (8)	δ_4 (9)
$SERVICES_{t-1}$	0.3586*** (0.090)	0.3472*** (0.081)	0.3453*** (0.089)	0.3450*** (0.090)
$\mathbf{W} \times SERVICES_t$	0.8120*** (0.176)	0.9856*** (0.214)	0.8821*** (0.091)	0.9496*** (0.093)
$\mathbf{W} \times SERVICES_{t-1}$	−0.2635** (0.129)	−0.3391** (0.148)	−0.3366*** (0.129)	−0.3018** (0.152)
$LERNER_{t-1}$	−0.2677** (0.110)	−0.2328** (0.109)	−0.2006*** (0.074)	−0.1035** (0.052)
LLP_{t-1}	3.2848*** (1.160)	2.6330** (1.057)	2.7768*** (0.950)	1.8483** (0.775)
$DEBT_{t-1}$	0.3192 (0.287)	0.3587 (0.275)	0.5298** (0.265)	0.9003*** (0.284)
$LN\,[EMPLOYEES]_{t-1}$	−0.0305** (0.015)	−0.0303** (0.015)	−0.0367*** (0.014)	−0.0354*** (0.013)
ΔGDP_{t-1}	−0.1149 (0.135)	0.0821 (0.142)	−0.0329 (0.103)	0.0172 (0.115)
$DENSITY_{t-1}$	0.0533 (0.058)	0.0355 (0.042)	0.0454 (0.035)	0.0581 (0.043)
No. Instruments	58	58	58	58
Years dummies	Yes	Yes	Yes	Yes
AR(1)	0.0000	0.0000	0.0000	0.0000
AR(2)	0.1396	0.1613	0.1473	0.1466
Hansen test	0.5967	0.5932	0.9740	0.4211

Note: Robust standard errors in parentheses. Estimates rely on the use of the two-step system GMM estimator. All the models instrument as endogenous the dependent variable and all the explanatory variables. Time dummies are considered as strictly exogenous instruments in the level equations. Not reported constant and time dummies; *p* values are indicated for Hansen, AR(1) and AR(2) tests. The estimates regard 259 banks for a total of 1813 observations.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

mutual banks to higher credit risk. Capitalisation has a nontrivial effect, as it contradicts the conventional wisdom that more risky assets necessitate increased bank capital. On the contrary, our evidence shows that, within the supervisory capital requirements, less leveraged local cooperative banks are more focused on operating outside of traditional lending activity, presumably because this channel is more profitable. Interestingly, our results seem to provide evidence that in adverse macroeconomic scenarios, CCBs have an important role in funding the most fragile borrowers through relationship lending practices that prevent the typical fly-to-quality of large banks. Further analysis is needed to validate this assumption.

Finally, direct policy implications flow from the critical role of the banking network and clusters in explaining the local cooperative bank diversification strategy and market power fostering a decrease in lending activity.

The study's results must be viewed in light of a few limitations. Because, the spatial technique requires a balanced panel, cooperative banks involved in mergers and acquisitions are not considered. Consequently, it is possible that our empirical findings do not fully account for all possible network effects related to the diversification strategy of banks. In addition, we did not look at other types of local bank borrowers, such as households and small and micro firms. Because of probable disparities in these sorts of bank customers, a different percentage of one of the groups in banks' loan portfolios might impact local banks' diversification tendencies. Moreover, we were unable to overcome this constraint owing to a lack of data. A similar restriction precludes us from confirming the presence of spatial spillover effects for larger banks, as this would require taking into account information about the banking agency's location. Moreover, there are other variables capturing bank diversification, such as a bank's involvement in different operative segments (e.g., retail, corporate, and so on) or geographical areas. As these alternative bank characteristics are not available in our data set, we leave them for further analysis.

DATA AVAILABILITY STATEMENT

Authors elects to not share data.

ETHICS STATEMENT

The authors have followed the required ethical standards.

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Non-technical Summary

In this study, we looked at factors that influence cooperative banks' diversification strategies. We clearly show that the asset diversification of mutual banks is influenced by the geographical proximity of similar banks that compete in the same territory and business. The findings reveal that all credit cooperative banks respond similarly to macroeconomic policies. Conversely, the competitive interaction determines dissimilar behaviors within the bank network, confirming that mutual banks form a distinct market category. Finally, cooperative banks with a greater market share are less diversified (granting less loans and services).

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APPENDIX A

The bank's cost function is defined as follows:

$$\begin{aligned}\ln C_{i,t} = \eta_0 + \eta_1 \ln Q_{i,t} + \frac{1}{2}\eta_2 \ln Q_{i,t}^2 + \textstyle\sum_{k=1}^{3} \xi_k \ln P_{k,i,t} \\ + \frac{1}{2}\textstyle\sum_{k=1}^{3}\sum_{j=1}^{3} \rho_{k,j} \ln P_{k,i,t} \ln P_{j,i,t} + \frac{1}{2}\textstyle\sum_{k=1}^{3} \varrho_k \ln Q_{i,t} \ln P_{k,i,t} + (\upsilon_{i,t} + v_{i,t})\end{aligned} \tag{A1}$$

where $C_{i,t}$ is the total cost (i.e., total operating expense) and $Q_{i,t}$ is the output proxied by total assets. P_1, P_2 and P_3 are the three inputs: P_1 is the labour price (i.e., personnel expenses divided by total assets), P_2 is the physical capital price (i.e., other administrative expenses plus other operating expenses over fixed assets), and P_3 is the borrowed funds price (i.e., interest expenses over bank funding). η, ξ, ρ, and ϱ are unknown parameters to be identified. Lastly, the sum of $\upsilon_{i,t}$ and $v_{i,t}$ is the decomposition of the error term. The two-sided error term $v_{i,t}$ denotes the usual statistical noise independent and identically distributed as a normal distribution with mean 0 and variance σ_v^2; the one-sided error term $\upsilon_{i,t}$, capturing the actual cost inefficiency term, is modelled as a truncated nonnegative random variable $N^{+}(0, \sigma_u^2)$.

The identified parameters from the above-mentioned cost function permit us to estimate the marginal cost for each ith bank at time t by calculating the partial derivatives of Equation (A1) with respect to the bank output Q. The formula is expressed as the following (see Tables A1–A4):

$$MC_{i,t} = \frac{\partial C_{i,t}}{\partial Q_{i,t}} = \frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} \frac{C_{i,t}}{Q_{i,t}} = \left(\hat{\eta}_1 + \hat{\eta}_2 \ln Q_{i,t} + \sum_{k=1}^{3} \hat{\varrho}_k \ln P_{k,i,t} \right) \frac{C_{i,t}}{Q_{i,t}}. \tag{A2}$$

TABLE A1 LM tests for spatial, serial correlation and random effects

LM test description	LOANS		SERVICES	
	Statistic	p value	Statistic	p value
Anselin (1988)				
Conditional test for spatial error autocorrelation (H_0: spatial error autoregressive coefficient equal to zero)	9.44	0.000	3.57	0.000
Conditional test for spatial lag autocorrelation (H_0: spatial lag autoregressive coefficient equal to zero)	24.99	0.000	2.55	0.010
Baltagi et al. (2003)				
Joint test (H_0: absence of random effects and spatial autocorrelation)	1757.6	0.000	26.8	0.000
Marginal test of random effects (H_0: absence of random effects)	38.96	0.000	4.97	0.000
Marginal test of spatial autocorrelation (H_0: absence of spatial autocorrelation)	15.49	0.000	9.42	0.000
Conditional test of spatial autocorrelation (H_0: absence of spatial autocorrelation, assuming random effects are nonnull)	18.05	0.000	13.42	0.000
Conditional test of random effects (H_0: absence of random effects, assuming spatial autocorrelation may or may not be equal to 0)	40.54	0.000	31.13	0.000
Baltagi et al. (2007)				
Joint test (H_0: absence of serial or spatial error correlation or random effects)	1835	0.000	35.43	0.000
One-dimensional conditional test (H_0: absence of spatial error correlation, assuming the existence of both serial correlation and random effects)	101.14	0.000	17.04	0.000
One-dimensional conditional test (H_0: absence of serial correlation, assuming the existence of both spatial error correlation and random effects)	196.67	0.000	21.72	0.000
One-dimensional conditional test (H_0: absence of random effects, assuming the existence of both serial and spatial error correlation)	108.46	0.000	131.01	0.000

TABLE A2 Testing for cross-sectional dependence

Test	Pesaran (2004)		Pesaran (2015)	
	LOANS	*SERVICES*	*LOANS*	*SERVICES*
CD	21.745	24.757	16.077	19.650
p value	0.000	0.000	0.000	0.000

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

TABLE A3 Cross-sectional independence test for *LOANS* models

Test	Time-space simultaneous				Time-space dynamic			
	δ_1	δ_2	δ_3	δ_4	δ_1	δ_2	δ_3	δ_4
CD	−1.245	−1.134	−1.165	−1.474	−1.431	−1.370	−0.994	−1.235
p value	0.213	0.257	0.244	0.140	0.153	0.171	0.320	0.217

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

TABLE A4 Cross-sectional independence test for *SERVICES* models

Test	Time-space simultaneos				Time-space dynamic			
	δ_1	δ_2	δ_3	δ_4	δ_1	δ_2	δ_3	δ_4
CD	−0.076	−0.368	−0.198	0.296	−0.771	−0.496	−0.247	−0.315
p value	0.940	0.713	0.843	0.767	0.441	0.620	0.805	0.753

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