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Four Essays on Spatial Dependence Effects of Local Banks

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Author's declaration

I, *Carmelo Algeri* declare that this thesis, titled "Four Essays on Spatial Dependence Effects on Local Banks", submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy, in the *Department of Economics* at the University of Messina, Italy, is wholly my own work unless otherwise referenced or acknowledged. In addition, I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
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DATE: December 10, 2020

PLACE: Messina, Italy

Dedication

To My Mother, My Father, And My Sister; And To My Beloved Grandparents, Who Passed Away Just Too Soon …

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Lastly, but not least, I would like to thank my family for all they have done for me and for being always proud of me. I dedicate the thesis to them because without them, I would not have come this far.

Table of Contents

List of Figures

Figure **Page**

List of Tables

List of Acronyms

BCCs	Banche di Credito Cooperativo
CD	Cross Section Dependence
DEA	Data Envelopment Analysis
DMUs	Decision Making Units
EAs	Supervisory Enforcement Actions
ETRs	Effective Tax Rates
LM	Lagrange Multiplier
NPLs	Non Performing Loans
SDPD	Spatial Dynamic Panel Data
SWM	Spatial Weighting Matrix
SYS-GMM	System Generalized Method of Moments Model
TAG	Tax Aggressiveness
TE	Technical Efficiency
TSD	Time Space Dynamic Model
TSS	Time Space Simultaneous Model
VRS	Variable Returns to Sale

Chapter 1

Introduction

It is widely known that the long process of banking liberalization has drastically weakened the historical chain that, over time, has linked the local community with the banks operating in the territorial through strategic factors such as direct relationship and reciprocal trust among the local agents (O'Brien, 1992; Berger et al., 1999; Boot, 2000; O'Brien and Keith, 2009; Goetz et al., 2016).

The bank market modified the way of relating to each customer and introduced several novelties to attract new customers via innovative tools like the use of online banking, ATMs (Automated Teller Machines), new credit scoring models in credit decision activities, and more efficient techniques of risk management. However, although these changes have induced to consider the role of the banking geography negligible (Chaouali et al., 2016; Takieddine and Sun, 2015), the latter continues to be crucial in the banking system (Gallup et al., 1999; Martin, 2011; Aguirregabiria et al., 2017; Brei and Von Peter, 2018; Coccorese and Shaffer, 2020).

This evidence underlines the need to thoroughly study geography's role in the local banking industry; that is, whether and to what extent spatial connections among small and local banks affect their policies, an issue largely ignored in the literature. In light of this background, this thesis is structured as follow:

- Chapter 2 examines the impact of the inclusion of spatial correlation in an empirical model measuring the small-cooperative banks' risk performance;

- Chapter 3 investigates whether the technical efficiency performance of local banks is affected by spatial dependence, applying a spatial analysis methodology;

- ▷ Chapter 4 considers the effects of spatial interdependence in an empirical model measuring local banks' tax aggressiveness, evaluating the co-movement between geographical units and the related spatial spillover effects;
- ▷ Chapter 5 considers both the presence and the role of the contemporaneous and non-contemporaneous spatial dependence in the Non-Performing Loans ratio of small cooperative banks;
- ▷ Chapter 6 concludes the thesis and proposes future works.

CHAPTER 2

SPATIAL DEPENDENCE IN SMALL COOPERATIVE BANK RISK BEHAVIOR. EFFECTS FOR BANK COMPETITIVENESS AND SMEs

Abstract

In this study I consider the effects of the inclusion of spatial dependence in the empirical model measuring the small-cooperative banks' risk performance. If there exists cross sectional dependence, spatial analysis deals with co-movement among geographical units, allowing the evaluation of spillover effects and ameliorating econometric models. I provide several contributions to the literature. First, I support the hypothesis that the inclusion of spatial terms improves the small bank soundness models. Second, since I control for the banks' market power, I expand the literature on the relationship between bank risk and market competitive pressure. Third, I find empirical evidence that the bank size does not affect the financial standing of the small banks. Finally, as I proxy bank soundness with the *Z-Score* index, I indirectly test the impacts on small firms of the relationship lending, a classic tool adopted by the small banks to assess the creditworthiness of small firms. My results strongly support the hypothesis that risk-performance bank models are enhanced with spatial variables and that relationship lending makes small firm loan demand low price-elastic.

Keywords: Spatial Dynamic Panel Data Models, Spatial Weight Matrix, Bank Soundness, Lerner Index, Relationship Lending, Bank Size.

2.1 Introduction

Small cooperative banks differ from commercial banks both in their financial structure and in their ability to process information deriving from local economic context. Such banks are involved in traditional lending activities more than non- and large-cooperative banks, showing a higher net loans-to-total assets ratio (Becchetti et al., 2016) and customers that are usually bank members. Despite the tightening of intermediation margins, lending activity is the main business of small cooperative banks. These loans are usually granted to small and medium sized enterprises (SMEs) operating in the same territory of the bank (Strahan and Weston, 1998; Peek and Rosengren, 1998; Clark et al., 2018).

The described background suggests that small cooperative bank performance is affected by local economic factors. Nguyen (2019) clarified that the small business lending market tends to have geographic proximity between borrower and lender. Similarly, Degryse and Ongena (2005) argue that location grants rents to financial intermediaries. It is well known that the availability of locally-based economic data is limited, and to calculate related variables expensive. Fernandes and Artes (2016) and Calabrese et al. (2019) have integrated the traditional credit scoring models considering spatial dependence effects, testing if this inclusion improves the discrimination capability of the models. The inclusion of spatial dependence effects in econometric models measuring local bank performance can be a way to deal with these problems, namely needs to consider local factors and lack of data.

The first goal of my research is to empirically verify if the inclusion of variables reflecting the spatial autocorrelation effect between small cooperative banks improves the models to estimate the *Z-Score* factor, namely a measure of the whole bank risk. For this purpose, I conducted an empirical analysis using a sample of Italian small cooperative banks (Banche di Credito Cooperativo -BCCs), which are the ideal laboratory to test my hypothesis.[1]

[1]BCCs form an important laboratory for different reasons. Firstly, the reorganization and liberalization process influenced these local banks in several ways. The amount of BCC branches drastically increased over time from 2,225 in 1993 to 4,270 in 2017. Their branches correspond to 15.2% (around 6% of the national banking industry) with respect to 10.4% in 1990 (Finocchiaro, 2002). The number of BCCs shifted from 700 in the 1990s to 313 in 2017 (see the report by Federcasse, http://static.publisher.iccrea.bcc.it/archivio/368/129393.pdf). Secondly, there exists an important heterogeneous banking morphology for all BCCs in the country: the northeast is rich with cooperative banks, especially in Trentino-Alto Adige, while the rest of the country is sparse. Thirdly, despite the negative effects of the economic crisis, BCCs have mostly enhanced their market share. During the two crises, the dimension of granted loans transitioned from 14.9% to 17%, especially for households and SMEs (Cannata et al., 2013). Finally, the macroeconomic conditions under which the BCCs operate differ inside the various geographical areas

Questioning if there exists spatial dependence in risk behavior and performance of small cooperative banks cannot disregard the effects of bank market competition on soundness.

Previous studies provide two alternative views regarding the relationship between bank competition and soundness: the competition-fragility view and the competition-stability view. The first view maintains that an increase in bank competition reduces bank margins and urges banks to take risks, which ultimately weakens banks and the whole banking system (Allen and Gale, 2004; Jiménez et al., 2013). The second view rests on the classical adverse selection assumption. Since a strong market power allows imposing on customers a surcharge, the resulting high interest rates payable by the latter end up to keep away the low risk borrowers. Consequently, the loan portfolio of banks enjoying strong market power is riskier than banks operating in competitive markets (Keeley, 1990; Boyd and De Nicolo, 2005; Carletti and Leonello, 2018).

The specific effects of market competition among small cooperative banks on their solvency has been analyzed by previous studies (Fiordelisi and Mare, 2014 and Clark et al., 2018), but with conflicting results. Fiordelisi and Mare (2014) provide evidence in favor 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. (2019) provide evidence in support of the competition stability hypothesis for small and medium banks. Conversely, Clark et al. (2018) find a negative relationship between competition and stability, albeit with a non-linear effect.

I contribute to this debate by evaluating the effect of small cooperative banks' *Z-Score* on a long-standing market competition indicator, such as the Lerner index, while also considering the spatial dependence.

Furthermore, my analysis focusing on the relationship between the *Z-Score* index and spatial dependence in the risk behavior of local banks contributes to a key debate regarding how banks are territorial with their customers through relationship lending.

Many studies have pointed out that the organizational structure of small banks exploits soft information (developed by personal interaction) accrued over the time, bolstering relationship lending (Degl'Innocenti et al., 2018). In this way, the financial constraints for the informationally opaque SMEs, who cannot provide adequate hard information obtained from borrowers' balance sheets, market price, and collateral guar-

of the country. The Italian territory involves 20 regions and 110 provinces generally conditioned by different levels of economic performance (the northern part generally more developed and the southern part typically less developed).

anties, can be mitigated (Berger and Udell, 2002; Stein, 2002; Berger et al., 2005; Liberti and Mian, 2008; Kysucky and Norden, 2015; Berger et al., 2017). Hasan et al. (2017) point out that the local banking market and the presence of cooperative banks is very important as they improve the creation of new firms, reduce financing costs supported by SMEs, and enhance access to medium and long-term financing. They also showed that a large quantity of foreign banks in local banking markets aggravates the structure and the perspectives of SMEs.

Credit relationships with SMEs allow banks to reap soft information in their lending activities (Berger et al., 2001; Coccorese and Ferri, 2020). Small banks with few managerial layers and independent decision-making autonomy have a competitive advantage compared to centralized nationwide banks in meeting the needs of local SMEs (Berger and Udell, 2002; Zhao and Jones-Evans, 2016).[2]

Small banks seem to be the silver bullet for SMEs who are otherwise credit constrained. However, scholars have pointed out possible opportunistic behavior from banks adopting the relationship lending against SMEs due to the market power of geographically close banks (Petersen and Rajan, 1995). Other studies insist on the high costs of relationship lending (Sharpe, 1990; Rajan, 1992; Weinstein and Yafeh, 1998). A deep review of the studies regarding relationship lending are Udell (2008) and Duqi et al. (2018), while Kysucky and Norden (2015) carried out a meta-analysis study.

Canales and Nanda (2012) specifically identify a "darker side" of decentralized banks without an adequate competitive environment against small firms. Relationship lending allows the banks to exploit their dominant market position and it spurs the cherry picking of firms and restricting credit behaviors.[3] Unsurprisingly, Coccorese and Santucci (2019) find that large banks have less market power than small banks.

Deepening the relationship between *Z-Score* index and the same variable properly weighted to capture spatial dependence in the data allows me to contribute to this literature. In my opinion, *Z-Score* indirectly provides evidence for whether small cooperative banks exploit the relationship with their customers to increase profitability (and capitalization) or not. My measure of bank risk is calculated as the standardized sum of bank profitability and capitalization. It is worth clarifying that capital injection in Italian small cooperative banks is carried out almost exclusively with their members, as the specific governance rules of "prevailing mutualism" discourage external investors.

[2] De la Torre et al. (2010) provide evidence that large banks apply specific business models for the SMEs niche different from relationship lending.

[3] Recently Levine et al. (2020) point out that geographic distance is negatively associated with lending to informationally opaque borrowers.

Such principles entail the adoption of the democratic guideline (one-head one-vote), the prohibition to own shares for a value higher than 50,000 euros, the instruction that bank members must be located in the areas where the same bank has its headquarters or branches, and that 70% of the bank profit must be held as reserve (Coccorese and Ferri, 2020). A cooperative bank modifies its *Z-Score* by increasing and/or decreasing the interest rate in loan and/or deposits.[4]

The spatial weighted dependent variables, expressing how the neighbor's soundness affects the i_{th} soundness, provides me insights regarding how bank management steers pricing following the competitors' actions in term of risk policy (i.e., the bank neighborhood *Z-Score*). This understanding shows that small firms and bank customers have no alternative at the BCCs credit supply. By verifying spatial dependence in the soundness of small cooperative banks, I indirectly check whether relationship lending makes BCCs demand low price-elastic.

Finally, the spatial specification model enables to shed new light on the connection between the small-bank risk failure and the bank size. Actually, Emmons et al. (2004) argue that if small bank increase scale it could benefit from portfolio diversification, but, as it seeks loan opportunity in farther markets, the relationship lending practices become less effective, weakening the bank's ability in screening borrowers creditworthiness. The empirical literature on this topic finds conflicting results. Mare (2015) shows a positive and statistically significant relationship between *Z-Score* and bank size for a sample of Italian BCCs. On the contrary, Mare and Gramlich (2020) examining the risk exposures of cooperative banks in Austria, Germany and Italy illustrate that bank size directly affects credit risk, interest rate and the residual bank risk. Again differently, Chiaramonte et al. (2020), carrying out a study focusing on banks operating in 27 EU member states, find an statistically insignificant relationship for the same variables in both two sub-samples of 2,972 cooperative and savings banks, and small banks.

To accomplish these aims, Section 2.2 introduces spatial econometric methodology and the data and variables adopted in the empirical specification. Section 2.3 presents the three steps of my empirical analysis: the diagnostic test to check for presence of spatial dependence and random effects in the sample, the System GMM estimation of my equation, and the test on the residuals of the estimation to assess the amendment of the cross-sectional dependence due to treatment. Some final remarks (Section 2.4) conclude the study.

[4] As shown, the capital injection in BCCSs is a quite complex operation achieved with the members.

2.2 Spatial Econometric Methodology and Data

This section introduces the spatial econometric models adopted in my analysis, the data employed to draw up my empirical research and reports the econometric specification.

2.2.1 Spatial Methods

The spatial econometric approach structures the relationships among the elements observed in diverse geographic areas, including spatial interaction (spatial autocorrelation) and spatial framework (spatial heterogeneity) in econometric models (Anselin, 2003; Asgharian et al., 2013; Elhorst, 2014). Spatial dependence concerns the relationship of one spatial unit with the neighboring by exploiting Tobler's first law of geography (Tobler, 1970). This relationship is defined as spatial autocorrelation, which represents an expression (weaker) of spatial dependence (Anselin, 2003).

In my analysis, I consider a Spatial Dynamic Panel Data (SDPD) model (Elhorst, 2005, 2014) which enables the investigation of the spatial spillovers among units. In particular, I consider the Time-Space Simultaneous (TSS) model proposed by Anselin et al. (2007) using the GMM estimator (Yu et al., 2008; Kukenova et al., 2009; Bouayad-Agha and Védrine, 2010; Bouayad-Agha et al., 2013; Cainelli et al., 2014). In detail:

$$y_{i,t} = \beta y_{i,t-1} + \rho \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{i,t} + \mathbf{x}_{i,t}\gamma + (\eta_i + \nu_{i,t}) \tag{2.1}$$

$$|\beta| < 1,\ |\rho| < 1;\quad i = 1 \dots N;\quad t = 1 \dots T$$

where $y_{i,t}$ is an observation of the dependent variable y for the i_{th} individual at the t_{th} time period, $y_{i,t-1}$ its lagged value, $\sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{i,t}$ represents the first order spatial lag of $y_{i,t}$,[5] 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.[6]

Anselin et al. (2007) also developed the Time-Space Dynamic (TSD) model, which includes first-order spatial lag of the lagged dependent variable (with respect to the spatial weight matrix $\boldsymbol{W}$) in the TSS model, since in some cases the omission of the lagged term could lead to biases in the estimates (Tao and Yu, 2012). Therefore, the equation 2.1 becomes:

[5] Generally, a spatial lag operator is the average of the values random variable observed in the nearby of a given spatial units.

[6] 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.

$$y_{i,t} = \beta y_{i,t-1} + \rho \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{i,t} + \psi \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{i,t-1} + \mathbf{x}_{i,t}\gamma + (\eta_i + \nu_{i,t}) \tag{2.2}$$
$$|\beta| < 1,\ |\rho| < 1,\ |\psi| < 1;\quad i = 1 \ldots N;\quad t = 1 \ldots T$$

In equation 2.2, the coefficient β incorporates the time dependence of the dependent variable, while ρ and ψ indicate the spatial effect and spatial-time effect, respectively, under the following constraint: $|\beta + \rho + \psi| < 1$.[7]

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 observations in the dataset with the following properties:

- $w_{ij} = 0$ if i and j are not spatially connected and if $i = j$ by definition, namely all elements on the principal diagonal are zero, this means an object is not spatially connected with itself;

- $w_{ij} \neq 0$ if i and j are spatially connected, and usually these values are higher than zero.

More specifically, to model spatial relations between point units the matrix $\boldsymbol{W}$ is built making use of the Gaussian kernel (Otranto et al., 2016). This weight matrix is based on the distances (d_{ij}) between each pair of spatial point units i and j. I recall that 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, in this research I use a modify Gaussian kernel matrix where the weighting function for computing the weight w_{ij} is given by:

$$w_{ij} = \begin{cases} \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{h_{ij}}\right)^2\right], & \forall i \neq j \\ 0, & \forall i = j \end{cases} \tag{2.3}$$

where d_{ij} is equal to the distance between the generic point units i and j and h_{ij}, called bandwidth, is a nonnegative parameter which produces a decay of influence with distance. Varying the bandwidth results in a different exponential decay profile, which in turn produces weights that vary more or less rapidly over space. So, the weighting of other data will decrease according to a Gaussian curve as the distance between the spatial units i and j increases. For spatial units far away from i the weight w_{ij} will fall

[7] See Yu and Lee (2010) for further information about the estimation of unit root of spatial dynamic panel data models.

to virtually zero. This approach is a generalization of neighbors based on distance that could 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.

To deal with spatial dependence in panel data requires me to adjust the weighted matrix as in Anselin et al. (2008), 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:[8]

$$\boldsymbol{W}_{NT} = \boldsymbol{I}_T \otimes \boldsymbol{W}_N, \tag{2.4}$$

where $\boldsymbol{I}_T$ represents an identity matrix of size T.

2.2.2 Data and Equation

My empirical analysis relies on a strongly balanced panel dataset for 264 active BCCs over the 2011-2017 period for about 1,848 observations. The data are collected from two sources: Bureau van Dijk Orbis Bank Focus (BvD Orbis) database for the bank-specific characteristic[9] and "Il Sole 24 Ore" for local economic data.[10]

Finally, by geocoding the address of the single BCCs headquarters, I have built a geospatial dataset containing geo-referenced variables (latitude, longitude) for each observation.

Figure 2.1 illustrates the geographic distribution of the BCCs.

Both the TSS and TSD models are estimated using the System-GMM (SYS-GMM) technique by Arellano and Bover (1995) and developed by Blundell and Bond (1998) to obtain consistent and unbiased estimates dealing with possible endogeneity issues. On this matter, the GMM models are estimated with Windmeijer (2005) finite sample correction and with forward orthogonal deviation (FOD) transformation.[11] All the explanatory variables have been lagged.

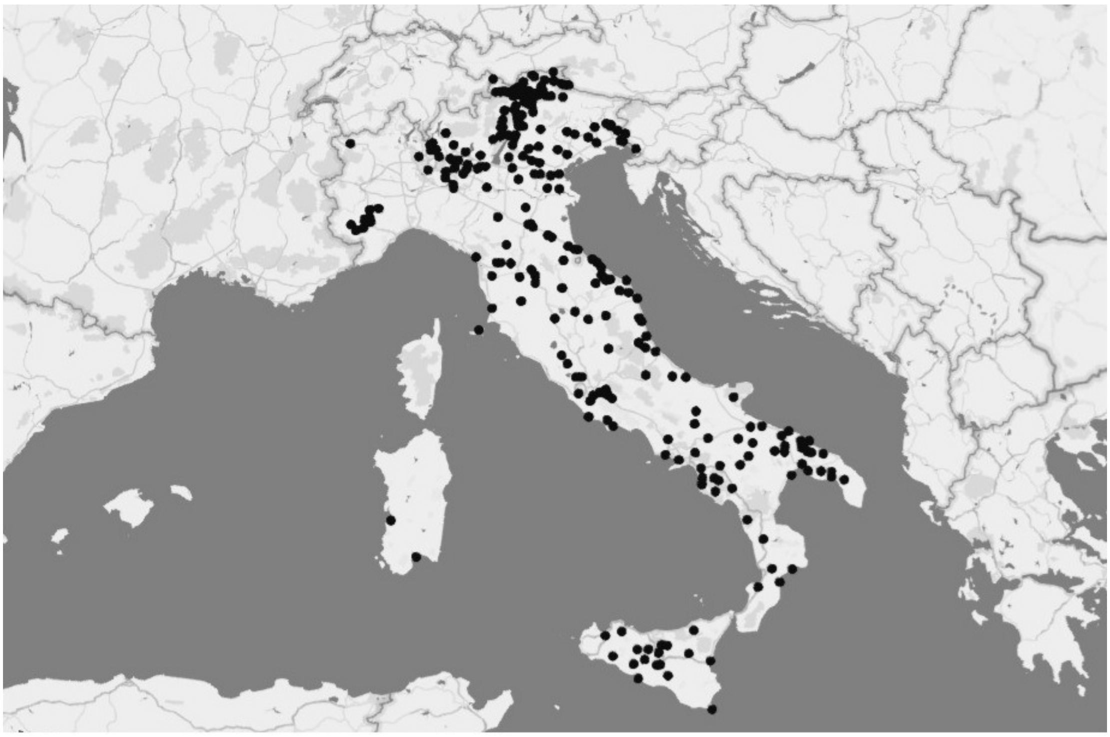
[8] See, Anselin et al. (2007).

[9] A large number of missing values at bank level have been filled consulting the BCCs balance sheet.

[10] Annually, Il Sole 24 Ore publishes a report called "Quality of Life" which includes the data of different environmental indexes at the Italian provincial level. It details a set of provincial data corresponding to social and economic indicators. https://lab24.ilsole24ore.com/qualita-della-vita/.

[11] In principle, SYS-GMM is usually preferred over standard GMM estimator (Arellano and Bond, 1991) since its performance is better in cases where the variables are highly persistent over time and for possible simultaneity bias (on this point, see Blundell and Bond, 1998, 2000).

Figure 2.1: Geographical distribution of BCCs



Therefore, the TSS equation is as follows:[12]

$$
\begin{aligned}
Z-Score_{i,t} = \alpha + \beta Z-Score_{i,t-1} + \rho \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot Z-Score_{i,t} + \gamma Lerner_{i,t-1} \\
+ \delta Cap_{i,t-1} + \zeta Size_{i,t-1} + \iota NPL_{i,t-1} + \varphi LLP_{i,t-1} \\
+ \kappa Service_{i,t-1} + \lambda Funding_{i,t-1} + \phi Branches_{i,t-1} \\
+ \omega GDP_{i,t-1} + (\eta_i + \nu_{i,t})
\end{aligned}
\tag{2.5}
$$

The dependent variable of my spatial econometric model is the $Z-Score$, namely a measure of bank soundness (Iannotta et al., 2007; Mercieca et al., 2007; Laeven and Levine, 2009). In more detail, it is calculated as the following:

$$Z-Score_{i,t} = \frac{ROA_{i,t} + \frac{E_{i,t}}{A_{i,t}}}{\sigma_{ROA_{i,t}}}$$

where, $ROA_{i,t}$ represents the return on assets ratio, $E_{i,t}/A_{i,t}$ constitutes the equity to

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

total assets and, finally, $\sigma_{ROA_{i,t}}$ indicates the standard deviation of ROA (Boyd and Runkle, 1993).

The $Z-Score$ reflects the main shields against banking risk, i.e. profitability and its volatility and capitalization. The higher the index is, the greater the bank stability (Hesse and Cihak, 2007; Ayadi et al., 2010; Beck et al., 2013b; Chiaramonte et al., 2015).

My models include four different types of explicative variables. The first involves 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 third measures the bank size. Finally, the models also include an extensive set of variables attributable to the bank-specific characteristic and to the macroeconomic environment.

My specifications include spatial terms, calculated by multiplying the dependent variable and its lagged value by three spatial weighted matrices. In particular, I use a Gaussian kernel matrix with three different bandwidths, expressed in kilometres (km):[13]

(1) $h(d_{ij}) = \text{Minimum}(d_{ij}) = h_{min}$

(2) $h(d_{ij}) = 0.01[\text{Maximum}(d_{ij})] = h_{01p}$

(3) $h(d_{ij}) = 0.5[(h_{min} + h_{Mm})] = h_{mm2}$

where h_{min} is equal to 3.5 km (i.e., the minimum distance considered so that each bank has at least one neighbor), h_{01p} equal to 12 km that is the 1% of the maximum distance among the BCCs (1200.69 km) and h_{mm2} equal to 61 km calculated as the mean between the minimum distance and the Maxmin distance (118.50 km).[14]

The covariate capturing the bank market power is the Lerner index, calculated as the difference between bank price and its marginal cost, divided by bank price: $Lerner = \left(P_{i,t} - mc_{i,t}\right)/P_{i,t}$. Its rationale is trivial: the more a bank gains market power, the more the price moves from marginal cost.

[13] I have considered spatial matrix with different bandwidths, but only these three bandwidths provide the best results.

[14] I recall that, in the "Maxmin" function h_{Mm} is chosen in such a way that the following relationship is satisfied:

$$h_{Mm} = max(e_1, e_2, \ldots, e_i, \ldots, e_n)$$

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 the others (for further information, see Mucciardi and Bertuccelli, 2012).

Unlike bank price, which can be easily calculated by accounting data (total interest income divided by the total asset),[15] the bank marginal cost require to calculate a standard translog cost function. In my specification, as in Fiordelisi and Mare (2014), Degl'Innocenti et al. (2019), Coccorese and Santucci (2019) and Coccorese and Ferri (2020), I consider one bank output Q (I proxied in the total asset) and three inputs (proxied by P_1, staff expenses on total asset, P_2, other administrative expenses over total asset, and P_3 interest expenses divided by bank funding).

The equation to be estimated is as follows:

$$\begin{aligned} lnTC_{i,t} = \beta_0 + \beta_1 lnQ_{i,t} + \frac{1}{2}\beta_2 lnQ^2_{i,t} + \sum_{k=1}^{3} \gamma_k lnP_{k,i,t} \\ + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \delta_{k,j} lnP_{k,i,t} lnP_{j,i,t} + \frac{1}{2}\sum_{k=1}^{3} \zeta_k lnQ_{i,t} lnP_{k,i,t} + u_{i,t} + v_{i,t} \end{aligned} \tag{2.6}$$

In equation 2.6, the error term consist of two components: the usual one $v_{i,t}$, that 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 me 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 $Q_{i,t}$.

Therefore:

$$mc_{i,t} = \frac{\partial C_{i,t}}{\partial Q_{i,t}} = \frac{\partial lnC_{i,t}}{\partial lnQ_{i,t}} \frac{C_{i,t}}{Q_{i,t}} = \left(\hat{\beta}_1 + \hat{\beta}_2 \, lnQ_{i,t} + \sum_{k=1}^{3} \hat{\zeta}_{k,i,t} \, lnP_k \right) \frac{C_{i,t}}{Q_{i,t}} \tag{2.7}$$

$Size$ captures the bank size effect, proxied by the natural logarithm of total assets. Countless of studies, referring either to cooperative or non-cooperative banks, measure the bank size throughout such variable (Clark et al., 2018; Mare and Gramlich, 2020; Chiaramonte et al., 2020). The expected effect is uncertain.

In what follows, I briefly describe the control variables and the expected sign.

Cap is the total capital ratio, calculated at bank level as regulatory capital over risk weighted assets. Highly capitalized lenders are able to absorb the negative impact of shocks (Bernanke et al., 1991; Gambacorta and Mistrulli, 2004; Berrospide et al., 2010;

[15] As specified, the BCCs focus on lending activity. Considering the non-interest income provides similar results.

Kapan and Minoiu, 2013), such as a greater capitalization might lead to lower bank risk taking it since decreases asset-substitution moral hazard (Coval and Thakor, 2005) and reinforces the incentives in banks monitoring (Mehran and Thakor, 2011). Therefore, the expected sign is positive.

I consider two different asset quality variables, namely NPL and LLP, capturing different aspects of the bank credit risk policies (Kim and Sohn, 2017). Specifically:

- The ratio of non performing loans to gross loans (NPL) represents a backward-looking measure of credit quality, since it refers the ability of banks in recovering their loans (Bouvatier and Lepetit, 2008). Greater values expressed poor credit decision making (Cucinelli, 2015);

- The ratio of loan loss provision to total loans (LLP) is instead a forward-looking gauge of credit quality and reveals bank hedging policies against expected losses on lending activity. Banks can manage the provision for loan loss to smooth their income (Mergaerts and Vander Vennet, 2016).[16]

$Service$ is the ratio of net interest income to operating revenue and represents both a measure of profitability and (indirectly) efficiency (Dombret et al., 2019). This ratio highlights the relative weight of the more profitable service sold by the banks with respect to the less lucrative credit service. As suggested by Lucas et al. (2018), fee-focused banks show 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 concerns the capability to collect funds for financing illiquid asset positions under the conditions laid down at a given moment (King, 2013).

My equation also incorporates the effects business cycle via the annual growth of real gross domestic product per capita (GDP) and the number of bank branches for 100,000 inhabitants ($Branches$) proxying the financial sector development (Vanroose and D'Espallier, 2013; Wang et al., 2019). Both the variables are expressed to Italian NUTS-3 regions (provinces).

Frame et al. (2001) highlight that the number of bank branches in the local market is positively correlated to the use of credit scoring. In addition, they find that the relation-

[16] The literature emphasizes that the banks have smoothed their income more intensely through loan loss provision during the crisis (El Sood, 2012; Manganaris et al., 2017). In addition, the level of loan loss provision can be distorted by forbearance (Laeven and Majnoni, 2003). Once again, Mergaerts and Vander Vennet (2016) highlight that greater loan loss provision is linked with a lower profitability and also to a higher risk in the long run. Concerning what I said, the expected sign is uncertain.

ship between share of loans to small businesses and number of branches is positive and statistically significant. Annual growth rate of real GDP is used to capture the cyclical movements, controlling for loans demand effects (Gambacorta, 2005). Specifically, more favorable economic conditions enhance the amount of projects that are profitable as the expected net present value improves and accordingly, enhances loan demands (Kashyap et al., 1993).

Table 2.1 lists all the variables employed in my specifications as well as their description and the specific data sources, whereas Table 2.2 reports the descriptive statistics.

Table 2.1: List of variables

Variable	Description	Source
ROA	Net income/Total assets	BankScope/BankFocus
$Equity$	Total equity (in thousand EUR)	BankScope/BankFocus
$Assets$	Total assets (in thousand EUR)	BankScope/BankFocus
$Z-Score$	(ROA+Equity/Assets)/σ(ROA)	Author's calculations
$Lerner$	Lerner Index	Author's calculations
Cap	(Tier 1 Capital + Tier 2 Capital)/Risk Weighted Assets	BankScope/BankFocus
$Size$	Natural logarithm of total bank assets	Author's calculations
NPL	Non-performing loans/Gross loans	BankScope/BankFocus
LLP	Loan loss provision/Total loans	BankScope/BankFocus
$Service$	Net interest income/Operating Revenue	BankScope/BankFocus
$Funding$	(Bank deposits + Customer deposits + Debt securities)/Assets	BankScope/BankFocus
$Branches$	Bank branches	Il Sole 24 Ore
GDP	GDP growth rate	Il Sole 24 Ore
TC	Sum of personnel expenses, other administrative expenses, and other operating expenses	BankScope/BankFocus
Q	Total bank assets	BankScope/BankFocus
P_1	Staff expenses/Total assets	BankScope/BankFocus
P_2	Other administrative expenses/Total assets	BankScope/BankFocus
P_3	Interest expenses/Total funds	BankScope/BankFocus
$Price$	Total interest income/Total assets	BankScope/BankFocus

Notes: This table supplies a description of the variables used in my specification model as well as the data sources.

The sample is strongly balanced panel data with 1,848 observations, while the period span is 2011-2017. The key variables of my analysis are $Z-Score$ and $Lerner$, which, while presenting a different variability, take negative values also. For $Z-Score$, this value is due to negative profitability, while for $Lerner$ it concerns only 0.4 percent of the sample for a total of 8 observations. As in a previous study (Fiordelisi and Mare, 2014), it assures representativeness to the sample pertaining to BCCs with high fixed costs (e.g., starting-up the intermediation activity).

Table 2.2: Summary statistics

Variable	No. Obs.	Mean	Std. Dev.	Min	Max
$Z-Score$	1,848	0.697	1.054	-9.672	9.474
$Lerner$	1,848	0.490	0.195	-4.711	0.841
Cap	1,848	0.196	0.079	0.059	0.860
$Size$	1,848	12.905	1.018	8.158	16.281
NPL	1,848	0.147	0.072	0	0.408
LLP	1,848	0.014	0.012	-0.009	0.097
$Service$	1,848	0.660	0.302	-9.363	7.045
$Funding$	1,848	0.857	0.055	0	0.953
$Branches$	1,848	60.44	21.850	18	104
GDP	1,848	0.003	0.112	-0.283	2.189

Table 2.3 shows the correlation matrix for the selected explanatory variables with significance levels. As can be seen, there is a significant correlation between $Z-score$ and NPL (-0.33), reflecting the fact that more non-performing loans mean lesser efficiency and, consequently, lesser resilience on the part of banks. Additionally, the correlation coefficients among all covariates are of rather low magnitude, which denotes that the multicollinearity problem in my empirical estimations should not be of concern.[17]

Table 2.3: Correlation matrix for the data shown in Table 2.2

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. $Z-Score_t$	1									
2. $Lerner_{t-1}$	0.1878*	1								
3. Cap_{t-1}	0.2752*	-0.1786*	1							
4. $Size_{t-1}$	-0.2477*	0.3301*	-0.4050*	1						
5. NPL_{t-1}	-0.3301*	0.0060	-0.0258	0.1692*	1					
6. LLP_{t-1}	-0.2176*	0.0947*	-0.0502*	0.2076*	0.6130*	1				
7. $Service_{t-1}$	-0.0719*	0.0464	0.0389	-0.0957*	-0.1287*	-0.1659*	1			
8. $Funding_{t-1}$	-0.0922*	0.3100*	-0.3843*	0.2894*	0.2468*	0.2058*	-0.0692*	1		
9. $Branches_{t-1}$	-0.0702*	0.1726*	-0.3510*	0.2570*	-0.2848*	-0.1636*	0.0050	-0.0920*	1	
10. GDP_{t-1}	-0.0636*	-0.0308	0.0313	-0.0231	0.0663*	0.0655*	-0.0501*	0.0052	-0.0574*	1

Notes: This table illustrates the correlation coefficients of the variables used in the empirical investigation over the period 2011-2017. * denotes significance at the 5% level or better.

2.3 Empirical Results and Discussion

This section illustrates the results of the empirical investigation. First, I describe the diagnostic tests implemented to check the existence of spatial dependence and random

[17] I tested for multicollinearity among the regressors by computing their variance inflation factors (VIFs, Neter et al., 1989). The mean VIF is equal to 1.48 and the highest VIF equals 2.05.

individual effects. Next, I report the empirical estimates of the GMM estimators and the Cross-section Dependence (CD) test as robustness of the models. Finally, I present a discussion of the evidence for explaining the spillover effects between cooperative banks.

2.3.1 Diagnostic tests for spatial dependence and random effects

I ran three different sets of Lagrange Multiplier (LM) tests to verify the existence of both spatial autocorrelation and random individual effects. If the data presented spatial autocorrelation and is disregarded, the statistical inference and estimates would be misleading (Sarafidis and Robertson, 2006; Kar et al., 2011).

Table 2.4 reports all the specification tests.

Table 2.4: LM test for spatial, serial correlation and random effects

LM test description	Statistic	P value
Anselin (1988)		
Conditional test for spatial error autocorrelation		
(H_0: spatial error autoregressive coefficient equal to zero)	5.69	< 0.01
Conditional test for spatial lag autocorrelation		
(H_0: spatial lag autoregressive coefficient equal to zero)	2.71	0.01
Baltagi et al. (2003)		
Joint test		
(H_0: absence of random effects and spatial autocorrelation)	123.59	< 0.01
Marginal test of random effects		
(H_0: absence of random effects)	10.24	< 0.01
Marginal test of spatial autocorrelation		
(H_0: absence of spatial autocorrelation)	4.33	< 0.01
Conditional test of spatial autocorrelation		
(H_0: absence of spatial autocorrelation, assuming random effects are non null)	4.60	< 0.01
Conditional test of random effects		
(H_0: absence of random effects, assuming spatial autocorrelation may or may not be equal to 0)	10.41	< 0.01
Baltagi et al. (2007)		
Joint test		
(H_0: absence of serial or spatial error correlation or random effects)	150.66	< 0.01
One-dimensional conditional test		
(H_0: absence of spatial error correlation, assuming the existence of both serial correlation and random effects)	17.07	< 0.01
One-dimensional conditional test		
(H_0: absence of serial correlation, assuming the existence of both spatial error correlation and random effects)	31.88	< 0.01
One-dimensional conditional test		
(H_0: absence of random effects, assuming the existence of both serial and spatial error correlation)	28.87	< 0.01

The LM first group tests verify the existence of spatial autocorrelation. The null hypothesis points out that both spatial lag autoregressive coefficient and spatial error autoregressive coefficient are equal to zero (Breusch and Pagan, 1980; Anselin, 1988). Therefore, rejecting the later hypothesis allows me to infer the presence of spatial correlation in the data. The test result strongly rejects the null hypothesis.

The second set of tests control for spatial correlation and random effects, considering the joint and conditional LM tests built by Baltagi et al. (2003). The results point out that all statistical tests regarding no spatial correlation and random individual effects are rejected. The joint LM test rejects the null hypothesis below the 1%, showing that at least one of the determinates of spatial dependence (spatial error correlation and/or random effects) exists in the residuals. Similarly, the marginal LM tests to verify the presence of no spatial autocorrelation or random effects significantly reject the null hypothesis of no spatial correlation and of no random effects, respectively. To confirm the presence of spatial correlation and random effects, I also ran conditional LM tests.[18] These tests again reject the null hypothesis, confirming the presence of both spatial autocorrelation and random effects.

Finally, the last array of tests developed by Baltagi et al. (2007) checks jointly and conditionally for spatial, serial correlation, and random effects. In addition to considering the presence of serial correlation, neglected in Baltagi et al. (2003), the latter LM tests allow to evaluate the existence of each of the three above mentioned components, assuming together the existence of the other two. Tests results significantly reject the null hypothesis showing the presence of serial correlation and confirming the presence of spatial correlation and random effects.[19]

All the previous tests are sensitive to the way the spatial weights matrix is specified. Therefore, following Arouri et al. (2012), Sarafidis and Wansbeek (2012), and Liddle (2018), I also ran a robustness check for spatial dependence by using both the CD tests proposed by Pesaran (2004) and Pesaran (2015). Such tests verify the presence of strict and weak cross-sectional dependence, respectively.[20] As Chudik et al. (2011) and Vega and Elhorst (2016) 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 2.5 reports the statistic of the tests and the p-value.

Results show the presence of both strict and weak cross-sectional dependence, con-

[18]In detail, the presence of spatial autocorrelation has been tested considering the conditional LM test for no spatial autocorrelation, allowing the presence of random effects. In the same way, the existence of random effect has been tested using the conditional LM test for no random effects, allowing the presence of spatial autocorrelation.

[19]In this regard, I estimate all the LM tests using the splm package in R developed by Millo and Piras, 2012. It should be noted that the tests reported in Table 2.4 have been estimated considering the matrix $\boldsymbol{W}$ with h_{min}. However, the tests were estimated considering the remaining two matrices with the other two bandwidths considered in my analysis: h_{01p} and h_{mm2}. The results highlight the same framework and, for reasons of space, I do not report the results but they can be supplied upon request.

[20]Testing for cross-sectional dependence corresponds to testing for the presence of contemporaneous correlations in the residuals. The first statistical test, compared to other specifications, is mainly suitable for sample where T is small and N is large as in my study. In addition, under the null hypothesis, it is asymptotically distributed as standard normal (De Hoyos and Sarafidis, 2006).

Table 2.5: Testing for cross-sectional dependence

Test	Pesaran (2004)	Pesaran (2015)
CD	5.753	3.045
P-value	0.000	0.002

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

firming the evidence provided by the LM tests reported in Table 2.4.

Therefore, the existence of spatial dependence supports the use of adequate spatial econometric techniques.

2.3.2 Empirical estimation

SYS-GMM estimates of the SDPD model specified in equation (2.5) are reported in Table 2.6, together with the results of the dynamic panel data model.[21] Table 2.7 only contains the estimation of the three TSD models.

The number of instruments (140) is equal along all the spatial specifications and lower than the number of groups. The result of the Hansen test highlights the overall validity of the instruments for all specifications, such as the test for first and second order autocorrelation of the residuals confirm the rejection of the AR(1) hypotheses and non-rejection of AR(2).

The coefficients of variables incorporating time dependence, spatial dependence, and spatial-time dependence fulfill the condition of global stationarity, namely the sum of the three parameters is less than 1.

The estimation results show a positive spatial dependence for the risk profile of Italian cooperative banks. This dependence holds along all the specifications and for both the contextual and the lagged $Z-Score$ index of the bank's neighbors, except for the greatest distance considered (61 km) in specification (7). This evidence means that an increase in the neighbors' bank risk leads to an increase in i_{th} bank risk and vice versa, since higher $Z-Score$ implies that the bank has more soundness.

The outcome is consistent with the clear assumption that local macroeconomic factors affect the performance of small banks strongly involved in financing the community

[21] It should be stressed that all estimates are performed using the Stata xtabond2 command developed by Roodman (2009a).

Table 2.6: Estimation results of dynamic and TSS model, using $Z-Score$ as dependent variable

Variable	Dynamic Model	Spatial Dynamic Models		
		h_{min}	h_{01p}	h_{mm2}
	(1)	(2)	(3)	(4)
$Z-Score_{t-1}$	0.1620** (0.082)	0.2029*** (0.076)	0.2250** (0.090)	0.2040** (0.087)
$Lerner_{t-1}$	0.9033*** (0.203)	0.6889*** (0.197)	0.6818*** (0.194)	0.7297*** (0.231)
Cap_{t-1}	4.0472** (1.561)	4.8523*** (1.734)	5.1797*** (1.727)	4.8897*** (1.882)
$Size_{t-1}$	-0.1858** (0.094)	-0.0705 (0.095)	-0.0328 (0.090)	0.0249 (0.099)
NPL_{t-1}	-4.2364*** (0.811)	-3.7351*** (0.777)	-3.7206*** (0.772)	-4.8316*** (0.788)
LLP_{t-1}	2.9247 (5.548)	6.4897 (4.806)	8.4004 (5.582)	8.2727 (5.740)
$Service_{t-1}$	-0.5528** (0.242)	-0.6002** (0.239)	-0.5383** (0.255)	-0.5064** (0.244)
$Fundings_{t-1}$	4.1905** (1.812)	5.2499*** (1.847)	5.3844*** (1.720)	4.0348** (1.797)
$Branches_{t-1}$	0.0023 (0.003)	0.0039 (0.003)	0.0042 (0.003)	0.0030 (0.003)
GDP_{t-1}	0.9260 (0.871)	-0.0071 (0.269)	-0.0510 (0.287)	-0.0907 (0.251)
$\boldsymbol{W} \times Z-Score_t$		0.4234*** (0.121)	0.4794*** (0.123)	0.7561*** (0.173)
No. Observations	1584	1584	1584	1584
No. Groups	264	264	264	264
No. Instruments	139	140	140	140
Years effects	Yes	Yes	Yes	Yes
AR(1)	0.0000	0.0000	0.0000	0.0000
AR(2)	0.9530	0.2417	0.2975	0.7576
Hansen test	0.1966	0.2393	0.3853	0.2472

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. 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.

economy. While the spatial weights variables are statistically significant, the macroeconomic variables reported in my specifications are not. Bearing in mind that the local macroeconomic variables I have considered are expressed at the Italian provincial level, my result highlights that the inclusion of spacial variables can be a way to consider the local effects regardless of the availability of specific indicators.

Turning to $Lerner$ variable, the estimate coefficients are statistically significant and positive along all specifications, showing how higher market power brings less bank risk. This result is in line with Clark et al. (2018) and in discordance with Fiordelisi and Mare (2014), supporting the competition fragility view. Unsurprisingly, the $Lerner$ coefficient of model (1), without the spatial lagged value, is higher than the remaining values that treat with the spatial dependence existing in the data as shown in the tests of section 2.3.1. Therefore, studying the relationship between small cooperative soundness and bank market power is helped by the use of the spatial econometric approach.

Table 2.7: Estimation results of TSD model for $Z-Score$

Variable	Spatial Dynamic Models		
	h_{min} (5)	h_{01p} (6)	h_{mm2} (7)
$Z-Score_{t-1}$	0.2013** (0.081)	0.2271*** (0.078)	0.1940** (0.075)
$Lerner_{t-1}$	0.6219*** (0.204)	0.5948*** (0.206)	0.6585*** (0.209)
Cap_{t-1}	4.7254** (1.940)	5.0378*** (1.867)	4.9192*** (1.683)
$Size_{t-1}$	-0.0547 (0.102)	-0.0284 (0.094)	-0.0129 (0.088)
NPL_{t-1}	-4.2102*** (0.771)	-3.9713*** (0.807)	-4.6832*** (0.745)
LLP_{t-1}	8.2327 (5.402)	9.8086* (5.150)	6.8208 (4.747)
$Service_{t-1}$	-0.5709* (0.292)	-0.5035* (0.257)	-0.6200* (0.331)
$Funding_{t-1}$	5.6185*** (1.862)	5.8534*** (1.961)	5.1537** (2.073)
$Branches_{t-1}$	0.0042 (0.003)	0.0047 (0.004)	0.0047 (0.003)
GDP_{t-1}	-0.0746 (0.282)	-0.1406 (0.286)	-0.0363 (0.263)
$\boldsymbol{W} \times Z-Score_t$	0.2698** (0.125)	0.3361** (0.145)	0.8334*** (0.192)
$\boldsymbol{W} \times Z-Score_{t-1}$	0.0880** (0.039)	0.1248** (0.057)	-0.0367 (0.100)
No. Observations	1584	1584	1584
No. Groups	264	264	264
No. Instruments	140	140	140
Years effects	Yes	Yes	Yes
AR(1)	0.0000	0.0000	0.0000
AR(2)	0.5722	0.5853	0.7529
Hansen test	0.1933	0.2619	0.2282

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. 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.

Finally, the estimation of spatially lagged variables provides evidence in favour of the existence of a dominant market position of small cooperative banks for their small firm customer.[22]

BCCs management takes into account neighborhood behavior in terms of risk performance. In this competitive environment, a BCC increases loan price to quickly increase its own $Z-Score$ if its competitors do. This scenario suggests that financially constrained small firms, the main BCCs customers, have poor options besides the small-banks credit channel to finance their investments. A fortiori, the aggressive pricing strategy from neighbor BCCs, induces the i_{th} BCC to adopt a retaliatory of strategy reducing or increasing the interest rate of loans or deposits to their customers. This may worsen their *Z-Score* index but preserve their market share. My estimation supports the view that

[22] I may speculate that on the funding side, the BCCs demand is more price sensitive.

relationship lending is a way to ensure market power for these banks.

Overall, the estimated coefficients of $\boldsymbol{W} \times Z - Score_t$ for the higher bandwidth (61 km) take the highest value, showing that the i_{th} BCC is also sensitive to the initiative of more distant competitors.

As in Mare and Gramlich (2020) and contrary to Mare (2015), the coefficient of $Size$ is negative in the dynamic model. Surprisingly, that is not more statistically significant for all the SDPD models. These results confirm that any disregard to spatial terms in an econometric specification can lead to bias estimations when spatial correlation exists. This evidence strongly suggests to deal with spatial dependence in the model considering the small-bank soundness.

The coefficients of the control variables substantially bear the inclusion of the spatial terms. Comparing the estimated coefficients of the dynamic model with the ones of the SDPD models shows a general consistency in terms of signs and significance but rather different values in the coefficients with very few exceptions.

The asset quality variables affect small cooperative bank performance differently, as the backward looking coefficients NPL were highly statistically significant, but LLP are not. Bank management often uses provisions for loan loss to smooth bank profits (Curcio et al., 2017). For the remaining bank-level variables, the related coefficients take the expected sign and are statistical significant. Instead, the macroeconomic variables are not statistically significant.

2.3.3 Testing for cross-sectional independence

As stated in section 2.3.1, the existence of spatial dependence and random individual effects in the data has led me to consider spatial lag operators in the model specifications. The inclusion of spatial lags allows me to control for the weak cross-sectional dependence in the data. Common factors generating strict cross-sectional dependence could still exist (Ditzen, 2018) even after the use of spatial models.

In order to verify this, I ran a post-estimation test on the errors of the spatial models. I used the test proposed by Pesaran (2004) to check the existence of cross-sectional independence on the residuals of SDPD specifications. In this way, I control whether the inclusion of the spatial lag operators deal with the cross-sectional dependence which I observed through the tests already reported in Table 2.5. In the later hypothesis, the estimations present several bais problem (Andrews, 2005; Bai and Ng, 2010).

Table 2.8 reports the CD test which points out the assumption of cross-sectional independence is not rejected for all the specifications, providing strong evidence regarding

Table 2.8: Testing for cross-sectional independence

Test	Time-Space Simultaneos			Time-Space Dynamic		
	h_{min}	h_{01p}	h_{mm2}	h_{min}	h_{01p}	h_{mm2}
CD	-1.141	-0.561	-0.203	0.144	-0.032	-0.159
P-value	0.254	0.575	0.839	0.885	0.974	0.874

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

the absence of correlation among panel units. The residual of all six SDPD models is not affected by strict cross-sectional dependence. Therefore, I conclude that the spatial econometric approaches employed fix the problem linked to the correlations between spatial panel units.

2.4 Concluding remarks

In this study I apply spatial analysis techniques to investigate the risk performance of small-cooperative banks, proxied by the *Z-Score* index. I ran this empirical analysis on a large sample of Italian small cooperative banks (BCCs), since the well-known Italian regional disparities and the features of Italian banking market appeared to be an ideal laboratory to test the hypothesis that spatial autocorrelation can impact small bank risk-taking behavior.

Notably, I calculated three Gaussian kernel matrices containing the spatial weights on the basis of three bandwidth distance (3.5, 12, and 61 km) and determined six spatial terms by multiplying the single matrices and both the dependent and lagged dependent variable. In this way, I incorporate contemporaneous and time-lagged spatial dependence in the econometric models. Finally, I ran several Lagrange Multiplier tests and CD tests that confirmed the existence of spatial dependence and estimated six SDPD models for each of the above described spatial terms, by means of SYS-GMM methods, along with a model without spatial terms.

The results provide evidence of a significant and positive neighbor effect along all the spatial variables. Similarly, the outcome shows possible bias in the empirical estimation if the spatial autocorrelation exists and the associated term is neglected. I observed a difference in the estimated coefficients between SDPD models and the specification without the spatial terms. Even more, the size effect is statistically significant in the non-spatial model, while it is not in the SDPD models. Considering the conflicting conclusions in the previous studies, my insight puts a step forward in the empirical research on small banks soundness.

Since my specification also controlled for the market competition effect throughout the Lerner index, the estimation results support the competition fragility view, which is that the 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 contributes to a definite backing of an empirical question. Finally, considering the composition of the dependent variable and the regulatory rules regard BCCs corporate governance structure, my results support the insight that the relationship lending procedure usually adopted by small banks makes their demand low price elastic. The customers of BCCs, mainly small firms, are fully exposed to the initiative of their lenders, who in turn hasten to change loan prices as a response to their neighbor's actions.

This study is the first attempt that considers spatial analysis techniques to explore the geographical spillover effect on managerial choices of small cooperative banks using two specifications of spatial dependence: contemporary and serially lagged or non-contemporary. I am aware that subsequent studies are required to clarify a number of points that remain in the shadows of my research due to lack of data, for instance whether the relationship holds considering the effect of unconventional monetary policies.

CHAPTER 3

Spatial dependence and the technical efficiency of local banks. Evidence from a spatial, two-stage bootstrap analysis

Abstract

A steady stream of literature has emphasized that small and local banks benefit from market power against large banks due to their ability to use soft information. Such banks serve small and micro enterprises and households; that is, niche markets from which large banks are usually barred. In light of this, I applied a spatial analysis methodology to test the hypothesis that the technical efficiency performance of local Italian banks is affected by spatial dependence. I posited that local banks mainly compete among themselves, and that the market discipline creates efficiency in this scenario. Using data envelopment analysis (DEA) methodology, I estimated the efficiency score at bank level and, in a second step, carried out a truncated bootstrap regression. My results provide robust evidence that spatial dependence has a positive effect on both the input and the output technical efficiency of local banks for three specifications based on specific spatial matrices while, for greater distances, the spatial lag parameter was not more statistically significant. Furthermore, in some cases, the spatial covariates had the opposite effect on a bank's technical efficiency compared to the same variables when considered alone. This result highlights that the level of a bank's strategy can contradict the effect of general market tendencies on a bank's performance in terms of efficiency.

Keywords: Bank Efficiency, DEA, Two-Stage Bootstrap Approach, Spatial Weight Matrix, Spatial Dependence.

3.1 Introduction

This study examines whether there is a spatial dependence in terms of the technical efficiency of small and local Italian banks. The extensive adoption of the relationship lending procedure in granting loans gives small banks a competitive advantage over large banks, particularly with regard to financing small and micro enterprises and household customers (Dell'Ariccia, 2001; Hauswald and Marquez, 2003; Schenone, 2010; Yosano and Nakaoka, 2019). However, this market condition may decrease the performance efficiency of small banks. Therefore, I aimed to verify the hypothesis of co-movement in the efficiency scores of neighboring small banks. If these banks dominated a market segment, their main competitors would be small banks that were nearby. Thus, a greater number of small, neighboring banks could imply more market discipline, and vice versa.

In fact, well-established literature has emphasized small banks' ability to use soft information in their relationships with their customers (Petersen, 2004; Baas and Schrooten, 2006; Garcia-Appendini, 2011; Ergungor and Moulton, 2014; D'Aurizio et al., 2015; Agarwal et al., 2018). This body of literature has stressed the ability of small and local banks to collect and process private and inherently qualitative information (see, for example, Cassar et al., 2015 and Liberti, 2018). Specifically, banks with a stronger hierarchy, in which the distance between the information collectors and the decision makers is greater, tend to be less able to provide credit to more opaque borrowers (Liberti and Petersen, 2019). Financing such customers requires the use of soft information derived from personal interactions which, once collected, is challenging to transmit to the highest level of management (Berger and Udell, 1995; Stein, 2003; Agarwal et al., 2012). Therefore, large banks adopting relationship lending practice encounter the additional cost of establishing adequate internal controls (Cerqueiro et al., 2009).

Other studies have posited that the short distance between small banks and their customers could be an additional source of competitive advantage. More specifically, this research has pointed out the role of the transportation costs borne by borrowers and lenders when entering into an agreement (Chiappori et al., 1995; Sussman et al., 1995; Almazan, 2002), while Gehrig (1998) emphasized that the burden for borrowers seeking the best loan conditions increased as the distance from the bank's offices increased.

Once the credit relationship has been established, banks maintain advantages because they possess soft, non-transferable information against opaque firms (Petersen and Rajan, 1994; Ongena and Smith, 2001; Elsas, 2005). This ability gives local banks a competitive advantage over large and hierarchical banks in the credit market for small enterprises and households (Berger and Udell, 2002; Stein, 2002; Berger et al., 2005; Liberti and Mian, 2008; Kysucky and Norden, 2015; Berger et al., 2017; Hasan et al., 2017; Degl'Innocenti et al., 2018). Thus, local banks enjoy location-based cost advantages in lending to small customers. Of interest, Coccorese and Santucci (2019) found that small Italian banks had more market power than did large ones due to niches in the credit market created by the relationship lending technique.

Despite the awareness that local banks enjoy possible monopolistic rent due to their local roots, little research has been conducted to verify whether such banks' efficiency was affected by spatial interdependence.

More specifically, Tabak et al. (2013) introduced the geographically weighted stochastic frontier model into the panel data framework. In this method, the unobserved macroeconomic environment determinants affecting a local bank's performance are inserted into a statistical model estimating the bank's efficiency. Tabak et al. (2013)'s approach has the advantage of comparing only those banks that experience the same local market conditions and excluding banks competing in distant markets with different economic trends. Their results indicated that geography played an important role in assessing a bank's efficiency.

Similarly, Zhao et al. (2019) conducted a study that considered both spatial dependence among urban commercial banks in China and the effects of the regional market environment on the banks' efficiency by applying a spatial Durbin production frontier model. This is in contrast to Tabak et al. (2013) work, as it included independent spatial variables within the translog function. A distinctive feature of Zhao et al. (2019) study is the use of a spatial contiguity matrix, which does not allow for a consideration of the spatial weights at bank level. More precisely, the spatial units are represented by geographical areas, whereby contiguity indicates the sharing of common boundaries. Therefore, the matrix ($n \times n$) represents a row for each region, in which the elements take the value of 1 if the region borders another, and 0 if it does not. The authors pointed out the existence of spatial spillover effects, since neighboring contiguous banks had similar levels of efficiency.

Aiello and Bonanno (2018) did not apply spatial methodology, but adopted an empirical strategy based on multilevel models to examine the impact of territorial conditions on banks' efficiency. Their results revealed that provincial-level geographical factors affected the efficiency of small Italian banks. Moreover, the authors argued that efficiency was correlated positively with the concentration within local markets.[1]

[1] In addition, many other researchers have emphasized that geographical determinants are a significant

Following this line of thought, the present research aimed to provide further evidence of spatial dependence in the technical efficiency of small, cooperative Italian banks (Banche di Credito Cooperativo - BCCs), namely local banks that grant credit by using relationship lending procedures.[2] Furthermore, I applied a robust two-step methodology that first estimated the technical efficiency score via a non-parametric frontier technique, and then regressed this score for a large set of explanatory variables and spatial terms. The second step involved the application of Simar and Wilson (2007) estimation with spatial variables; unlike other methods, this allows for the control of the assumption of the separability condition. As explained in the methodology section, the efficiency score estimated in the first stage has to have specific characteristics in order to be used in the model in the second stage; otherwise, the estimation may suffer from severe bias.

Another advantage of my empirical strategy is the ability to include a large set of covariates to explain the banks' efficiency scores (Skevas and Grashuis, 2020). Using this procedure, I could verify whether the efficiency of neighboring BCCs affected the efficiency level of the i_{th} bank. It also permitted me to control how a bank's efficiency score was affected by explanatory control variables, as well as by the existence of spatial autocorrelations in each of these covariates. Thus, I tested for the presence of spatial dependence not only with regard to a bank's efficiency score, but also concerning factors affecting the same bank's efficiency performance.

I argue that BCCs experience competitive pressure from other BCCs because the relationship lending practices create niche markets in which large banks struggle to compete. As a result, the market discipline is more effective in the presence of other small banks that are able to compete with the i_{th} bank. This effect needs to be explored via a methodology that allows for the control of the many bank characteristics that affect the performance score.

My results indicated that spatial dependence had a strong effect on the efficiency performance of small, cooperative Italian banks. Conversely, the control variables that contributed significantly to the determination of the banks' efficiency scores, when considered in their spatial lag versions, did not always explain the technical efficiency score.

factor in explaining the efficiency of local banks. Bos and Kool (2006) pointed out that local economic factors were able to explain the technical efficiency scores, albeit to a limited extent. Dietsch and Lozano-Vivas (2000) suggested that an analysis of a bank's efficiency without checking for environmental variables may lead to invalid scores for efficiency. Similarly, Pasiouras et al. (2011) found that environmental factors, such as market-specific factors, affected local efficiency.

[2] BCCs operate in a limited area, apply the one member one vote principle, are not allowed to distribute earnings, and mainly have their members as customers. In brief, BCCs tend to operate in a specific market.

This study is structured as follows, Section 3.2 presents the two-stage bootstrap method: The first stage estimates the efficiency scores, and the second stage is a statistical examination of the relationship between a bank's efficiency and the determinants thereof. Section 3.3 introduces the data and the variables considered in the empirical specification. Section 3.4 presents the three phases of my investigation, namely the tests to control for the existence of spatial correlations in the variables, the bootstrap estimation of my equation, and the diagnostic test of the errors in the estimation to check for the modification of cross-sectional dependence following the treatment. Section 3.5 concludes the study and presents the final remarks.

3.2 Two-stage methodological approach

This section introduces the econometric methodology, including the procedure to estimate the technical efficiency scores in the first step, and the spatial econometric model in the second.

3.2.1 DEA method

The measure of a bank's efficiency utilized in this empirical investigation was attained by considering a non-parametric DEA frontier approach. This method allows for the detection of the best practice frontier within a particular assumption of constant or variable returns to sale (VRS) (Cook et al., 2014).[3] More precisely, the DEA model permits the identification of the best practice individuals that constitute the non-parametric efficient frontier and those that deviate, with the latter showing a certain degree of technical inefficiency indicated by the distance from the best performers. The greatest benefit of the non-parametric technique is not assuming a particular functional shape of the production frontier with respect to the parametric model; therefore, it does not impose a particular structure on the form of the efficient frontier (Cooper et al., 2006).

The first stage employed a DEA-BCC procedure, as this is the most frequently used non-parametric method in situations involving numerous inputs and outputs, and in cases in which the variations in inputs or outputs do not impact linearly on the others. Specifically, this approach considers mathematical programming to compute the scores

[3]The first technique of non-parametric efficiency was introduced by Farrell (1957). Subsequently, in the literature on efficiency, Charnes et al. (1978) and Banker et al. (1984) developed the two main DEA models: DEA-CCR under the hypothesis of constant return to scale, and DEA-BCC under the hypothesis of VRS.

for the efficiency of the multiple decision-making units (DMUs) that are either input- or output-oriented. The use of an input orientation was intended to obtain the maximum proportional decrease in the inputs while remaining within the production possibility frontier. Thus, one entity is inefficient when there is a possibility of decreasing the quantity of inputs without changing the outputs. By contrast, output orientation examines how the level of outputs can be increased without altering the input vector always staying inside the production possibility frontier. In any event, the two orientations indicate the same set of efficient and inefficient DMUs.

Assume the existence of data on k inputs and m outputs for each n bank. Let $x_i = (x_{1i}, x_{2i}, \ldots, x_{ki})$ as a $k \times 1$ input vector for the i_{th} bank, $X = (x_1, x_2, \ldots, x_n)$ as a $k \times n$ input matrix, $y_i = (y_{1i}, y_{2i}, \ldots, y_{ki})$ as an $m \times 1$ output vector for the i_{th} bank, and $Y = (y_1, y_2, \ldots, y_n)$ as an $m \times n$ output matrix, respectively. The technical efficiency (TE) score for each DMU is obtained by dividing the weighted sum of the outputs by the weighted sum of the inputs. Thus:

$$TE = \frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{s=1}^{k} u_s x_{sj}} \tag{3.1}$$

where u is the weight given to the output r, v is the weight given to the input s, and y_i and x_i symbolize the output and input, respectively.

To determine the optimal weights, a linear programming methodology is used to maximize the ratio of weighted outputs to weighted inputs for the DMU in question, subject to the constraint that the ratio is a value between 0 and 1. A DMU is efficient if and only if the ratio is equal to 1.

Following Banker et al. (1984), the input- and output-oriented DEA estimators are found by solving the two optimization problems below. In more detail, the input-oriented BCC model is designed to minimize inefficiency, and is defined as follows:

$$
\begin{aligned}
\phi^* &= \text{Min } \phi \\
&\text{subject to} \\
\sum_{j=1}^{n} \lambda_j x_{ij} &\leq \phi x_{i0}, \quad i = 1,2,\ldots,k, \\
\sum_{j=1}^{n} \lambda_j y_{rj} &\geq y_{r0}, \quad r = 1,2,\ldots,m, \\
\sum_{j=1}^{n} \lambda_j &= 1, \\
\lambda_j &\geq 0, \quad j = 1,2,\ldots,n,
\end{aligned}
\tag{3.2}
$$

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

The output-oriented BCC model, which is designed to maximize TE, utilizes the following linear programming problem:

$$
\begin{aligned}
\theta^* &= \text{Max } \theta \\
&\text{subject to} \\
\sum_{j=1}^{n} \lambda_j x_{ij} &\leq x_{i0}, \quad i = 1,2,\ldots,k, \\
\sum_{j=1}^{n} \lambda_j y_{rj} &\geq \theta y_{r0}, \quad r = 1,2,\ldots,m, \\
\sum_{j=1}^{n} \lambda_j &= 1, \\
\lambda_j &\geq 0, \quad j = 1,2,\ldots,n,
\end{aligned}
\tag{3.3}
$$

in which x_i, y_i and λ are equal to the specification 3.2, and θ^* represents the output-oriented TE score.

According to the assumption of constant return to scale proposed by Charnes et al. (1978), the programming models (3.2) and (3.3) do not consider the convexity constraint ($\sum_{j=1}^{n} \lambda_j = 1$); therefore, the VRS assumption guarantees that each inefficient DMU is only compared to the DMUs that are similar in size, thus enabling the measure of economies of scale.

In the literature pertaining to DEA, a common procedure adopted to regress the estimated efficiency on a set of explanatory variables has been based on the use of a censored (Tobit) model, and on a linear model by ordinary least squares (OLS) in other instances.[4] However, Simar and Wilson (2007) have argued that the covariates are correlated with the error term, given that the variables of output and input are related to the covariates. Furthermore, they highlighted that DEA efficiency estimates are correlated serially by construction, thereby providing invalid estimates in the second stage.

To address this issue, Simar and Wilson (2007) proposed an alternative estimation based on bootstrap methods in order to obtain unbiased and valid inferences. Nonetheless, if there is a spatial dependence of variables, the results present bias problems that require the use of appropriate spatial econometric approaches.

3.2.2 Spatial truncated regression model

The spatial econometric technique examines the relationships among the observations located in different territorial areas, by embedding spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in econometric model specifications (Anselin, 1988; Elhorst, 2014). Spatial dependence refers to the relationship between a single spatial element and a neighboring one via the use of Tobler (1970)'s first law of geography. This relationship is called spatial autocorrelation, and indicates a weaker expression of spatial dependence (Anselin, 2003).

In the second stage of my analysis, I used a spatial Durbin model (SDM) (LeSage, 2008; Elhorst, 2014; Halleck Vega and Elhorst, 2015), as it is a quite general specification of a spatial econometric model that allowed me to examine the interaction effects among the spatial units.[5] Specifically, I used a bootstrap truncated regression model (Algorithm 1) as proposed by Simar and Wilson (2007). In more detail:

$$\delta_t = \boldsymbol{W}\delta_t\lambda + \mathbf{z}_t\gamma + \boldsymbol{W}\mathbf{z}_t\rho + \varepsilon_t \tag{3.4}$$

where δ_t is the TE score obtained in the first stage, $\mathbf{z}_t$ is the covariate vector, including the constant, $\boldsymbol{W}$ represents the spatial weighting matrix (SWM), λ, γ, and ρ are unknown parameter vectors to be estimated, and ε_t is the residual vector. To compute the spatial variables $\boldsymbol{W}\delta_t$ and $\boldsymbol{W}\mathbf{z}_t$, a well-balanced dataset is needed (Elhorst, 2014).

[4] See, for example, Aly et al. (1990), Binam et al. (2003), Okeahalam (2004), Speelman et al. (2008).

[5] Elhorst (2010a) suggested that the spatial correlation in the data could be analyzed not only by a spatial lag model (SAR) and a spatial error model (SEM) which consider a spatial lag of the dependent variable or error, but also by endogenous spatial effects and exogenous interaction effects through the SDM.

The SWM ($\boldsymbol{W}$) is the basis for the spatial analysis. Each non-negative matrix (w_{ij} : $i, j = 1, \ldots, n$) is a possible SWM that specifies the degree of territorial interaction among n spatial units. Following standard conventions, I excluded self-influence by assuming that $w_{ii} = 0$ for all $i = 1, \ldots, n$ (no unit is a neighbor to itself); thus, $\boldsymbol{W}$ has a zero diagonal (Cliff and Ord, 1968; Kelejian and Prucha, 2010).

In relation to my typology of spatial data, this work followed a distance-based approach. Specifically, the SWM used to generate weights was a particular Gaussian kernel matrix (Otranto et al., 2016), in which the generic element w_{ij} is a continuous and monotonic decreasing function of the (Euclidean) distance d_{ij} (Fotheringham et al., 2003).

The general weighting function of the kernel matrix is defined as follows:

$$w_{ij} = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right] \tag{3.5}$$

in which d_{ij} is equal to the distance between the spatial units i and j, and the parameter b is a non-negative bandwidth function that produces a decay of influence with distance. Varying the bandwidth results in a different exponential decay profile, which in turn produces weights that vary more or less rapidly across distance. Thus, the weighting of other data will decrease according to a distance-decay curve as the distance between the spatial units i and j increases. For spatial units far away from i, the weight w_{ij} will decrease to virtually zero. The choice of kernel functions is particularly appropriate because the bandwidth b provides a control for the circular area of influence of each observation. Therefore, each w_{ij} element corresponds to a kernel matrix (rows standardized) that is based on a specific bandwidth b.

3.3 Data and Empirical Specification

My empirical analysis considered an annual panel dataset of 264 BCCs for the period from 2011 to 2017.[6] The data were taken from the Bureau van Dijk Orbis Bank Focus' (BvD Orbis) database.[7] The sample included 1,848 observations in total, and all of

[6]Looking at the intermediaries list to 2017-12-31 on the website of Bank of Italy, the overall number of credit cooperative banks amounts to 289 (see, https://infostat.bancaditalia.it/GIAVAInquiry-public/ng/). However, since my spatial model needs a balanced data, I remove all the BCCs that do not report data throughout the period under consideration.

[7]As some values were missing, I accessed the balance sheets published on the websites of the BCCs concerned in order to construct a strongly balanced dataset.

the cooperative Italian banks except for Popular Banks.[8] To construct the geospatial dataset, I geo-referenced the data by geocoding the address of each BCC's headquarters to obtain the respective geographic coordinates (latitude and longitude) for each individual observation. Figure 3.1 presents the spatial distribution of all the headquarters.

Figure 3.1: Spatial pattern of Italian local banks

To examine whether spatial spillover effects existed among the Italian BCCs, I estimated the following empirical equation:

$$\hat{\delta}_{i,t} = \alpha_i + \psi \sum_{j=1}^{n} w_{ij} \cdot \hat{\delta}_{i,t} + \mathbf{x}_{i,t}\beta + \varphi \sum_{j=1}^{n} w_{ij} \cdot \mathbf{x}_{i,t} + \varsigma\Gamma + \nu_t + \epsilon_{i,t} \tag{3.6}$$

$$i = 1,2,\ldots,n; \; t = 1,2,\ldots,t$$

To estimate the bank's efficiency scores ($\hat{\delta}_{i,t}$) in both orientations using the DEA technique discussed in Section 3.2.1, I needed to specify the set of outputs and inputs. Typically, an analysis of a bank's efficiency is conducted on the basis of the financial

[8] In Italy, Popular Banks are a particular category of cooperative banks. They differ from BCCs in that they have different governance and business models, as well as with regard to the diverse managerial objectives in terms of the principle of mutuality that distinguishes the cooperative banks from the commercial ones. Since they have characteristics that are typical of commercial banks, I excluded them from the dataset and considered only the BCCs.

intermediation method, according to which the banks are processed as enterprises that supply services, such as lending, through the employment of inputs (deposits, labor, capital, and so on). Thus, following several applications (for example, Kulasekaran and Shaffer, 2002; Drake et al., 2006; Barth et al., 2013; Diallo, 2018; Asimakopoulos et al., 2018), I adopted a particular model of intermediation with two outputs and four inputs. The outputs (Y_i) were Y_1 (total customer loans + total other lending) and Y_2 (other earning assets).[9] The four inputs (X_i) were X_1 (total funds; that is, total deposits + total money market funds + total other funding), X_2 (staff expenses as input for labor), X_3 (fixed assets as input for physical capital), and X_4 (loan loss provisions and other provisions). The last (X_4) input included the risk/loan quality in the estimation of a bank's efficiency (Drake et al., 2006).[10]

Table 3.1 presents the descriptive statistics of the variables used to estimate the DEA efficiency score.

Table 3.1: Descriptive statistics of outputs and inputs variables

Variable	No. Obs.	Mean	Std. Dev.	Min	Max
Total loans	1,848	441707.6	596866.2	3315	8817072
Other earning assets	1,848	3154.193	16439.08	1	416193
Total funds	1,848	596816.1	830277.1	1	10731222
Staff expenses	1,848	7091.739	8512.344	1	109671
Fixed assets	1,848	9119.081	12196.64	12	149812
Loan loss provisions	1,848	8208.208	9676.098	1.762	127877

Notes: The variables are derived from the Bank Focus database and are expressed in thousands of Euros.

My model included three different kinds of covariates. The first included the spatially lagged dependent variable, the second a large set of bank-specific characteristics,[11] and the third incorporated the spatial lags of the explanatory variables.

[9]The outputs were chosen based on the previous literature (Casu and Girardone, 2004; Casu et al., 2004) and the availability of data. However, various empirical analyses of banking efficiency use other outputs (such as other, non-interest, or income) in order not to penalize banks that are engaged in non-traditional banking activities (Barth et al., 2013). In my case, as I estimated the efficiency of small, cooperative banks that were mainly involved in traditional banking activities, I only considered two outputs.

[10]Laeven and Majnoni (2003) claimed that risk should be embedded in an efficiency investigation by adding the loan loss provisions. In particular, the loan loss provisions necessary to set up loan loss reserves should be considered and handled as an input or a cost.

[11]At a preliminary stage, I also include macroeconomic environment variables at the provincial level (growth domestic product and the logarithm of the population density). However, the coefficients of these control covariates were never statistically significant.

The spatial lag operators were computed by multiplying the dependent and independent variables by four spatially weighted matrices. Specifically, I employed a Gaussian kernel matrix with four different dispersion parameters (bandwidths) expressed in kilometers (km):

(1) $b = \text{Minimum}(d_{ij}) = b_{min}$

(2) $b = 0.01[\text{Maximum}(d_{ij})] = b_{01p}$

(3) $b = 0.5[(b_{min} + b_{Mm})] = b_{mm2}$

(4) $b = \text{Maxmin}(d_{ij}) = b_{Mm}$

in which b_{min} is equivalent to 3.6 km,[12] b_{01p} is equivalent to 13.4 km; that is 1% of the greatest distance between two BCCs (1336.6 km), b_{mm2} is equivalent to 67.8 km and corresponds to the mean between the minimum distance and the Maxmin distance and, finally, b_{Mm} is equivalent to 131.9 km and provides the Maxmin distance.

With regard to the Maxmin function, b_{Mm} was selected to provide the relationship below:

$$b_{Mm} = max(e_1, e_2, \dots, e_i, \dots, e_n), \tag{3.7}$$

where e_i is the shortest distance between the generic spatial element i and another elements j (with $i \neq j$). Therefore, each spatial element was linked to every other one (Mucciardi and Bertuccelli, 2012).

I considered several explanatory variables as determinants. The description and expected signs were as follows:

CAP represents the regulatory capital at bank level, and was obtained via the ratio of total capital to risk-weighted assets. Higher capitalized banks had better results in terms of efficiency (Fiordelisi et al., 2011; Berger and Bouwman, 2013; Bitar et al., 2018). The sign was expected to be positive.

The $Z - Score$ was obtained by dividing the return on assets (ROA) plus the equity to assets ratio by the standard deviation of ROA, and was a proxy for a bank's financial stability. The higher the value, the greater the bank's stability (Shim, 2019). However, since a bank's soundness may be obtained at the expense of efficiency (Miah and Uddin, 2017), the sign was expected to be uncertain.

[12] This represents the minimum distance, whereby each bank has at least one neighbor.

The LIQ was computed by dividing the liquid assets (that is, the sum of cash and balances with other banks, money market instruments, and marketable securities) by the total assets; this showed a bank's overall liquidity. Lenders with higher levels of liquidity tended to be more efficient, and had less need of capital because they were able to generate more output, part of which consisted of liquid and other assets (Altunbas et al., 2007). The sign was expected to be positive.

The LA was obtained from the ratio of net loans to total assets, which indicates a bank's asset risk. Of note, it is a specific financial ratio that measures the relationship between a bank's loan portfolio and its total assets (Sanya and Wolfe, 2011; Meslier et al., 2014). A higher ratio should indicate a greater net interest income, as granting loans is the most risky and profitable activity (Claeys and Vander Vennet, 2008). More efficient lenders tend to show greater loan-to-asset ratios (Maudos et al., 2002); thus, the sign was expected to be positive.

The NPL was calculated based on the ratio of non-performing loans to gross loans, and represented the bank's asset quality (Berger and Mester, 1997; Podpiera and Weill, 2008). It constitutes a backward-looking measure of credit quality according to which a higher ratio leads banks to have less cost efficiency (Berger and DeYoung, 1997; Fries and Taci, 2005). The sign was expected to be negative.

The LLP was the ratio of loan loss provision to total loans, and was considered, even in this case, to be a proxy for asset quality. However, compared to the NPL, it is a forward-looking measure of credit quality, whereby a higher ratio implies that a bank is less efficient (Sufian, 2009). The sign was expected to be negative.

The CF was computed by dividing the interest expense by the total funds, and indicated the cost of funding. The interest expenditure paid for the funds affects the technical inefficiency (Chortareas et al., 2013; Silva et al., 2016; Pérez-Cárceles et al., 2019); however, sign was expected to be uncertain.

The DEP was obtained from the ratio of total deposits to total assets, and was a proxy for the deposit structure. Deposits are the main component of funds, and require correct handling at the allocative stage. Therefore, more deposits can improve interest margins (Asongu and Odhiambo, 2019). The sign was expected to be positive.

$Equity$ represented the ratio of equity to total loans, and was used as a proxy for capital adequacy because it denotes the level of equity coverage required to absorb the losses in a bank's loan portfolio (Pasiouras and Tanna, 2010; Ata and Buğan, 2016). The sign was expected to be positive.

$Service$ represented the ratio of net interest income to operating revenue, and indicated the bank's dependence on interest income (Fraser et al., 2002; Foos et al., 2017). The sign was expected to be uncertain.

The OETA was calculated by dividing the operating expenses by the total assets. It was used as a proxy for management quality (Roman and Şargu, 2013), whereby the most efficient banks were more able to control their operating expenses (Saha et al., 2015). The sign was expected to be negative.

Finally, my specifications also included four dummy variables to account for the region in which the bank had its headquarters (north-east, north-west, central, or south). These variables controlled for both the regional Italian disparity in terms of economic development and for the concentration of BCCs in Italian regions, as shown in Figure 3.1.

Table 3.2 shows all the variable list employed in this study as well as their detailed description and the data sources, while Table 3.3 presents the descriptive statistics for the variables considered in the second stage of the estimation.

Table 3.2: List of variables

Variable	Description	Source
X_{TE}	Input technical efficiency	Author's calculations
Y_{TE}	Output technical efficiency	Author's calculations
CAP	(Tier 1 Capital + Tier 2 Capital)/Risk Weighted Assets	BankScope/BankFocus
ROA	Net income/Total assets	BankScope/BankFocus
$Equity$	Total equity (in thousand EUR)	BankScope/BankFocus
$Assets$	Total assets (in thousand EUR)	BankScope/BankFocus
$Z-Score$	(ROA + Equity/Assets)/σ(ROA)	Author's calculations
LIQ	Liquid Assets/Assets	BankScope/BankFocus
LA	Net loans/Total assets	BankScope/BankFocus
NPL	Non-performing loans/Gross loans	BankScope/BankFocus
LLP	Loan loss provision/Total loans	BankScope/BankFocus
CF	Interest expense/Total funds	BankScope/BankFocus
DEP	Total deposits/Assets	BankScope/BankFocus
$Equity$	Total equity/Loans	BankScope/BankFocus
$Service$	Net interest income/Operating Revenue	BankScope/BankFocus
$OETA$	Operating expense/Assets	BankScope/BankFocus

Notes: This table contains a description of the variables and the data sources.

As stated previously, the sample consisted of strongly balanced panel data containing 1,848 observations for the period from 2011 to 2017. It included both the top performing banks in terms of efficiency, and other banks that were far from the mean. On average, the BCCs were quite far from the efficiency frontier, particularly on the output side.

With regard to the specific characteristics of banks, I noted that the mean, except for

Table 3.3: Descriptive statistics of the two-step variables

Variable	No. Obs.	Mean	Std. Dev.	Min	Max
Dependent variables					
X_{TE}	1,848	0.700	0.138	0.308	1
Y_{TE}	1,848	0.654	0.149	0.203	1
Bank-specific characteristic variables					
CAP	1,848	0.196	0.079	0.059	0.860
$Z-Score$	1,848	0.697	1.054	-9.672	9.474
ROA	1,848	0.271	0.552	-5.562	4.658
LIQ	1,848	0.091	0.062	0.011	0.950
LA	1,848	0.649	0.118	0.216	0.941
NPL	1,848	0.147	0.072	0	0.408
LLP	1,848	0.014	0.012	-0.009	0.097
CF	1,848	0.011	0.005	0	0.060
DEP	1,848	0.671	0.112	0	0.916
$Equity$	1,848	0.183	0.217	0.045	6.524
$Service$	1,848	0.660	0.302	-9.363	7.045
$OETA$	1,848	0.020	0.005	0.003	0.077

a few variables, was greater than was the standard deviation, thus indicating that my samples consists of banks with fairly similar features. For the $Z-Score$, the negative values were due to negative profitability while, for the other variables, the extreme values came from a bank that began operations in 2011. However, as it reported normalized values in the following year, the bank was not excluded to preserve the representativeness of the sample.

Table 3.4 reports the correlation matrix, which shows the correlation coefficients with significance levels between the covariates included in the regression models. To assess the possibility of multicollinearity among the regressors, I employed the Variance Inflation Factor tests (VIF, Neter et al., 1989). On average, the VIF values were equal to 1.90 for both efficiency models, and no VIF presented a value that exceed 3.0; therefore, this evidence indicates that the multicollinearity issue should not be of concern.

3.4 Results and Discussion

In this section, I report on the empirical results of the analysis. I first present the statistical tests considered to verify the presence of spatial dependence. Following this, I report on the estimates of the spatial truncated regression models and the cross-section dependence (CD) test to confirm the robustness of the estimators. Lastly, I discuss the

Table 3.4: Correlation matrix for the variables used in the second-step estimation

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. X_{TE}	1												
2. Y_{TE}	0.7942*	1											
3. CAP	0.0295	-0.3535*	1										
4. $Z-Score$	0.2566*	0.0369	0.2765*	1									
5. LIQ	0.2425*	0.1154*	0.2182*	0.0614*	1								
6. LA	0.5591*	0.7654*	-0.5257*	-0.0648*	0.0378	1							
7. NPL	-0.5975*	-0.3994*	-0.0616*	-0.5198*	-0.0340	-0.3028*	1						
8. LLP	-0.5567*	-0.4297*	-0.0322	-0.3699*	-0.1080*	-0.3568*	0.5847*	1					
9. CF	0.0187	0.1243*	-0.2625*	-0.0432	-0.0817*	0.2731*	0.1800*	0.0039	1				
10. DEP	-0.1294*	-0.2593*	0.1633*	0.0150	0.0873*	-0.3919*	-0.0020	0.0907*	-0.5563*	1			
11. $Equity$	0.0496*	-0.1200*	0.4080*	0.3488*	0.0724*	-0.1946*	-0.0588*	-0.0350	-0.1238*	0.0512*	1		
12. $Service$	0.1239*	0.0380	0.0443	0.1447*	-0.0582*	0.1246*	-0.1624*	-0.1268*	0.0113	-0.0371	0.0224	1	
13. $OETA$	0.0176	-0.1678*	0.1215*	-0.1367*	0.1467*	0.0801*	-0.0193	0.0592*	0.0412	0.0447	0.0690*	0.0294	1

Notes: This table provides the correlation coefficients of the variables used in the empirical investigation over the period 2011-2017. * denotes significance at the 5% level or better.

evidence in order to explain the spatial interdependence among cooperative banks.

3.4.1 Testing for spatial autocorrelation, random effects and serial correlation

To verify the presence of spatial dependence, I executed several Lagrange multiplier (LM) tests to control the existence of spatial, serial correlation, and random effects in my data. Ignoring spatial dependence leads to biased estimates and misleading statistical inferences (Mur and Angulo, 2006; Kar et al., 2011; Kutlu and Nair-Reichert, 2019).

Table 3.5 presents the results of all the diagnostic tests.

Table 3.5: LM test for spatial, serial correlation and random effects

LM test description	Input Oriented Model		Output Oriented Model	
	Statistic	P-value	Statistic	P-value
Anselin (1988)				
Conditional test for spatial error autocorrelation				
(H_0: spatial error autoregressive coefficient equal to zero)	9.64	< 0.01	9.40	< 0.01
Conditional test for spatial lag autocorrelation				
(H_0: spatial lag autoregressive coefficient equal to zero)	5.17	< 0.01	3.63	< 0.01
Baltagi et al. (2003)				
Joint test (H_0: absence of random effects and spatial autocorrelation)	2208.9	< 0.01	1739.5	< 0.01
Marginal test of random effects (H_0: absence of random effects)	46.77	< 0.01	41.50	< 0.01
Marginal test of spatial autocorrelation (H_0: absence of spatial autocorrelation)	4.64	< 0.01	4.18	< 0.01
Conditional test of spatial autocorrelation (H_0: absence of spatial autocorrelation, assuming random effects are non null)	3.11	< 0.01	3.12	< 0.01
Conditional test of random effects (H_0: absence of random effects, assuming spatial autocorrelation may or may not be equal to 0)	46.24	< 0.01	40.83	< 0.01
Baltagi et al. (2007)				
Joint test (H_0: absence of serial or spatial error correlation or random effects)	2251	< 0.01	1793.2	< 0.01
One-dimensional conditional test (H_0: absence of spatial error correlation, assuming the existence of both serial correlation and random effects)	5.90	0.05	5.79	0.05
One-dimensional conditional test (H_0: absence of serial correlation, assuming the existence of both spatial error correlation and random effects)	14.25	< 0.01	15.05	< 0.01
One-dimensional conditional test (H_0: absence of random effects, assuming the existence of both serial and spatial error correlation)	152.31	< 0.01	152.17	< 0.01

The first set of LM tests checked for the presence of spatial correlation. The null hypothesis stated that both the spatial error autoregressive coefficient and the spatial lag autoregressive coefficient would be equal to zero (Breusch and Pagan, 1980; Anselin, 1988). Thus, the rejection of this hypothesis enabled me to identify the existence of spatial autocorrelation. The tests rejected the null hypothesis categorically.

The second group of tests corresponded to the joint and conditional LM tests proposed by Baltagi et al. (2003) to verify spatial autocorrelation and random effects. The results indicated the presence of these items in all the diagnostic tests. In more detail, the joint LM test strongly rejected the null hypothesis, indicating that at least a component, such as spatial error correlation and/or random individual effects, were present in the error term. Similarly, the spatial autocorrelation and the random effects were tested separately via the marginal LM tests. On consideration of the results, the null hypotheses regarding no spatial autocorrelation and no random individual effects were both rejected. Moreover, I conducted conditional LM tests to confirm the existence of spatial dependence.[13] The tests rejected the null hypothesis and revealed the existence of co-movement in the data.

The latest set of tests created by Baltagi et al. (2007) controls for spatial, serial autocorrelation and random effects jointly and conditionally. The joint LM takes the question of the serial correlation with regard to Baltagi et al. (2003) specifications into account, while the one-dimensional conditional tests allow testing for the presence of each them individually, while allowing for the existence of the other two. The results rejected the hypothesis concerning the absence of serial correlation, and once again rejected the absence of spatial autocorrelation and random effects.[14]

The statistical tests described thus far were linked to the spatial weight matrix that was taken into consideration. Subsequently, I also estimated the CD tests proposed by Pesaran (2004, 2015) as a robustness check to detect spatial dependence, as also suggested by Sarafidis and Wansbeek (2012), Millo (2017), and Elhorst et al. (2020). As clarified by Vega and Elhorst (2016), these tests control for the existence of strong and weak cross-sectional dependence resulting from unobserved common factors (strong cross-sectional dependence) and spatial dependence (weak cross-sectional dependence). Table 3.6 summarizes the results, and indicates the existence of cross-sectional dependence (strong and weak).

Accordingly, the presence of spatial dependence in the LM tests and in the CD tests necessitated the use of appropriate spatial econometric methods.

[13] More specifically, spatial autocorrelations are tested allowing for the existence of random effects, and random effects are tested allowing for the presence of spatial autocorrelations.

[14] All the LM tests were estimated using the splm package in R proposed by Millo and Piras (2012). The tests results presented in Table 3.5 were estimated using the matrix with h_{min} as the bandwidth; however, the statistical tests were computed considering the other three matrices. Since the results present the same picture, I have not presented the results due to space constraints, but they are available on request.

Table 3.6: Testing for cross-sectional dependence

Test	Pesaran (2004)		Pesaran (2015)	
	Input Oriented Model	Output Oriented Model	Input Oriented Model	Output Oriented Model
CD	11.035	13.113	8.925	15.214
P-value	0.000	0.000	0.000	0.000

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

3.4.2 Estimations

The empirical estimates of the spatial bootstrapped truncated regression model specified in Equation 3.6 for both input and output orientations are presented in Tables 3.7-3.8, together with the results of the non-spatial bootstrap truncated regression model.

Table 3.7: Estimation results for Input Technical efficiency (X_{TE})

Variable	Truncated Regression Model	Spatial Truncated Regression Models			
		b_{min}	b_{01p}	b_{mm2}	b_{Mm}
	(1)	(2)	(3)	(4)	(5)
$\mathbf{W} \times X_{TE}$		0.1530*** (0.024)	0.2359*** (0.033)	0.3027*** (0.087)	0.0797 (0.136)
CAP	0.5184*** (0.035)	0.4861*** (0.036)	0.4766*** (0.035)	0.4658*** (0.036)	0.4872*** (0.037)
$Z-Score$	-0.0073*** (0.003)	-0.0066** (0.003)	-0.0054* (0.003)	-0.0044 (0.003)	-0.0040 (0.003)
LIQ	0.2467*** (0.039)	0.2685*** (0.039)	0.2884*** (0.038)	0.2967*** (0.039)	0.2951*** (0.040)
LA	0.6661*** (0.027)	0.6219*** (0.028)	0.6087*** (0.028)	0.6259*** (0.028)	0.6516*** (0.028)
NPL	-0.2076*** (0.037)	-0.2141*** (0.037)	-0.2142*** (0.038)	-0.2438*** (0.037)	-0.2338*** (0.037)
LLP	-4.1368*** (0.254)	-3.9678*** (0.252)	-3.8627*** (0.251)	-3.7507*** (0.265)	-3.8340***(0.263)
CF	1.4556** (0.600)	2.7700*** (0.650)	3.3474*** (0.641)	3.4170*** (0.693)	3.1450*** (0.684)
DEP	0.1531*** (0.025)	0.1615*** (0.025)	0.1718*** (0.026)	0.1769*** (0.025)	0.1845*** (0.026)
$Equity$	0.0265* (0.014)	0.0269* (0.014)	0.0247* (0.013)	0.0228* (0.013)	0.0238 (0.015)
$Service$	0.0014 (0.012)	-0.0007 (0.011)	-0.0005 (0.011)	-0.0059 (0.011)	0.0027 (0.012)
$OETA$	-2.9221*** (0.456)	-2.7025*** (0.447)	-2.5542*** (0.447)	-2.5046*** (0.464)	-2.8619*** (0.452)
$\mathbf{W} \times CAP$		-0.0172 (0.037)	0.0593 (0.052)	0.2856** (0.118)	0.4357** (0.188)
$\mathbf{W} \times Z-Score$		0.0021 (0.003)	0.0018 (0.004)	-0.0026 (0.008)	-0.0114 (0.011)
$\mathbf{W} \times LIQ$		-0.1759*** (0.039)	-0.2788*** (0.057)	-0.0651 (0.115)	0.0600 (0.151)
$\mathbf{W} \times LA$		0.0086 (0.033)	0.0264 (0.046)	0.1167 (0.106)	0.2694* (0.162)
$\mathbf{W} \times NPL$		0.0854** (0.039)	0.1197** (0.052)	0.3804*** (0.106)	0.3965** (0.181)
$\mathbf{W} \times LLP$		0.3850 (0.277)	0.7253* (0.384)	-0.0405 (0.887)	-0.5140 (1.304)
$\mathbf{W} \times CF$		-2.3319*** (0.749)	-3.7049*** (0.854)	-2.6346* (1.383)	-3.2976* (1.837)
$\mathbf{W} \times DEP$		-0.0106 (0.027)	-0.0325 (0.035)	-0.0524 (0.082)	-0.1465 (0.121)
$\mathbf{W} \times Equity$		-0.0103 (0.014)	-0.0099 (0.019)	-0.0160 (0.038)	0.0567 (0.085)
$\mathbf{W} \times Service$		0.0001 (0.011)	-0.0081 (0.017)	-0.0086 (0.030)	0.0010 (0.051)
$\mathbf{W} \times OETA$		-0.2528 (0.477)	-0.8509 (0.599)	-3.3934*** (1.290)	-4.2551** (1.790)
No. Observations	1807	1807	1807	1807	1807
No. Efficient DMUs	41	41	41	41	41
Wald χ^2	3095.2***	3582.1***	3348.2***	3539.5***	3550.1***
Years effects	Yes	Yes	Yes	Yes	Yes
Geo dummies	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates rely on the usage of the truncated regression proposed by Simar and Wilson (2007) with 2,000 bootstrap replications. The constant is included but not reported.

The number of bootstrap replications (2,000) was the same for all the specifications, as was the number of efficient DMUs (41) and the number of observations (1,807). The result of the Wald chi-square test indicated that the covariates (taken together)

Table 3.8: Estimation results for Output Technical efficiency (Y_{TE})

Variable	Truncated Regression Model	Spatial Truncated Regression Models			
		b_{min}	b_{01p}	b_{mm2}	b_{Mm}
	(6)	(7)	(8)	(9)	(10)
$\boldsymbol{W} \times Y_{TE}$		0.1439*** (0.024)	0.2253*** (0.034)	0.1905** (0.093)	-0.0560 (0.133)
CAP	0.0914*** (0.032)	0.0843*** (0.031)	0.0791** (0.031)	0.0939*** (0.032)	0.1090*** (0.032)
$Z-Score$	-0.0062** (0.003)	-0.0045*(0.003)	-0.0038 (0.003)	-0.0030 (0.003)	-0.0026 (0.003)
LIQ	0.1561*** (0.035)	0.1731*** (0.035)	0.1910*** (0.034)	0.1921*** (0.035)	0.1871*** (0.035)
LA	0.9424***(0.025)	0.8997*** (0.025)	0.8782*** (0.025)	0.8976*** (0.026)	0.9126*** (0.026)
NPL	-0.0496 (0.033)	-0.0653* (0.034)	-0.0510 (0.035)	-0.0378 (0.034)	-0.0406 (0.035)
LLP	-2.0518*** (0.227)	-1.8731*** (0.232)	-1.8280*** (0.246)	-1.7807*** (0.227)	-1.7829*** (0.239)
CF	-0.1080 (0.547)	1.5903***(0.599)	2.0377*** (0.610)	1.8645*** (0.647)	1.6097** (0.654)
DEP	0.1020*** (0.023)	0.1220*** (0.023)	0.1264*** (0.023)	0.1477*** (0.024)	0.1516*** (0.024)
$Equity$	0.0165* (0.009)	0.0173* (0.009)	0.0162* (0.009)	0.0132 (0.009)	0.0112 (0.009)
$Service$	-0.0309*** (0.010)	-0.0296***(0.010)	-0.0270*** (0.010)	-0.0289*** (0.010)	-0.0257** (0.010)
$OETA$	-7.6358*** (0.413)	-7.6044*** (0.412)	-7.5481*** (0.406)	-7.3337*** (0.433)	-7.2676*** (0.435)
$\boldsymbol{W} \times CAP$		0.0124 (0.032)	0.0700 (0.045)	0.1312 (0.092)	0.0772 (0.161)
$\boldsymbol{W} \times Z-Score$		0.0004 (0.003)	-0.0014 (0.004)	-0.0069 (0.008)	-0.0187* (0.010)
$\boldsymbol{W} \times LIQ$		-0.1116*** (0.035)	-0.2441*** (0.052)	-0.2146** (0.107)	-0.0575 (0.143)
$\boldsymbol{W} \times LA$		0.0076 (0.034)	0.0382 (0.049)	0.0572 (0.119)	0.2840 (0.187)
$\boldsymbol{W} \times NPL$		0.0727** (0.036)	0.0990** (0.047)	0.0269 (0.098)	0.0014 (0.171)
$\boldsymbol{W} \times LLP$		0.2591 (0.243)	0.3420 (0.339)	0.1222 (0.762)	0.0837 (0.989)
$\boldsymbol{W} \times CF$		-3.0502*** (0.681)	-3.3911*** (0.787)	-3.5325*** (1.316)	-4.5106*** (1.713)
$\boldsymbol{W} \times DEP$		-0.0410 (0.025)	-0.0075 (0.032)	-0.1109 (0.071)	-0.2180** (0.110)
$\boldsymbol{W} \times Equity$		-0.0038 (0.012)	0.0001 (0.017)	-0.0068 (0.034)	0.0557 (0.076)
$\boldsymbol{W} \times Service$		-0.0140 (0.010)	-0.0320** (0.016)	-0.0406 (0.027)	-0.0494 (0.047)
$\boldsymbol{W} \times OETA$		1.0478** (0.472)	1.0273* (0.593)	-0.2725 (1.256)	-2.6512 (1.798)
No. Observations	1807	1807	1807	1807	1807
No. Efficient DMUs	41	41	41	41	41
Wald χ^2	5099.6***	5823***	5466.9***	5163.9***	5436.5***
Years effects	Yes	Yes	Yes	Yes	Yes
Geo dummies	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates rely on the usage of the truncated regression proposed by Simar and Wilson (2007) with 2,000 bootstrap replications. The constant is included but not reported.

were statistically significant with regard to explaining the TE in the input and output orientations.

The evidence indicated positive spatial spillover effects in the efficiency of neighboring cooperative Italian banks. In particular, these outcomes supported the insight that an increase in the neighboring bank's efficiency led to an enhancement in the i_{th} bank's efficiency performance and vice versa. However, the coefficients of spatially lagged dependent variables, based on the greater distance decay parameter (131.9 km), were not significant. In other words, only the efficiency scores for the closer BCCs affected the TE of the i_{th} BCC. This result supports the idea that such banks compete among themselves: They tend to serve specific niche markets consisting of small firms and household customers - large banks are quite weak competitors in these markets because relationship lending practice is required in order to compete. The market discipline seems to operate between the nearest BCCs; that is, those that are able to entice customers away from the i_{th} BCC. As the bandwidth increased, the spatial relationships were boosted (the number of BCCs increased) and, beyond a certain threshold (131.9 km), my econometric specification also considered BCCs that were not able to compete with the i_{th} BCC because the distance was too great. Therefore, a greater number of BCCs included banks that were unable to have a share in the market, thus eliminating the spatial dependence in the efficiency scores. By contrast, the specifications based on lower dispersion parameters (3.6, 13.4, and 67.8 km) revealed statistical significance in spatially lagged dependent variables.

The coefficients of the control explanatory variables indicated comprehensive consistency in terms of the signs and the statistical significance. This evidence was almost always independent of the distance decay parameters considered in the four specifications, and for the one that did not consider the spatial variables. The signs and the statistical significance were consistent according to the bank profiles considered (bank capitalization, liquidity, credit quality, risk, and cost of funds).

The input and output efficiency scores were both correlated statistically to CAP, LIQ, LA, LLP, CF, DEP, and $OETA$. The coefficients of NPL were only statistically significant for the input TE, whereas $Service$ was only significant for the output TE. $Z-Score$ and $Equity$ were either barely significant or not significant in terms of explaining the two efficiency orientations, except for the $Z-Score$ in the specification (2).

It is interesting to note that the spatial lag of the covariates was not statistically significant, except in a few cases. In contrast to the efficiency scores, there was no spatial dependence in most of the variables affecting the banks' efficiency scores, which determines such scores when considered independently. Many of the neighboring banks' managerial choices, which have an influence on variables that affect a bank's efficiency, had no impact on the efficiency of the i_{th} bank.

In summary, the i_{th} bank's efficiency score efficiency score was related to the efficiency performances of the nearest BCCs, but almost never by the neighbors' covariates.

The variable CF when considered in isolation was statistically significant in both the input- and output-oriented models, while its spatial lags were negative. Interpreting this evidence is challenging. One way to understand it is to consider the possible combined effects of monetary policy initiatives that involve the entire banking system, and a single bank market strategy, such as direct to conquer market shares or to entice customers away from other banks. In this scenario, my results suggest that the overlap determines a negative effect of the monetary policy initiatives on the bank's TE, as it weakens the market discipline, while a bank's strategy involving the funding price requires high internal efficiency.

In the input-oriented model, the spatial lag variable of NPL was positive and statistically significant for all the specifications, while it was only so for the two models based on smaller bandwidths on the output side. Conversely, the coefficients of the variable when considered separately were negative; even for the output specifications, I found statistical significance for only one parameter. Therefore, a high level of customer insolvency has a negative effect on the TE, as confirmed by the literature (see, for example, Fukuyama and Weber, 2008; Podpiera and Weill, 2008; Barros et al., 2012; Luo et al., 2016), both on the input side and on the output side. Instead, the variable NPL's spatial lags incorporate the effect of the deterioration of regional macroeconomic conditions. The worsening of regional economic conjuncture causes more delinquencies; at the same time, it leads to greater efficiency, particularly on the input side.

The variable LIQ was positive and statistically significant for both the efficiency models, but the signs of its spatial lags were negative and statistically significant, except for the specifications based on higher bandwidths. Interpreting this evidence requires the application of a kind of fly-to-quality scheme. Since the variable reflects the weight of interest-bearing assets, except for loans, in relation to a bank's total assets, the coefficient sign of the variable when considered separately indicates an improvement in a bank's efficiency as a result of having fewer loans on the bank's balance sheet. In other words, a reduction on lending activity, conceivably with regard to low-performing customers, results in enhanced efficiency for the bank. By contrast, the competitive mechanism seems to explain the negative signs of the spatial lag variables: The more competitors increase their liquid assets, the more the former competitors' customers ask for loans from the i_{th} bank. Since these new i_{th} bank customers should be marginal borrowers, their contribution to the bank's TE is negative.

Finally, none of the other spatial variables were statistically significant, except for the spatial lags of CAP, $OETA$, and $Service$, and only for some specifications of the efficiency models (input or output). In this regard, the coefficient signs of the latter variables were always consistent with those of the relative variables when considered separately.

3.4.3 Diagnostic test for cross section independence

The presence of spatial interdependence discussed in Section 5.4.1 led to the use of spatial terms in the two-stage econometric model. This procedure enabled me to control for co-movement among the spatial units. However, common factors could persist after the use of the spatial model specification.

To test this, I performed a post-estimation test on the residuals of the spatial truncated models using Pesaran (2004) CD test in order to verify the presence of cross-sectional independence in the errors of the spatial models. If the test were to reject such a hypothesis, the estimates would exhibit a bias problem (Andrews, 2005; Bai and Ng, 2010).

Table 3.9: Testing for cross-sectional independence

Test	Input Oriented Model				Output Oriented Model			
	b_{min}	b_{01p}	b_{mm2}	b_{Mm}	b_{min}	b_{01p}	b_{mm2}	b_{Mm}
CD	0.970	-1.202	-1.349	0.662	0.987	-0.586	-0.410	0.057
P-value	0.332	0.230	0.177	0.508	0.324	0.558	0.682	0.955

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

Table 3.9 shows the result of the CD test that indicated the hypothesis of cross-sectional independence for all the spatial specifications was not rejected, thus providing proof concerning the absence of co-movement among spatial units. The errors in the eight spatially truncated models were not influenced by strong cross-sectional dependence. Consequently, I argue that the techniques of spatial econometrics that were used solved the problem connected to the correlations among panel units.

3.5 Conclusion

This study used a spatial two-stage bootstrap DEA approach to analyze the role of spillover effects on the TE performance of small and local banks. I conducted this investigation using an extensive sample of cooperative Italian banks, as they represent an important geographical section within the Italian banking market, and the characteristics of Italian regions differ across Italy. Thus, local Italian banks (BCCs) constituted a suitable sample to test the hypothesis that spatial dependence is an important factor in explaining the efficiency scores in both input- and output-oriented DEA models.

Specifically, I computed four Gaussian kernel matrices incorporating the spatial weights based on several dispersion parameters (3.6, 13.4, 67.8, and 131.9 km) in order to determine the spatial lags of dependent and independent variables. In the initial phase, I estimated different LM and cross-sectional tests to identify the presence of spatial correlations and cross-sectional dependence (strict and weak). Following this, the spatial bootstrap regression models were estimated via Simar and Wilson (2007) estimator, together with a model without spatial components. Finally, I controlled for cross-sectional independence to ensure the robustness of the estimates.

My results revealed that there was a positive spatial autocorrelation in the TE scores of Italian BCCs up to 67.8 km, and that this effect disappeared at a distance of 131.9 km; that is, a distance at which the spatial matrix also included banks that did not compete with the i_{th} bank. Therefore, only the TE of the nearest banks was important for explaining the i_{th} bank's efficiency performance. Moreover, when more distant banks that were therefore not direct competitors of the i_{th} bank were considered, the efficiency of the other banks did not affect that of the i_{th} bank. This means that having efficient neighbors triggers virtuous behaviors in terms of efficiency for the banks. In reality, efficient banks are capable of taking customers away, and this determines the market discipline of the i_{th} bank. This is indirect confirmation that local banks operate in niche markets in which large banks have difficulty competing.

My specifications also included the spatial lags of the explanatory control variables. Of interest, the variables capturing the cost of funds, non-performing loans, and liquid assets had different signs from those of the variables when considered separately. I interpreted these results as the effects of forces acting on bank technical efficiency, both at bank level (managerial strategy) and outside bank level (monetary policies and regional macroeconomic conditions).

Supervisors should be aware that local bank efficiency also depend by the neighboring effects, and therefore this effect should be considered to promote the competition among local banks.

My analysis did not control for different kinds of local bank borrowers, such as households and small and micro enterprises. Due to possible differences in the demand elasticity of these kinds of bank customers, a different weight of one of the other categories in the banks' loan portfolio could affect the efficiency of local banks. A lack of data prevented me from overcoming this limitation in the study.

In addition, future research could use my methodological approach to investigate whether there is spatial dependence in the efficiency performance of local banks by controlling for the distance between bank branches, for which this study did not control.

CHAPTER 4

Spatial patterns and local banks' tax aggressiveness: an empirical analysis in Italy

Abstract

In this study, I consider the spatial dependence effects in an empirical model measuring local banks' tax aggressiveness, assessing the interdependence between geographical units and the related spillover effects. My results strongly support the existence of co-movements among banks' tax avoidance policies. The findings indicate that local banks compete mainly among themselves, even on the funding side, and that certain tax behavior can trigger loss of customers, which limits banks' tax avoidance activities. However, neighbors' adoption of aggressive tax strategies can remove the competition hurdle in pursuing tax avoidance policies. In addition, I find that greater bank market power increases spatial spillover effects, showing that neighbors' tax management strategies matter in planning a local bank's tax policies. These findings point out a virtuous effect of customer pressure, which could take effect in other areas of bank management.

Keywords: Tax Aggressiveness, Spatial Dependence, Small Cooperative Banks, Lerner Index.

4.1 Introduction

In the last decade, tax aggressiveness has been a matter of growing interest, not only for academic researchers and policy makers (Chen and Lin, 2017; Wilde and Wilson, 2018; Kovermann and Velte, 2019; Baudot et al., 2019) but also for the general public via media reports (Kanagaretnam et al., 2018). Tax aggressiveness refers to all tax planning practices, legal or otherwise, undertaken in order to minimize tax payments (Frank et al., 2009). Terms such as tax management or tax avoidance can also be used to describe the same issue (e.g., Lanis and Richardson, 2012).

Although scholars have often studied tax-planning strategies in manufacturing industries (e.g., Rego and Wilson, 2012; Chyz et al., 2013; Kim and Zhang, 2016; Balakrishnan et al., 2019), more work is needed to characterize tax planning behavior in the banking industry (see Gawehn and Müller, 2019; Gawehn, 2019, Shackelford and Shevlin, 2001 for a call for research on this topic). Specifically, despite the well-documented relevance of tax planning in the banking industry and the appeal of an empirical explanation, few studies directly explore whether and how neighboring local banks can impact each other's tax aggressiveness, which plays a fundamental role in an economy. In this study, I try to fill this gap by compiling a unique panel dataset of Italian small cooperative banks (Banche di Credito Cooperativo- BCCs) and examining their tax aggressiveness in terms of the tax strategy of nearby banks. Previous studies have investigated banks' overall reaction to taxation, highlighting a dynamic response to tax rate differentials by profit-shifting strategies (Meeks and Meeks, 2014; Merz and Overesch, 2016; Schandlbauer, 2017; Janský, 2020).

In general, banks might be less inclined to engage in aggressive tax avoidance strategies compared to non-financial firms, due to the extensive control of banking supervision and regulation - and the related enforcement power of supervisors (Graham et al., 2014; Dyreng et al., 2016; Boyer and Kempf, 2020). If unsound or illegal practices are detected, regulators are empowered to enforce sanctions by requiring adequate remedial actions and imposing safe practices, thereby preventing financial reputational losses and guaranteeing solidity in the banking industry (Pereira et al., 2019).

Interestingly, though, previous studies on bank tax aggressiveness focus on large and listed banks and do not consider the relevance of local bank tax behavior. Indeed, such banks constitute a unique universe within the banking system. Local banks compete mainly among themselves, serving the niche markets of households and micro and small enterprises (De Masi and Gallegati, 2012; Coccorese et al., 2016; Yosano and Nakaoka,

2019) and representing high retail funding stability, even in economic downturn periods (McKillop et al., 2020). Additionally, since local banks are often cooperative, the owners and depositors usually correspond, avoiding the agency problems between shareholders and depositors. This scheme explains why cooperative banks fund via deposits. Besides, the low reliance on market capital for funding entails high dependence on depositors to collect financial resources (Ayadi et al., 2010). Consistent with the high commitment of local banks in funding with deposits, Hannan and Prager (2006), Beyhaghi et al. (2014), and Jacewitz and Pogach (2018) showed that the largest banks pay significantly lower interest rates for funding from deposits products. Recently, Sedunov (2020) argued that smaller financial institutions pay greater attention than large banks to their customers' degree of satisfaction. This finding confirms the results of the Wave 24 Chicago Booth/Kellogg School Financial Trust Index Survey, which showed that households trust local banks more than large national banks.[1]

I chose to examine BCCs' tax aggressiveness for one key reason. The market structure of local banks highlights the non-tax costs of tax avoidance, in particular the reputational risk, which the literature has introduced as a key factor in explaining firm tax management (Chen et al., 2010; Allen et al., 2016).[2] Corporate reputation is one of the most important intangible assets leading corporate performance (Gibson et al., 2006). Despite significant scholarly debate (Barnett and Pollock, 2012), firm reputation is intended to reflect the expectations that stakeholders have about a corporation's future behavior based on their sense of its past conduct (Deephouse and Carter, 2005; Carroll, 2013). But reputation also denotes an accountability system, one that constituents have notable control over as a form of social assessment (Lange et al., 2011). Consequently, negative (positive) reputational influences generate economic sanctions (rewards) for the entities (Cable and Graham, 2000; Brammer and Pavelin, 2006). Additionally, the research on corporate accountability has expanded traditional discussions on social responsibility to wider stakeholders (Freeman, 2010), incorporating civic accountability towards the citizens of the country in which the enterprise operates, particularly through taxation (Christensen and Murphy, 2004; Russell and Brock, 2016; Payne and Raiborn, 2018).

[1] See the following website for more information: http://www.financialtrustindex.org/resultswave24.htm.

[2] The literature also includes disclosure and agency costs within non-tax costs (Garbarino, 2011). The former are linked with communication on tax matters, specifically the description of corporate tax policies alongside their adequate exposure (Erle, 2008). The latter are the agency costs accompanying tax aggressiveness activities. Managers might hide rent extraction via tax aggressiveness when the two actions are complementary. This might, however, produce significant agency costs for shareholders (Laguir et al., 2014).

Hanlon and Slemrod (2009) argued that revealing aggressive tax management activities might even lead to customer boycotts, which might provide sufficient incentive to renounce tax avoidance possibilities in order to support current revenues.

One of the main principles that shapes the structure of Italian BCCs and distinguishes them from shareholder-based banks is that they serve the interest of their members, who are also their customers, and aim to reach pre-established economic and social goals. Bank members are generally located in the areas where these banks have their headquarters or branches, and their membership is also concentrated at a local or regional level, satisfying the financial needs of members, small firms, and community groups (Barra and Zotti, 2019; Botta and Colombo, 2020). Furthermore, cooperative banks use a democratic guideline (one head, one vote), 70% of the bank's profit must be held as reserve, and no shareholder is permitted to own shares valued higher than 50,000 euros (Coccorese and Ferri, 2020).

The influence of local conditions underlines how the banking environment can strongly influence the tax behavior of a small bank. A bank's tax behavior might likewise be influenced by the tax conduct of the neighboring banks. Consistent with the prediction that bank tax behavior is essentially affected by its reputational position among customers with respect to their competitors (that is, nearby banks), I first use a spatial econometrics approach to empirically investigate Italian local banks' co-movements in tax aggressiveness. This spatial technique allows me to assess if a bank's tax behavior is affected by the tax strategy of the neighboring banks, and therefore considers the possible reputational risk effect of adopting tax aggressiveness policies.

The possible negative reputational effects of tax avoidance for a local bank might discourage it from undertaking such a strategy, but that hesitance could vanish as more direct competitors practice tax aggressiveness. In fact, the tax aggressiveness policies of nearby banks can significantly affect a given bank's tax management policies, as a result of the trade-off between the effects of tax aggressiveness strategies on banks' cash flows and on their reputations. In this respect, bank customers might punish a tax avoidance initiative as they become increasingly aware of corporate tax conduct (Graham et al., 2014). Furthermore, I also verify whether banks' market power, supervisory enforcement actions, and other bank-specific control variables affect their tax aggressiveness.

I proxy the cooperative banks' tax aggressiveness via their effective tax rates (see most recently Chen et al., 2020; Fatica and Gregori, 2020; Ortas and Gallego-Álvarez, 2020). My results indicate that spatial dependence has a strong effect on the tax management of Italian small cooperative banks, even after controlling for bank competition. I carry out several tests in order to detect the presence of spatial dependence in the data, showing a strong existence of co-movement in the banks' tax policies. These results validate the adoption of spatial econometrics techniques, which I conduct along four different distance ranges, inside of which other local banks are considered competitors. The subsequent spatial regressions allow me to observe a significant and positive relationship between a local bank's tax avoidance and the neighboring banks' tax avoidance behavior, for all the distance ranges considered in the spatial techniques.

The remainder of the study is organized as follows. Section 4.2 shows the data and variables used in my empirical specification, and discusses the spatial econometrics techniques. Section 4.3 presents and debates the diagnostic tests to control for the presence of spatial correlation and random effects in my dataset, as well as the empirical estimation of the model. Finally, Section 4.4 offers some final remarks and concludes the study.

4.2 Data, methodology, and variable definitions

4.2.1 Data and Empirical Model

To conduct my empirical investigation, I utilize a set of panel data over the 2011-2018 period for 259 BCCs with 2,072 observations.[3] The dataset come from two several sources: Bureau van Dijk Orbis Bank Focus' (BvD Orbis) database for the banks' balance sheet information[4] and "Il Sole 24 Ore" for the local macroeconomic indicators at the provincial level.[5] In order to geo-reference the individual observations for building the geospatial dataset, I geocoded the address of each BCC's headquarters using the latitude and longitude geographic coordinates. Figure 4.1 exhibits the geographical distribution of the BCC's headquarters.

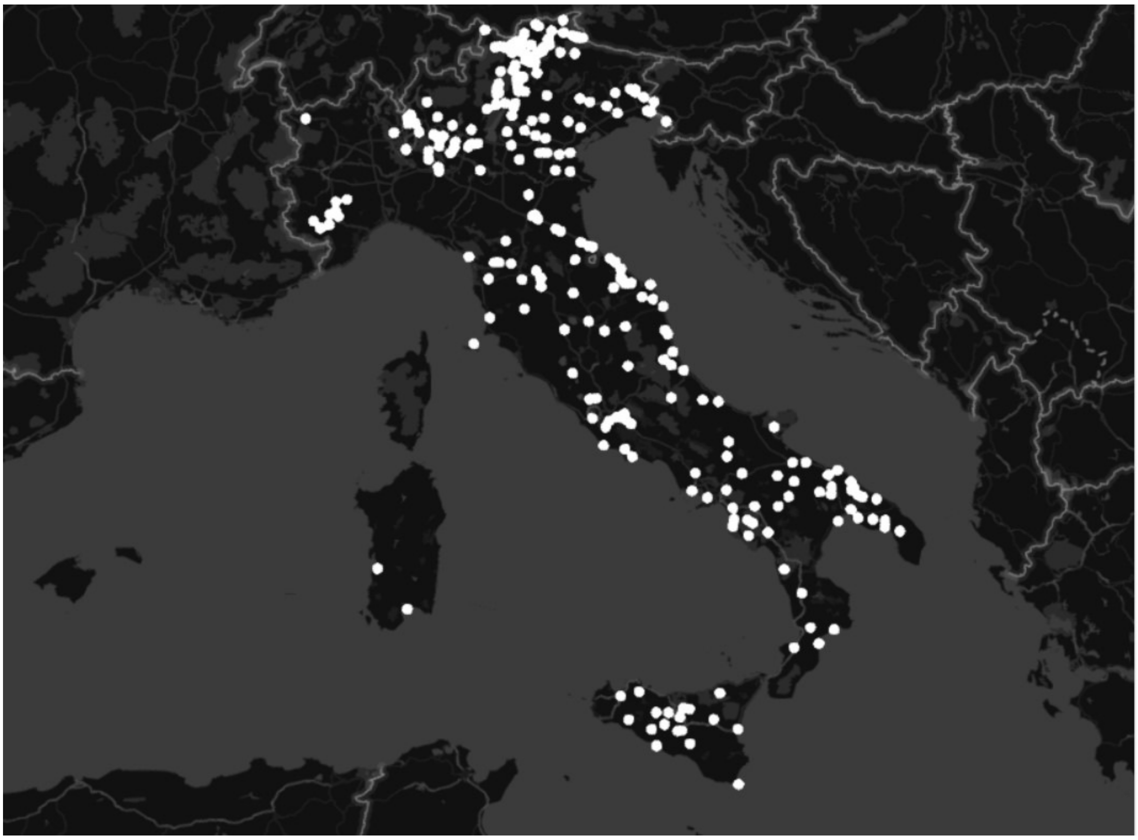
To investigate the determinants of the cooperative banks' tax aggressiveness, my empirical model assumes the following form:

[3] Since the econometric model requires a strongly balanced panel dataset, I removed all the banks that do not report data for the whole spanning period considered.

[4] The missing values have been replenished by consulting the balance sheets that the BCCs published online.

[5] Il Sole 24 Ore regularly publishes a report defined "Quality of Life", which shows a set of provincial data (on an annual basis) regarding the main social and economic indexes. See https://lab24.ilsole24ore.com/qualita-della-vita/.

Figure 4.1: Spatial distribution of Italian cooperative banks



$$TAG_{i,t} = \alpha + \lambda \sum_{j=1}^{n} \tilde{w}_{ij}\, TAG_{i,t} + \vartheta Lerner_{i,t} + \varphi Post-Sanction_{i,t} + \gamma Employees_{i,t} + \phi Loan\ to\ Assets_{i,t} + \kappa \Delta GDP_{i,t} + (\eta_i + \epsilon_{i,t}) \tag{4.1}$$

where α is a constant term, λ is the spatial autoregressive parameter and ϑ, φ, γ, ϕ and κ are the coefficients of the control variables. Finally, $(\eta_i + \epsilon_{i,t})$ represents the disturbance term expressed as sum of two components: the fixed effects η_i and random error $\epsilon_{i,t}$.[6]

4.2.2 Measure of Tax Aggressiveness

The dependent variable is represented by TAG, an indicator of tax aggressiveness based on effective tax rates (ETRs). ETRs are usually measured via the information drawn from financial statements as tax liability divided by income. The decision to use ETRs is based on two principal reasons. First, empirical tax analysis has discovered that ETRs

[6]The random error is assumed to be normally distributed with zero mean and unit variance.

embody tax aggressiveness (e.g., Chen et al., 2010; Hoi et al., 2013; Minnick and Noga, 2017; Jarboui et al., 2020). Second, ETRs constitute the main proxy of tax aggressiveness employed by academic scholars (e.g., Lanis and Richardson, 2012; Zhang et al., 2016; Drake et al., 2020).

There are two other important matters in the context of selecting the ETR measures. First, ETRs denote a measure of the relative tax burden between corporations. Therefore, since ETRs compare the current tax liability, gathered by taxable income and earnings before tax (pre-tax income) on the basis of the generally accepted accounting principles (GAAP), they are designed to measure the corporation's ability to reduce its current tax liability relative to its pre-tax accounting income (Rego, 2003). Second, considering the difference between accounting (book) income and tax income, accounting profit might not constitute the effective chargeable income of a firm (Derashid and Zhang, 2003). Following conventional scholarship (e.g., Gupta and Newberry, 1997; Lanis and Richardson, 2012; Laguir et al., 2015), to improve the robustness of my empirical investigation I use two measures of ETRs. The first one ($ETR1$) is calculated as the ratio between total tax expense and pre-tax income, while the second ($ETR2$) is defined as total tax expense divided by operating cash flows. The higher the value of ETR is, the lower the tax aggressiveness level will be, and the lower the ETR is, the greater the tax aggressiveness level will be.

4.2.3 Spatial Autoregressive Parameter

In equation (4.1), the first covariate is represented by the first-order spatial lag of TAG with respect to the spatial weight matrix $\boldsymbol{W}$.

Since the mid-nineties, the techniques of spatial econometrics (Anselin, 1988) have received wide interest and have led to numerous methodological contributions and applications (e.g., Ord, 1975; Cliff and Ord, 1981; Kelejian and Prucha, 1999; Baltagi and Li, 2001; Lee, 2002), dedicated to tracking the relations among spatial units. The methodology of spatial econometrics treats the connections between cross-sectional units situated in different territorial areas, by entering spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in econometric models (Anselin, 2003; Elhorst, 2014). Spatial dependence regards the relationship between an individual spatial unit and a neighboring one by means of the exploitation of Tobler's first law of geography (Tobler, 1970). This relationship is usually defined as spatial autocorrelation, although it represents a fainter expression of spatial dependence (Anselin, 2003).

In my empirical study, I use the Spatial Autoregressive (SAR) model originally developed by Cliff and Ord (1973) which allows modeling the spatial interaction and dependence among geographical units (Lee and Yu, 2010a,b; Banerjee et al., 2014; Qu and Lee, 2015; Baltagi and Deng, 2015; Wang and Yang, 2019). In particular, the spatial lag model is formulated as follows:

$$y_t = \rho \boldsymbol{W} y_t + \mathbf{z}_t \beta + \varepsilon_t \tag{4.2}$$

where y_t is the dependent variable vector, $\mathbf{z}_t$ is the matrix of the control variables, $\boldsymbol{W}$ is the spatial weight matrix, and ε_t is the vector of idiosyncratic errors. Lastly, ρ and β are unknown parameters to be identified.

Spatial econometric techniques enable me to verify the effects of spatial interdependence by setting out a spatial weighting matrix. Thus, $\boldsymbol{W}$ depicts the main component for spatial analysis, since it permits me to create the first-order spatial lag of the dependent variable $\boldsymbol{W} y_t$ and take into account the cross-sectional interdependence of spatial units with respect to y_t (Anselin, 1988). To construct $\boldsymbol{W} y_t$, as well as the spatial model, a well-balanced dataset is required (Chi and Zhu, 2019).

Denote n as the set of all the cross-sectional units. The spatial weight matrix $\boldsymbol{W}$ is a non-stochastic, fixed, and non-negative $n \times n$ matrix with zero on the diagonal by definition (Cliff and Ord, 1968; Kelejian and Prucha, 2010), since no spatial unit is spatially connected with itself; therefore, $w_{ii} = 0$ for all $i = 1, \ldots, n$. In more in detail, the matrix $\boldsymbol{W}$ denotes a spatial weighting scheme capturing the spatial relationship (autocorrelation) framework between pair of units, such that each element ($w_{ij} : i, j = 1, \ldots, n$) takes the following properties:

(i) $w_{ij} \neq 0$ if i and j are spatially correlated;

(ii) $w_{ij} = 0$ if i and j are spatially uncorrelated.

To structure the geographical connections among spatial units, my exogenous spatial matrix $\boldsymbol{W}$ is built following Tabak et al. (2013). Each element w_{ij} is computed by applying the maximum likelihood method sequentially to each spatial unit, and each separate observation gains a weight according to the geographical distance relationship to the reference unit.

Formally, the values of w_{ij} are defined as follows:

$$w_{ij} = \frac{e^{-\left(\frac{d_{ij}}{\sigma}\right)^2}}{\sigma\sqrt{2\Pi}} \tag{4.3}$$

where w_{ij} is the weight of the connection between points i and j, d_{ij} is the orthodromic distance (in kilometers) between spatial units i and j, and σ is a distance-decay parameter (bandwidth) that begets a decrease of influence with increasing distance. Changing the bandwidth produces several profiles of exponential decay and generates spatial weights ranging more or less quickly over space. Therefore, given increasing distance between units i and j, the weighting of other data will diminish according to a distance-decay curve (Fotheringham et al., 1998). The weight w_{ij} approaches zero for the units farthest from i. Such spatial matrix specification, permitting structural dependence in behavior, is particularly suitable for my study, as the distance-decay parameter σ offers an inspection of the circular area of influence in each observation. In order to normalize the influence on each spatial data, the weight matrix $\boldsymbol{W}$ is row-standardized, that is, each row sum is equal to 1.

Formally, the normalized nonnegative weights can be expressed as follows:

$$\tilde{w}_{ij} = \frac{w_{ij}}{\sum_j w_{ij}} \tag{4.4}$$

where w_{ij} is specified in (4.3) and $\sum_j w_{ij}$ is the sum of w_{ij} for each row of the matrix $\boldsymbol{W}$ (not standardized).

In the panel data framework, the exogenous $nt \times nt$ spatial weights matrix, under the hypothesis of constant distance, is given by:

$$\boldsymbol{W}_{nt} = \boldsymbol{I}_t \otimes \boldsymbol{W}_n \tag{4.5}$$

where $\boldsymbol{I}_t$ is an identity matrix of dimension t and $\boldsymbol{W}_n$ is the row-normalized spatial weight matrix of size $n \times n$.[7]

The spatially lagged term, which captures the influence of the neighborhood, is computed by multiplying the dependent variables ($ETR1$ and $ETR2$) by four different spatial weighting matrices. In detail, I make use of spatial matrix $\boldsymbol{W}$ with four dispersion parameters expressed in kilometers (km):

(1) $\sigma = \text{Minimum}(d_{ij}) = \sigma_{min}$

(2) $\sigma = 0.01[\text{Maximum}(d_{ij})] = \sigma_{01p}$

(3) $\sigma = 0.02[\text{Maximum}(d_{ij})] = \sigma_{02p}$

(4) $\sigma = 0.5[(\sigma_{min} + \sigma_{10p})] = \sigma_{mm}$

[7] For further information, see Anselin et al. (2007).

where σ_{min} (equal to 3.6 km) constitutes the minimum distance so that each bank has at least one neighbor, σ_{01p} (equal to 13.37 km) indicates the 1% of the maximum distance between two BCCs (1336.6 km), σ_{02p} (equal to 26.73 km) represents 2% of the maximum distance, and σ_{mm} (equal to 68.63 km) corresponds to the average between σ_{min} and σ_{10p} (i.e., 10% of the maximum distance).

4.2.4 Control Variables

In equation (4.1), I include other variables used as control variables. More specifically, the second variable constitutes a measure of market power of banks proxied by the Lerner index. The third one indicates the supervisory enforcement actions (EAs) against banks. Finally, other bank-specific determinants are included as control variables.[8]

In order to define the measure of the cooperative bank market power, I consider the Lerner Index (Lerner, 1934) commonly used in the conventional banking literature (e.g., Ariss, 2010; Weill, 2013; Fernández et al., 2016; Ahamed and Mallick, 2017; Leroy and Lucotte, 2019; Shaffer and Spierdijk, 2020). It captures the degree to which a bank can boost its marginal price beyond its marginal cost (Berger et al., 2009). The higher (lower) the value of the index is, the greater (lower) the bank's market power is - and the greater the market power, the higher the price compared to the marginal cost.

Formally, the Lerner index of monopoly power is constructed as follows:

$$Lerner = \frac{P_{i,t} - MC_{i,t}}{P_{i,t}} \tag{4.6}$$

where $P_{i,t}$ is the output price of bank i at time t and $MC_{i,t}$ is the total marginal cost. If the value of $Lerner$ is equal to zero, it denotes perfect competition (i.e., the bank has no market power), while if the index value is equal to unity, it indicates a monopoly.

Following recent literature (e.g., Carbó et al., 2009; Fiordelisi and Lopes, 2013; Fiordelisi and Mare, 2014; Degl'Innocenti et al., 2014; Coccorese and Santucci, 2019; Degl'Innocenti et al., 2020; Coccorese and Ferri, 2020), the bank price $P_{i,t}$ is calculated as total revenue (interest plus non-interest income) divided by total assets. The marginal cost $MC_{i,t}$ is computed from a standard translog cost function with a single output (total assets) and three input prices (labor, physical capital, and deposits). The bank's cost function is specified as follows:

[8] I tested for multicollinearity among the explanatory and control variables by calculating their variance inflation factors (VIFs, Neter et al., 1989). The mean VIF is equal to 1.05 for both specifications and the highest VIF equals 1.11.

$$
\begin{aligned}
lnTC_{i,t} = {} & \theta_0 + \theta_1 lnQ_{i,t} + \frac{1}{2}\theta_2 lnQ^2_{i,t} + \sum_{k=1}^{3}\psi_k lnP_{k,i,t} \\
& + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3}\tau_{k,j} lnP_{k,i,t} lnP_{j,i,t} + \frac{1}{2}\sum_{k=1}^{3}\delta_k lnQ_{i,t} lnP_{k,i,t} + (u_{i,t} + v_{i,t})
\end{aligned}
\tag{4.7}
$$

where $TC_{i,t}$ stands for the total cost of the i_{th} bank at time t (i.e., total operating expenses), Q is the total assets, P_1 is the price of labor (staff expenses divided by total assets), P_2 is the price of capital (other administrative expenses on total assets), P_3 is the price of borrowed funds (interest expenses over bank funding), θ, ψ, τ as well as δ are unknown parameters to be identified, and $(u_{i,t} + v_{i,t})$ is the decomposition of the error term. That is, the two-sided error term, $v_{i,t}$, means the statistical noise i.i.d. as $N(0, \sigma_v^2)$, the one-sided error term, $u_{i,t}$, catching the actual cost inefficiency term shaped as a truncated non-negative random variable $N^+(0, \sigma_u^2)$.

Once I derive the parameters from the estimation of the cost function, the marginal cost for each bank i at time t is computed via the partial derivatives of Equation (4.7) with respect to the bank output Q. Formally:

$$
MC_{i,t} = \frac{\partial C_{i,t}}{\partial Q_{i,t}} = \frac{\partial lnC_{i,t}}{\partial lnQ_{i,t}} \frac{C_{i,t}}{Q_{i,t}} = \left(\hat{\theta}_1 + \hat{\theta}_2\, lnQ_{i,t} + \sum_{k=1}^{3} \hat{\delta}_k\, lnP_{k,i,t} \right) \frac{C_{i,t}}{Q_{i,t}} \tag{4.8}
$$

To catch the influence of the EA on tax aggressiveness, I determine a dummy (binary) variable, $Post-Sanction$, similarly to Roman (2020). It assumes a value of one for the years after the enforcement actions (sanctions) carried out by the bank supervisors, and zero otherwise.[9]

Finally, I consider several other bank-specific control variables. $Employees$ denotes the number of employees for each bank and is used as a proxy of bank size (Tran et al., 2019). It controls for the economies of scale in terms of tax planning (Rego, 2003). $Loan\ to\ Assets$ is a financial ratio that measures the net loans outstanding as a percentage of total assets. It is a proxy of the bank's asset risk and liquidity (Hanif et al., 2012). The higher the ratio is, the higher the degree of bank involvement in traditional activities is. ΔGDP represents the growth of real gross domestic product (GDP) per capita and is used to capture the effects of the economic performance at the provincial level (Zeng, 2019).

[9]For a focus on EAs, see the recent studies by Caiazza et al. (2018) and Pereira et al. (2019).

Table 4.1 reports the set of the variables used in this analysis as well as their detailed description and the data sources, whereas Table 4.2 shows the descriptive statistics of all the covariates employed in my benchmark model specification.

Table 4.1: List of variables

Variable	Description	Source
$ETR1$	Total tax expense/Pre-tax income	BankScope/BankFocus
$ETR2$	Total tax expense/Operating cash flows	BankScope/BankFocus
$Lerner$	Lerner Index	Author's calculations
$Post-Sanction$	Dummy variable	Roman (2020)
$Employees$	Number of employes	BankScope/BankFocus
$Loan\ to\ Assets$	Net loans/Total assets	BankScope/BankFocus
ΔGDP	GDP growth rate	Il Sole 24 Ore
TC	Sum of personnel expenses, other administrative expenses, and other operating expenses	BankScope/BankFocus
Q	Total bank assets	BankScope/BankFocus
P_1	Personnel expenses/Total assets	BankScope/BankFocus
P_2	Other administrative expenses/Total assets	BankScope/BankFocus
P_3	Interest expenses/Total funds	BankScope/BankFocus
$Price$	Total revenue/Total assets	BankScope/BankFocus

Notes: This table provides a data description and the data sources.

Table 4.2: Bank-level variables and correlation matrix bank-level

Variables	Sample Averages			Correlations						
	No. Obs.	Mean	Std. Dev.	1.	2.	3.	4.	5.	6.	7.
1. $ETR1$	2,072	0.212	0.209							
2. $ETR2$	2,072	0.074	0.127	.35						
3. $Lerner$	2,072	0.328	0.122	.03	.04					
4. $Post-Sanction$	2,072	0.130	0.336	-.05	-.13	-.02				
5. $Employees$	2,072	99.70	118.4	-.00	-.14	.08	.04			
6. $Loan\ to\ Assets$	2,072	0.584	0.132	.03	.02	-.21	-.06	.17		
7. ΔGDP	2,072	0.004	0.106	-.12	-.11	.05	.04	.00	-.08	

The dependent variables and the $Lerner$ have been winsorized by limiting extreme values at 1 percent. Although the BCCs pursue mutual purposes, they have tax burden weight of about 21 percent of bank profit and 7 percent of operating cash flow. The high standard deviation for these two variables shows instances of taxation quite similar to profit-oriented companies. It is worth noting that my sample also includes BCCs with negative $ETR1$ (140 cases) and $ETR2$ (234 cases). Unlike in the empirical literature on firms' tax aggressiveness, I keep these negative values, both because excluding just one year entails removing the banks from the dataset and because my dataset covers a period of severe economic downturn for Italian economics that caused losses for the banks. In addition, the panel structure of my dataset allows me to treat potential fiscal planning strategies from banks.[10] The remaining control variables present summary statistics similar to previous studies referring to Italian BCCs (e.g., Becchetti et al., 2016). Turning to the correlation matrix, the coefficients do not suggest multicollinearity issues among the variables.

4.3 Results and Discussion

In order to validate the use of spatial econometrics techniques, I ran three groups of Lagrange Multiplier (LM) tests to bring out the presence of serial correlation, spatial autocorrelation, and random effects in my data. Disregarding spatial dependence leads to inconsistent and misleading estimates (see Anselin and Florax, 1995; Bai and Kao, 2006; Kutlu and Nair-Reichert, 2019). Table 4.3 shows all the diagnostic tests.

Table 4.3: LM test for spatial, serial correlation and random effects

LM test description	$ETR1$		$ETR2$	
	Statistic	P-value	Statistic	P-value
Anselin (1988)				
Conditional test for spatial error autocorrelation				
(H_0: spatial error autoregressive coefficient equal to zero)	2.29	0.05	4.36	< 0.01
Conditional test for spatial lag autocorrelation				
(H_0: spatial lag autoregressive coefficient equal to zero)	6.24	< 0.01	6.13	< 0.01
Baltagi et al. (2003)				
Joint test (H_0: absence of random effects and spatial autocorrelation)	42.05	< 0.01	76.82	< 0.01
Marginal test of random effects (H_0: absence of random effects)	2.29	0.05	6.67	< 0.01
Marginal test of spatial autocorrelation (H_0: absence of spatial autocorrelation)	6.07	< 0.01	5.69	< 0.01
Conditional test of spatial autocorrelation (H_0: absence of spatial autocorrelation, assuming random effects are non null)	6.25	< 0.01	5.58	< 0.01
Conditional test of random effects (H_0: absence of random effects, assuming spatial autocorrelation may or may not be equal to 0)	2.94	< 0.01	6.58	< 0.01
Baltagi et al. (2007)				
Joint test (H_0: absence of serial or spatial error correlation or random effects)	80.11	< 0.01	134.35	< 0.01
One-dimensional conditional test (H_0: absence of spatial error correlation, assuming the existence of both serial correlation and random effects)	22.43	< 0.01	20.95	< 0.01
One-dimensional conditional test (H_0: absence of serial correlation, assuming the existence of both spatial error correlation and random effects)	26.49	< 0.01	56.86	< 0.01
One-dimensional conditional test (H_0: absence of random effects, assuming the existence of both serial and spatial error correlation)	133.8	< 0.01	140.3	< 0.01

The first group of LM tests verifies the existence of co-movement between units. The null hypothesis points out that the coefficients of spatial error autocorrelation and spatial lag autoregressive are equal to zero (Breusch and Pagan, 1980; Anselin, 1988). Thus, rejecting the null hypothesis enables me to infer the presence of spatial dependence. The result of the tests rejects the latter hypothesis.

The second set of diagnostic tests control for the presence of both spatial autocorrelation and random individual effects, via the joint and conditional LM tests proposed by

[10] Indeed, the landmark paper of Zimmerman (1983), often cited to remove firms that present a negative value for tax avoidance proxy, is founded on a rationale that refers to cross-sectional data. In addition, its analysis does not hold for banks due to the actions of the banking supervisory.

Baltagi et al. (2003). The results of the tests denote that the null hypothesis of no spatial autocorrelation and no random effects is rejected for all the specifications of the test. In particular, the joint LM test claims that at least one factor, such as spatial autocorrelation and/or random effects, is present in the error term. Analogously, such spatial items are tested separately using the marginal LM tests. Test results reject the null hypothesis, confirming both the spatial autocorrelation and random effects. Moreover, to reiterate the presence of spatial correlation and random effects, I also ran the conditional LM tests.[11] In these cases as well, the test results reject the null hypothesis, showing the presence of both spatial autocorrelation and random individual effects.

The last range of tests, developed by Baltagi et al. (2007), check for serial correlation, spatial autocorrelation, and random individual effects jointly and conditionally. These tests represent an extension of the earlier LM tests suggested by Baltagi et al. (2003). In particular, the joint LM test verifies the presence of serial, spatial correlation and random effects, whereas the conditional LM tests allow to derive the existence of each individual component, permitting the presence of the other two. The test results reject the null hypothesis, thus highlighting the presence of serial correlation and providing, once again, evidence of the existence of spatial correlation and random effects.[12]

All the tests mentioned so far are tied to the spatial matrix taken into consideration. Therefore, following several studies (e.g., Kar et al., 2011; Sarafidis and Wansbeek, 2012; Millo, 2017; Yang, 2020; Elhorst et al., 2020), I also ran, as a robustness check, the Cross-sectional Dependence (CD) tests proposed by Pesaran (2004) and Pesaran (2015) to reiterate interaction among panel units. Such tests check, respectively, for strong and weak cross-sectional dependence; that is, as stressed by Chudik et al. (2011) and Vega and Elhorst (2016), for unobserved common factors (strong cross-sectional dependence) and spatial dependence (weak cross-sectional dependence). Table 4.4 reports test the results and exhibits the presence of both strong and weak cross-sectional dependence.

In order to identify the appropriate panel estimation (fixed or random effect), the Hausman (Hausman, 1978) and robust Hausman (Kaiser, 2014) specification tests are used. The test results, as well as the empirical estimates of the SAR regression model specified in Equation (4.1) for both the tax aggressiveness proxies, along with the results of the non-spatial model, are reported in Tables 4.5-4.6. The empirical estimations

[11] Spatial autocorrelation is tested, enabling the existence of random effects, and random individual effects are tested, allowing the presence of spatial autocorrelation.

[12] All the LM diagnostic tests were computed using the package splm written by Millo and Piras (2012). The test results reported in Table 4.3 are estimated by making use of the spatial weighting matrix $\boldsymbol{W}$ with the minimum bandwidth. These tests were also estimated using the other three matrices; however, since they show the same picture, I did not report them to save space. They can be supplied on request.

Table 4.4: Testing for cross-sectional dependence

Test	Pesaran (2004)		Pesaran (2015)	
	$ETR1$	$ETR2$	$ETR1$	$ETR2$
CD	66.80	89.68	37.82	53.79
P-value	0.000	0.000	0.000	0.000

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

summarized in these tables show results that are the same in terms of coefficient significance.

Table 4.5: Estimation results of non-spatial and spatial panel-data regression models, using $ETR1$ as dependent variable

Variable	Fixed Effects	Spatial Fixed Effects			
		σ_{min}	σ_{01p}	σ_{02p}	σ_{mm}
	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{W} \times ETR1$		0.1291*** (0.029)	0.1800*** (0.037)	0.3409*** (0.046)	0.6452*** (0.056)
$Lerner$	0.3096*** (0.062)	0.2817*** (0.062)	0.2662*** (0.062)	0.2236*** (0.063)	0.1521** (0.064)
$Post-Sanction$	-0.2038*** (0.025)	-0.1803*** (0.026)	-0.1724*** (0.026)	-0.1494*** (0.025)	-0.1140*** (0.025)
$Employees$	-0.0015*** (0.000)	-0.0014*** (0.000)	-0.0013*** (0.000)	-0.0010*** (0.000)	-0.0007*** (0.000)
$Loan\ to\ Assets$	0.1441** (0.059)	0.1419** (0.060)	0.1339** (0.060)	0.1092* (0.060)	0.0808 (0.059)
ΔGDP	-0.2159*** (0.076)	-0.1828*** (0.065)	-0.1699*** (0.061)	-0.1339*** (0.049)	-0.0806*** (0.030)
No. Observations	2,072	2,072	2,072	2,072	2,072
No. Banks	259	259	259	259	259
Within R^2	0.104	0.119	0.125	0.146	0.187
Between R^2	0.023	0.024	0.024	0.021	0.018
Overall R^2	0.002	0.005	0.007	0.018	0.065
Hausman test	214.39***	182.38***	161.56***	108.15***	55.17***
Robust Hausman test	93.78***	80.43***	67.03***	55.60***	36.47***

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The constant is included but not reported.

As shown in Table 4.5 and 4.6, the original and robust Hausman tests strongly reject, at the less than 1% significance level, the null hypotheses of random individual effects for all the specifications; thus, the models are estimated using fixed effects.

As a preliminary remark, note that the BCCs operate in the same fiscal jurisdiction, which implies that they share many tax policies at the corporation level in common. This effect conditions my estimations on two profiles. In more detail, the neighboring effects do not disappear, even for the farthest distance decay parameter considered in my specifications (68.63 km), meaning that even for large distances, neighbor effects persist. Additionally, my models perform better in explaining the within-firm effects over time

Table 4.6: Estimation results of non-spatial and spatial panel-data regression models, using $ETR2$ as dependent variable

Variable	Fixed Effects	Spatial Fixed Effects			
		σ_{min}	σ_{01p}	σ_{02p}	σ_{mm}
	(6)	(7)	(8)	(9)	(10)
$\boldsymbol{W} \times ETR2$		0.1507*** (0.033)	0.2428*** (0.043)	0.3988*** (0.054)	0.6487*** (0.060)
$Lerner$	0.0912* (0.048)	0.1016** 0.048)	0.1047** (0.048)	0.1039** (0.048)	0.1076** (0.047)
$Post-Sanction$	-0.0797*** (0.023)	-0.0684*** (0.023)	-0.0612*** (0.023)	-0.0504** (0.023)	-0.0325 (0.023)
$Employees$	-0.0008*** (0.000)	-0.0007*** (0.000)	-0.0007*** (0.000)	-0.0006*** (0.000)	-0.0004*** (0.000)
$Loan\ to\ Assets$	0.2196*** (0.039)	0.1986*** (0.039)	0.1833*** (0.039)	0.1528*** (0.038)	0.1180*** (0.038)
ΔGDP	-0.1193** (0.057)	-0.1043** (0.050)	-0.0938** (0.045)	-0.0791** (0.038)	-0.0573** (0.029)
No. Observations	2,072	2,072	2,072	2,072	2,072
No. Banks	259	259	259	259	259
Within R^2	0.082	0.102	0.115	0.133	0.158
Between R^2	0.064	0.072	0.078	0.089	0.094
Overall R^2	0.037	0.049	0.059	0.077	0.108
Hausman test	93.19***	78.69***	68.91***	50.77***	28.76***
Robust Hausman test	49.88***	49.78***	41.21***	35.71***	25.96***

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The constant is included but not reported.

rather than the variation between banks.

Tables 4.5 and 4.6 report the estimation results of the spatial panel data models to determine if a spatial model is more appropriate for estimation. I find that neighbors' tax aggressiveness positively affects the i_{th} BCC tax management for the two proxies adopted and along the four dispersion parameters, with a statistical significance of less than 1%. Therefore, the neighboring BCCs' tax behavior matters in defining the fiscal strategy: as the nearby banks adopt tax avoidance behavior, the i_{th} BCC tends to favor tax aggressiveness, and vice versa.

This effect could be charged to reputational concerns that arise for a local bank pursuing benefits that stress tax avoidance policies. In the niche market of local banks, depositors could impose a kind of market discipline by penalizing opportunistic fiscal behavior for a specific bank. Thus, firm tax behavior in a given area is determined by the characteristics of the area, but is also influenced by the characteristics of neighboring banks (e.g., Frank et al., 2009; Chen et al., 2010; Coccorese et al., 2016; Chen and Lin, 2017).

Tables 4.5 and 4.6 also show that the statistical and positive coefficients for the variable $Lerner$ imply that less market competition reduces the tax avoidance strategies. Therefore, the monopoly rent decreases the incentive to use tax management behaviors. Although the relationship between bank competition (or market power) at the bank level and tax management strategies has not been sufficiently examined yet, similar results have been found for the firms market (e.g., Cai and Liu, 2009; Wang, 2012; Brown and

Drake, 2014): more market competition stimulates greater tax avoidance behaviors.

The coefficient for the dummy variable $Post-Sanction$ has a negative and statistically significant effect for both the tax aggressiveness proxies. Therefore, the sanctioned BCCs tend to adopt more tax avoidance behaviors in the years after an administrative procedure.[13] A possible explanation is that most BCCs have been sanctioned because of weaknesses in their credit decision process.[14] Consequently, in the year in which the penalties are imposed, bank management accounts for the impaired loans surfaced by the supervisor's report, which determines losses that in turn reduce the bank's fiscal burden in the following years.

With regard to the effects of the size proxy ($Employee$) on tax aggressiveness, I detect that the larger BCCs have greater possibilities to perform tax management strategies. Such effects concur with previous studies (e.g., Zimmerman, 1983; Rego, 2003; Hanlon et al., 2005; Kraft, 2014; Taylor and Richardson, 2013; Richardson et al., 2015) showing a significant positive relationship between company size and tax avoidance. Thus, more economies of scale increase tax avoidance initiatives.

The positive and statistically significant connection between $Loan\ to\ Assets$ and both the dependent variables could reflect the reduced aptitude of the lending activities in fostering tax management from banks. On the contrary, more involvement in non-credit investments increases the tax avoidance activities. Finally, the negative and significant effects of the growth rate of GDP at the provincial level suggests that BCCs follow a cyclical pattern.

4.4 Conclusions

In this study, I applied a spatial econometrics approach to analyze the tax aggressiveness of small cooperative banks, proxied by two effective tax rates measures. I conducted this empirical research on a dataset of small Italian cooperative banks, since the characteristics of the Italian banking market, alongside the various disparities in terms of economics and demographics between regions, form an important laboratory to verify the hypothesis that spatial dependence can affect tax avoidance behaviors of small banks.

My empirical results provide strong evidence regarding the existence of spatial autocorrelation in the tax aggressiveness variable. Including a spatial operator in the

[13] In separate specifications, I tested the effect of the sanction in the same year, but it was never significant.

[14] In my sample, more than the 70% of the fines imposed by supervisors are related to deficiency of the banks in their procedure for granting credit.

specification explaining local banks' tax behaviors improves its explanatory performance, which otherwise suffers from an omitted variable bias.

The spatial panel regression models show a positive and significant effect regarding the influence of the neighborhood on the tax management policies of small cooperative banks, along the dispersion parameters adopted. I interpret my results as evidence of the existence of reputational concerns that restrict bank management in following tax aggressiveness policies. As cooperative banks compete mainly among themselves, the spreading of rumors regarding incorrect tax behaviors of a certain bank could induce customers to withdraw deposits. Thus, tax aggressiveness strategies are pursued only under the conditions of similar behaviors from their competitors.

Additionally, I also find that a bank's market power reduces its tax aggressiveness. Finally, administrative sanctions negatively affect the tax avoidance activities in the following years. Since bank supervisor sanctions mainly affect the credit policies of the banks, the resulting losses arising from impaired loans rest on the same year of the sanction, lightening the bank's tax for the following years.

Overall, the empirical results in this study, highlighting the importance of considering the spatial co-movements of local banks for their tax planning activities, open avenues for further research in a cross-country context. Moreover, the availability of infra-annual data could strongly improve the accuracy of local banks' tax aggressiveness.

CHAPTER 5

SPATIAL DEPENDENCE IN NON-PERFORMING LOANS OF SMALL COOPERATIVE BANKS: EVIDENCE FROM ITALY

Abstract

This study investigates the existence of spatial dependence in the Non-Performing Loans ratio of Italian small cooperative banks, a model of local banking. Since these banks operate in a delimited area, their recovery strategies for bad loans can produce spatial spillover effects in neighboring banks' ability to recover credit. My empirical estimations provide strong evidence that both spatial and spatial-temporal variables improve the analytical model by identifying the drivers of impaired loans for local banks. Specifically, the empirical results underline a different effect of the spatial terms, highlighting a direct impact of the contemporaneous spatial lag variable and a negative effect of the space-time autoregressive coefficient. Whereas the former effects can be ascribed to changes in the macroeconomic cycle, the latter confirms the insight that neighboring credit recovery policies can harm local banks' recovery abilities. Moreover, I also control for market power at the bank level, providing evidence supporting the competition-stability view.

Keywords: Non-Performing Loans, Local banks, Spatial Dynamic Data Panel Model, Spatial Dependence, Bad Loan Recovery, Lerner Index.

5.1 Introduction

Non-performing loans (NPLs hereafter) are usually defined as loans for which interest and principal payments have been past due for at least 90 days (Lee et al., 2019). NPLs represent a backward-looking measure of credit risk, as well as an indicator of banks' asset quality and the soundness of their loan portfolios (Irina and Angela, 2016; Behr and Wang, 2020; Davis et al., 2020). Evocatively, they are termed "financial pollution," reflecting their adverse impact on bank soundness (González-Hermosillo, 1999; Nkusu, 2011). Indeed, high levels of NPLs and higher NPL volatility often indicate the start a banking crisis and continue throughout the crisis (Reinhart and Rogoff, 2011; Ari et al., 2019).

Many studies have been carried out on the determinants of non-performing loans, including several systematic literature reviews (e.g., Quagliariello, 2008; Nikolopoulos and Tsalas, 2017; Manz, 2019; Naili and Lahrichi, 2020) and a recent meta-analysis exploring the credit risk-business cycle relationship (Chortareas et al., 2020). Previous empirical studies mainly considered macroeconomic factors and bank-specific variables. In fact, Louzis et al. (2012) argued that to examine the determinants of bank loan quality, scholars should consider not only systematic risk but also bank-level variables.

The literature relating the business cycle to bank loan portfolio soundness rests on the financial accelerator theory (Gertler and Bernanke, 1989) and enumerates several measures that proxy the macroeconomic condition. Indeed, many of these studies adopt the real gross domestic product (GDP) as a driver of NPLs; Chortareas et al. (2020), for instance, performed a meta-regression analysis on the effect of GDP growth on NPLs. The literature also uses the unemployment rate to represent the economic cycle in empirical models explaining credit risk (e.g., Dimitrios et al., 2016). Finally, interest rate, price level and exchange rate, and stock and house price are often included in models on the determinants of NPL (Beck et al., 2013a; Manz, 2019). For emerging countries, Kuzucu and Kuzucu (2019) found a direct relationship between foreign direct investments and bad loans.

Turning to the bank-level factors affecting NPLs, empirical studies have tested several related profiles, such as managerial behavior, bank performance, economic information, and corporate governance. Berger and DeYoung (1997) focused on the negative effect of cost efficiency and moral hazard on bank credit-portfolio soundness (a similar analysis regarding European banks is in Williams (2004), while Podpiera and Weill (2008) analyzed transition countries). In more detail, Berger and DeYoung (1997) tested four causes of cost efficiency affecting bank portfolios: moral hazards, "bad management," "bad luck," and "skimping." They showed that bad management caused a larger increase in NPLs than any of the other three tested in the study. Low-quality bank management made banks unable to sufficiently evaluate the borrower creditworthiness and monitor it over time, negatively affecting bank credit risk. Similarly, the "bad luck" hypothesis postulates a negative effect of exogenous occurrences on bank cost efficiency, as external negative factors burst NPLs and created more costs. Under the "skimping" hypothesis, banks pursuing a myopic strategy that allocates few resources to credit functions increased their short-term cost efficiency, but paved the way for an increase of NPLs in the long run. Finally, the management of low capitalized banks can adopt moral hazard behavior with the ultimate effect of increasing NPLs.

Among many others, Louzis et al. (2012) provided evidence of the dynamic relationship between bank performance indicators and credit portfolio soundness, while Makri et al. (2014) and Ghosh (2017) focused on accounting-based profitability indicators and NPLs. A stream of literature has posited information asymmetry problems as determinants of NPLs. Specifically, less capitalized banks can suffer from moral hazard issues and end up taking more risk, increasing problematic bank loans (Keeton et al., 1987; Berger and DeYoung, 1997; Salas and Saurina, 2002). In this vein, the well-known too-big-to-fail principle (Stern and Feldman, 2004), according to which larger banks can rely on government support if their financial instability is impaired, can be adopted to explain increasing NPLs. In addition, the standard adverse selection approach (Stiglitz and Weiss, 1981) can be useful to explain bad bank loans.

Interestingly, Ghosh (2015), carrying out an estimation based on macroeconomic data, showed that region-level economic conditions are key determinants of NPLs for US commercial banks and savings institutions. In this respect, it can be assumed that the dynamic NPLs of local banks are also affected by local macroeconomic data - and consequently, that spatial dependence affects these banks' NPLs.

To the best of my knowledge, no previous studies have verified the existence of spatial co-movements in the loan portfolio risk levels of local banks. This lack of research is surprising, since the management of NPLs, particularly for local banks, can be strongly influenced by neighboring effects. In fact, the procedures adopted by a bank to deal with its own bad loans stock (mainly foreclosures, bankruptcies, arrangements with creditors, restructuring agreements, recovery plans, and out-of-court agreements, but also portfolio straight sales or securitization; see Carpinelli et al., 2017) can convey individual effects on the neighboring banks' efficiency in handling NPLs. For instance, it is well known that foreclosures have spillover effects which end up lowering the price of nearby houses (see Frame, 2010) for a literature review and Campbell et al. (2011) and Gerardi et al. (2015) for additional insights), which in turn jeopardize loan recovery from other banks at a later stage. Similarly, relevant negative externalities for a local economy arise as a consequence of the liquidation of bankrupt firms (e.g., Bernstein et al., 2019) impairing the ability of nearby banks in their debt collection process.

To address this research gap, this study first tests whether spatial dependence exists in the loan portfolio soundness of local banks. Measuring this potential spatial correlation requires an adequate spatial model, since standard econometric estimators can suffer from mis-specification. Next, by means of regression analysis, I verify whether the spatial terms included to control for the neighboring effects are statistically significant, shedding light on the causes of local banks' NPLs. In more detail, my model includes both spatial and spatial-temporal variables, considering not only the current level of neighboring NPLs but also the previous year's levels. Indeed, this empirical strategy for considering two spatial operators is strongly recommended to deal with spatial dependence and spatial heterogeneity in the data; otherwise, the model could not overcome the bias problem caused by spatial interactions (Tao and Yu, 2012).[1] Due to the persistence of NPLs (Tabak et al., 2011; Tajik et al., 2015; Gulati et al., 2019), the regression analysis calls for the adoption of a dynamic panel model, which I perform by using a System-GMM estimator to overcome possible endogeneity issues. Finally, I run a set of diagnostic tests to assess the hypothesis that the spatial techniques treat the spatial co-movement among the variables of my model and therefore using them is required to avoid the consequent bias.

The outline of the article proceeds as follows. Section 5.2 discusses the spatial econometrics methodology. Section 5.3 presents the data and variables employed in the empirical analysis. Section 5.4 shows and discusses the statistical tests to control for the existence of spatial dependence in my sample and the empirical estimation of my equation. It also discusses the residuals of the estimation, which are important for verifying the cross-sectional dependence after the treatment. Finally, Section 5.5 concludes the study and offers some closing remarks.

[1]Several empirical studies adopt both spatial and spatial-temporal variables (Ho et al., 2013; Han et al., 2017; Basile et al., 2018; Li and Yang, 2020; Servén and Abate, 2020).

5.2 Spatial methodology

The development of sophisticated spatial techniques is linked to recent advances in spatial econometrics. A basic model involving the presence of spatial terms was proposed by Cliff and Ord (1981), but several significant theoretical extensions were introduced after the mid-1990s.

To treat co-movement among cross-sectional units located in different geographic areas, the spatial econometrics literature has drawn up methods to incorporate spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in linear regression models (Elhorst, 2014). Spatial dependence describes the relationship between a single spatial observation and a neighboring one through the exploitation of Tobler's first law of geography (Tobler, 1970). Such relationship is termed as spatial autocorrelation, which is a weaker expression of spatial dependence (Anselin, 2003).

In my empirical investigation, I make use of the Spatial Dynamic Panel Data (SDPD) model (Elhorst, 2005, 2010b, 2014; Yu et al., 2008; Lee and Yu, 2010b,c, 2014; Shi and Lee, 2017; Hory, 2018; Jeong and Lee, 2020), which allows me to model the spatial interdependence among panel units. More specifically, I consider the Time-Space Dynamic (TSD) model suggested by Anselin et al. (2007), using the GMM estimator (Bouayad-Agha and Védrine, 2010; Cainelli et al., 2014; Segura III, 2017; Donfouet et al., 2018). My model is represented by the following equation:

$$y_{i,t} = \vartheta y_{i,t-1} + \delta \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{i,t} + \varrho \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{i,t-1} + \mathbf{z}_{i,t}\tau + (\mu_i + \varepsilon_{i,t}) \tag{5.1}$$

$$|\vartheta| < 1, \ |\delta| < 1, \ |\varrho| < 1; \quad i = 1 \dots N; \quad t = 1 \dots T$$

where $y_{i,t}$ and $y_{i,t-1}$ denote the value of the dependent variable y and its lagged value (one period lag) for individual i at time t. $\sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{i,t}$ and $\sum_{j \neq i} \boldsymbol{w}_{ij} \cdot y_{i,t-1}$ represent a first-order spatial lag of the dependent variable (with respect to the spatial weight matrix $\boldsymbol{W}$) and its time-lagged value, respectively. $\mathbf{z}_{i,t}$ is a $(k \times 1)$ vector of explanatory variables, and $(\mu_i + \varepsilon_{i,t})$ is the decomposition of the error term.[2] Finally, ϑ, δ, ϱ, and τ are unknown parameters to estimate.

In Equation (5.1), ϑ catches the serial dependence of the dependent variable, while the parameters δ and ϱ capture the intensity of the contemporaneous and non-contemporaneous spatial dependence, respectively, under the following constraint: $|\vartheta + \delta + \varrho| < 1$.[3]

[2]With regard to the erratic component, μ_i means the individual effect and $\varepsilon_{i,t}$ is the random error, normally distributed with zero mean and unit variance.

[3]For more specifics about the analysis of the unit root of a SDPD model, see Yu and Lee (2010).

Spatial econometric models allow researchers to deal with the effect of spatial connections among variables via the specification of a spatial matrix. Therefore, the spatial weighting matrix $\boldsymbol{W}$ is the main element for spatial investigation. To build the spatial and spatial-temporal variables (generally indicated with $\boldsymbol{W}y_t$ and $\boldsymbol{W}y_{t-1}$), as well as the estimate of the spatial dependence tests, a well-balanced panel dataset is required (Elhorst, 2014; Millo, 2014; Chi and Zhu, 2019).

Let n be the number of cross-sectional units. $\boldsymbol{W}$ is a non-negative, fixed, and non-stochastic $n \times n$ matrix of spatial weights with zero on the principal diagonal (Cliff and Ord, 1968; Kelejian and Prucha, 2010),[4] where each element ($w_{ij} : i, j = 1, \dots, n$) for each pair of geographic locations assumes the following properties:

(i) $w_{ij} = 0$ if i and j are spatially unconnected;

(ii) $w_{ij} \neq 0$ if i and j are spatially connected.

To shape the geographical interactions between spatial units, I construct the exogenous spatial matrix $\boldsymbol{W}$ in Equation model (5.1) , making use of a Gaussian kernel matrix (Lu et al., 2014; Otranto et al., 2016; Otranto and Mucciardi, 2019),[5] in which the weight w_{ij} is a continuous and monotonic decreasing function of the Euclidean distance between i and j (Fotheringham et al., 2003).

In my kernel matrix, according to the standard concept of contiguity, the Gaussian distance decay-based weighting function for determining w_{ij} is given by:

$$w_{ij} = \begin{cases} \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{\lambda}\right)^2\right], & \forall i \neq j \\ 0, & \forall i = j \end{cases} \tag{5.2}$$

where d_{ij} is the geographical distance between point i and point j, and λ is a non-negative dispersion parameter (bandwidth) that generates an influence decay with increasing distance. If the bandwidth varies, the exponential decay profile changes, forming weights that vary more or less rapidly over space. Therefore, as the distance between the cross-sectional units i and j increases, the weighting of other data will decrease according to a distance-decay curve (Fotheringham et al., 1998). For geographic units far away from i, the weight w_{ij} tends toward zero. The use of a Gaussian kernel function is especially helpful since the dispersion parameter λ gives a check for the circular area of

[4]The values on the main diagonal are equal to zero by definition, as no unit is spatially correlated with itself; thus, $w_{ii} = 0$ for all $i = 1, \dots, n$.

[5]Remember, the Gaussian kernel is positive definite (Cristianini et al., 2000; Hofmann et al., 2008).

influence for each spatial data. Finally, the kernel matrix is row-normalized so that the sum of elements in each row is equal to one.

Under the hypothesis of constant distance, the Gaussian kernel matrix $nt \times nt$ in the panel data framework is determined as follows (Anselin et al., 2007):

$$\boldsymbol{W}_{nt} = \boldsymbol{I}_t \otimes \boldsymbol{W}_n \tag{5.3}$$

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

5.3 Data and empirical equation

My empirical study is based on a panel of annual data from 259 Italian cooperative banks (Banche di Credito Cooperativo, BCCs), ranging from 2011 to 2018 for a total of 2,072 observations. As explained above, the SDPD model requires a strongly balanced panel dataset, so I remove all the banks that do not report data over the whole period considered.[6]

The data are drawn from the Bureau van Dijk Orbis Bank Focus' (BvD Orbis) database.[7] By geocoding the address of each BCC's headquarters via the geographic coordinates (latitude and longitude), I provide a geo-reference for each (single) observation. Figure 5.1 shows the BCC headquarters' spatial distribution.

In order to provide valid and unbiased inference and face the endogeneity problem, I consider the System Generalized Method of Moments (SYS-GMM) method advanced by Arellano and Bover (1995) and Blundell and Bond (1998).[8] In this regard, the GMM specifications are estimated with Windmeijer (2005) finite sample correction and with forward orthogonal deviation (FOD) transformation. All the control variables are lagged one period.

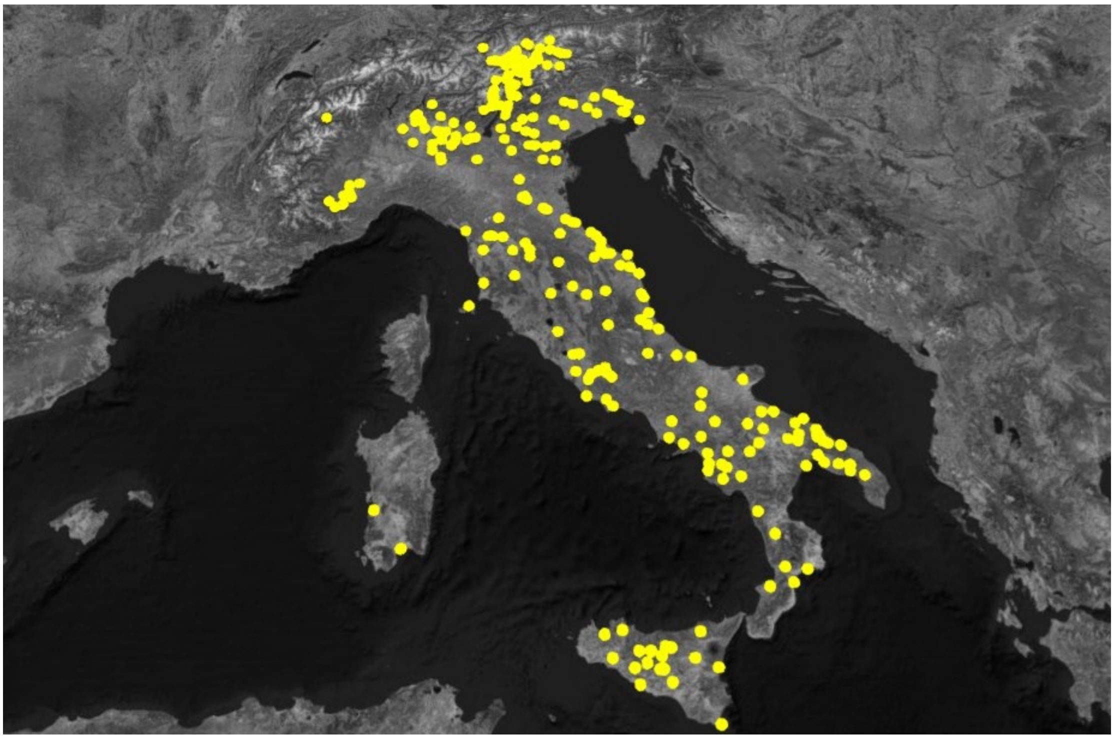
The empirical equation of the TSD model is as follows:

[6] Based on the intermediaries list on the Bank of Italy website, as of December 31, 2018 there were 268 credit cooperative banks (see https://infostat.bancaditalia.it/GIAVAInquiry-public/ng/).

[7] To build a strongly balanced dataset, the missing values were filled in using the balance sheets published on the banks' respective websites.

[8] SYS-GMM is preferable over the Difference GMM estimator (Arellano and Bond, 1991) when the variables are highly persistent over time and to reduce simultaneity bias (for insights, see Alonso-Borrego and Arellano, 1999; Blundell and Bond, 1998, 2000), as in my case (see, among others, Beck et al., 2013a).

Figure 5.1: Geographical dislocation of Italian BCCs



$$
\begin{aligned}
NPL_{i,t} = {} & \alpha + \beta NPL_{i,t-1} + \varsigma \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot NPL_{i,t} + \phi \sum_{j \neq i} \boldsymbol{w}_{ij} \cdot NPL_{i,t-1} \\
& + \varphi Lerner_{i,t-1} + \gamma Debt_{i,t-1} + \iota Z-Score_{i,t-1} + \kappa FX_{i,t-1} \\
& + (\mu_i + \varepsilon_{i,t})
\end{aligned}
\tag{5.4}
$$

The dependent variable of my spatial model is NPL, which is defined as the ratio of non-performing loans to total gross loans (Ghosh, 2017; Cucinelli et al., 2018; Karadima and Louri, 2020). My specification model incorporates three different kinds of covariates. First, the spatially lagged dependent variable and its lagged value. Second, the Lerner index estimated at the bank level, as a measure of bank competitiveness. Lastly, a set of bank-specific control variables.

The first-order spatial lag operator is obtained by multiplying the dependent variable (NPL) by three spatial weighting matrices. In more detail, I consider a kernel matrix with three distance-decay parameters (bandwidths) expressed in kilometers (km):

(1) $\lambda = \text{Minimum}(d_{ij}) = \lambda_{min}$

(2) $\lambda = 0.01[\text{Maximum}(d_{ij})] = \lambda_{01p}$

(3) $\lambda = 0.02[\text{Maximum}(d_{ij})] = \lambda_{02p}$

where λ_{min} (equal to 3.6 km) represents the minimum distance so each bank has at least one neighbor, λ_{01p} (equal to 13.37 km) corresponds to 1 percent of the maximum distance between two BCCs (1336.6 km) and λ_{02p} (equal to 26.73 km) corresponds to 2 percent of the maximum distance.

My specification also controls for the banking market-competition degree, following Natsir et al. (2019). Empirical research has widely confirmed that market power affects bank stability, but has provided ambiguous results regarding the direction of the effect. In particular, according to the competition-fragility view, more market power induces bank management to pursue a less risky strategy to preserve the rent arising from the market structure (Keeley, 1990). Alternatively, the competition stability hypothesis is based on the assumption that high rates on the loan market following by high market power can trigger classical moral hazard and adverse selection issues, stressing the positive effect of competition on banking soundness (Boyd and De Nicolo, 2005).

There is no shortage of studies suggesting a non-linear relationship between the relevant variables (Martinez-Miera and Repullo, 2010). To check for this effect, I have added the Lerner Index (Lerner, 1934) in my model, the well-known measure of a firm's ability to establish prices above its marginal cost, which is a standard measure adopted in the banking literature to measure the degree of market power (e.g., Ariss, 2010; Cipollini and Fiordelisi, 2012; Spierdijka and Zaourasa, 2018; Clark et al., 2018; Coccorese and Ferri, 2020; Degl'Innocenti et al., 2020; De-Ramon and Straughan, 2020).

For this purpose, I calculate the index as follows:

$$Lerner = \frac{P_{i,t} - MC_{i,t}}{P_{i,t}} \tag{5.5}$$

where $P_{i,t}$ is the bank price and $MC_{i,t}$ represents the marginal cost. Higher values indicate greater market power. The price of a bank is obtained by dividing its total revenues (the sum of interest and non-interest income) by total assets, whereas, in line with recent studies (Fiordelisi and Mare, 2014; Coccorese and Santucci, 2019; Coccorese and Ferri, 2020; Degl'Innocenti et al., 2020), the bank's marginal cost is estimated using a translog cost function with one output (total assets) and three input prices (price of labor, price of physical capital, and price of borrowed funds).

The translog specification is given by:

$$
\begin{aligned}
lnTC_{i,t} = {} & \xi_0 + \xi_1 lnQ_{i,t} + \frac{1}{2}\xi_2 lnQ_{i,t}^2 + \sum_{k=1}^{3}\phi_k lnP_{k,i,t} \\
& + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3}\theta_{k,j} lnP_{k,i,t} lnP_{j,i,t} + \frac{1}{2}\sum_{k=1}^{3}\sigma_k lnQ_{i,t} lnP_{k,i,t} + u_{i,t} + v_{i,t}
\end{aligned}
\tag{5.6}
$$

where $TC_{i,t}$ represents the total cost of the i_{th} bank at time t (i.e., total operating expense) and Q is the bank one output proxied by total assets. P_1, P_2 and P_3 are the three inputs: P_1 is the labor price (i.e., staff expenses divided by total assets), P_2 is the physical capital price (i.e., other administrative expenses over total assets), and P_3 is the borrowed funds price (i.e., interest expenses on bank funding). ξ, ϕ, θ, and σ are unknown coefficients to be estimated. Finally, $u_{i,t}$ and $v_{i,t}$ are the two components of the error term. The two-sided error term, $v_{i,t}$, symbolizes the usual statistical noise i.i.d. as $N(0,\sigma_v^2)$, the one-sided error term, $u_{i,t}$, capturing the actual cost inefficiency term, is modeled as a truncated non-negative random variable $N^+(0,\sigma_u^2)$.

Once the coefficients from Equation (5.6) are estimated, the marginal cost of bank i at time t is calculated through the partial derivatives of the mentioned equation with respect to the bank output Q. The formula is expressed below.

$$
MC_{i,t} = \frac{\partial C_{i,t}}{\partial Q_{i,t}} = \frac{\partial lnC_{i,t}}{\partial lnQ_{i,t}}\frac{C_{i,t}}{Q_{i,t}} = \left(\hat{\xi}_1 + \hat{\xi}_2\, lnQ_{i,t} + \sum_{k=1}^{3}\hat{\sigma}_k\, lnP_{k,i,t}\right)\frac{C_{i,t}}{Q_{i,t}}
\tag{5.7}
$$

Regarding the remaining control variables, the description and expected signs are as follows.[9]

Debt is the ratio of total bank funding (i.e., short- and long-term debts) to total assets and is a measure of bank capitalization, the backbone of bank regulation. In fact, capital is the buffer to cushion potential bank losses and their possible consequences such as bankruptcy and/or restructuring. The moral hazard hypothesis predicts an indirect effect of bank capitalization on NPLs and this forecasting is confirmed in the empirical literature (for instance, Berger and DeYoung, 1997; Salas and Saurina, 2002).

$Z-Score$ is the ratio of return on assets (ROA) plus the equity to assets ratio to the standard deviation of ROA, and is a measure of bank soundness (Houston et al., 2010). The greater the value, the greater the bank's soundness (Shim, 2019). More stable banks

[9]Explanatory and control variables have been tested for multicollinearity considering the Variance Inflation Factor (VIF). The mean VIF is equal to 1.57, and no VIF value exceeds 2.0.

tend to be less risky and therefore grant loans to more creditworthy applicants (Ozili, 2019). As a consequence, the expected sign is negative.

FA is the ratio of fixed assets to total assets (Campello and Giambona, 2010) and controls for the degree of bank opaqueness, since the more fixed assets the bank has, the more transparency it exhibits. Fixed assets mainly include real estate and premises owned by the bank, which are less opaque and harder to change than the bank's financial assets (e.g., loan and trading assets) (Morgan, 2002; Iannotta, 2006). In my view, controlling for local bank opacity should allow me to discern the bank's credit risk strategy, which in turn affects the NPL level. Handling an increase in NPLs requires either raising more capital or downsizing bank assets, but proceeding with a capital increase can be very difficult for a local cooperative bank and downsizing can imply devaluation in the sold assets (Spargoli, 2012). Consequently, to preserve the high net present value of its fixed assets, a bank can pursue a less risky credit strategy. Therefore, I expect an indirect effect of the variable on the NPLs.

Table 5.1 lists all the variables employed in this study as well as their description and the specific data sources, whereas Table 5.2 reports the descriptive statistics for the explanatory variables considered in my specifications.

Table 5.1: List of variables

Variable	Description	Source
NPL	Non-performing loans/Gross loans	BankScope/BankFocus
$Lerner$	Lerner Index	Author's calculations
ROA	Net income/Total assets	BankScope/BankFocus
$Equity$	Total equity (in thousand EUR)	BankScope/BankFocus
$Assets$	Total assets (in thousand EUR)	BankScope/BankFocus
$Debt$	(Short-term + Long-term debts)/Assets	BankScope/BankFocus
$Z-Score$	(ROA+Equity/Assets)/$\sigma(ROA)$	Author's calculations
FA	Fixed assets/Assets	BankScope/BankFocus
TC	Sum of personnel expenses, other administrative expenses, and other operating expenses	BankScope/BankFocus
Q	Total bank assets	BankScope/BankFocus
P_1	Personnel expenses/Total assets	BankScope/BankFocus
P_2	Other administrative expenses/Total assets	BankScope/BankFocus
P_3	Interest expenses/Total funds	BankScope/BankFocus
$Price$	Total revenue/Total assets	BankScope/BankFocus

Notes: This table exhibits a detailed description of the variables and the data sources.

The data refer to the period 2011-2018, with a total of 2,072 strongly balanced observations. Among the variables involved in my analysis, I note that the means (except for the $Z-Score$) are higher than the standard deviation, thus denoting that

Table 5.2: Summary statistics

Variable	No. Obs.	Mean	Std. Dev.	Min	Max
NPL	2,072	0.142	0.076	0	1.30
$Lerner$	2,072	0.322	0.214	-6.622	0.821
$Debt$	2,072	0.892	0.043	0.005	0.985
$Z-Score$	2,072	0.718	1.052	-9.915	9.712
FA	2,072	0.014	0.008	0.001	0.061

my sample is made up of banks with quite similar characteristics. The $Z-Score$ and $Lerner$ variables present negative values. For $Z-Score$, such values are due to negative profitability, while for $Lerner$ it involves only 0.91 percent of the data reflecting a total of 19 observations. According to Fiordelisi and Mare (2014), this trend demonstrates the sample's representativeness, showing that it includes BCCs with high fixed costs (e.g., starting up the intermediation activity).

Table 5.3 provides the correlation matrix for the selected variables with significance levels. As can be noted, there exists a significant (negative) correlation between NPL and $Z-score$ (-0.29), reflecting the case in which a greater bank soundness, or a reduction in its default probability, lead to a higher resilience on the part of banks, as expected. The correlation coefficients among all the explanatory varibales do not denote multicollinearity issues; however, explanatory and control variables have been tested for multicollinearity considering the Variance Inflation Factor (VIF, Neter et al., 1989). The mean VIF is equal to 1.57, and no VIF value exceeds 2.0.

Table 5.3: Correlation matrix for the regressor variables presented in Table 5.2

	1.	2.	3.	4.	5.
1. NPL_t	1				
2. $Lerner_{t-1}$	0.1088*	1			
3. $Debt_{t-1}$	0.2430*	0.0201	1		
4. $Z-Score_{t-1}$	-0.2914*	0.2652*	-0.3047*	1	
5. FA_{t-1}	0.0078	-0.1445*	-0.0824*	-0.0685*	1

Notes: This table exhibits the correlation coefficients of the variables used in the empirical investigation over the period 2011-2018. * denotes significance at the 5% level or better.

5.4 Empirical evidence and discussion

This section provides the empirical results of the analysis. First of all, I exhibit the statistical tests used to control for the existence of spatial dependence. After this, I show and discuss the GMM estimates to explain the spatial interaction effects among cooperative banks. Finally, I report the cross-section independence test to assess the robustness of the spatial models.

5.4.1 Testing for spatial dependence

In order to check the existence of spatial dependence, I ran different Lagrange Multiplier (LM) tests to look for serial correlation, spatial autocorrelation, and random effects in my sample. Neglecting spatial dependence, when it is present in the data, leads to misspecification and biased (inaccurate) estimates (Anselin and Florax, 1995; Moscone et al., 2014; Zhang et al., 2017; Kutlu and Nair-Reichert, 2019). Table 5.4 sets out all the diagnostic tests.

Table 5.4: LM test for spatial, serial correlation and random effects

LM test description	Statistic	P value
Anselin (1988)		
Conditional test for spatial error autocorrelation		
(H_0: spatial error autoregressive coefficient equal to zero)	9.18	< 0.01
Conditional test for spatial lag autocorrelation		
(H_0: spatial lag autoregressive coefficient equal to zero)	20.79	< 0.01
Baltagi et al. (2003)		
Joint test		
(H_0: absence of random effects and spatial autocorrelation)	1748.40	< 0.01
Marginal test of random effects		
(H_0: absence of random effects)	37.73	< 0.01
Marginal test of spatial autocorrelation		
(H_0: absence of spatial autocorrelation)	18.03	< 0.01
Conditional test of spatial autocorrelation		
(H_0: absence of spatial autocorrelation, assuming random effects are non null)	15.03	< 0.01
Conditional test of random effects		
(H_0: absence of random effects, assuming spatial autocorrelation may or may not be equal to 0)	33.72	< 0.01
Baltagi et al. (2007)		
Joint test		
(H_0: absence of serial or spatial error correlation or random effects)	1836.60	< 0.01
One-dimensional conditional test		
(H_0: absence of spatial error correlation, assuming the existence of both serial correlation and random effects)	72.62	< 0.01
One-dimensional conditional test		
(H_0: absence of serial correlation, assuming the existence of both spatial error correlation and random effects)	162.75	< 0.01
One-dimensional conditional test		
(H_0: absence of random effects, assuming the existence of both serial and spatial error correlation)	119.70	< 0.01

The first series of LM tests controls for the presence of spatial correlation. The null hypothesis indicates that both the coefficient of spatial error autocorrelation and the coefficient of spatial lag autoregressive are equal to zero (Breusch and Pagan, 1980;

Anselin, 1988). Hence, the rejection of the null hypothesis permits me to deduct the presence of spatial interdependence. Test results reject the null hypothesis.

The second sequence of tests verifies the existence of spatial autocorrelation and random effects through the LM tests (joint and conditional) developed by Baltagi et al. (2003). The test results highlight that both the hypotheses of no spatial correlation and of no random effects are categorically rejected for all the test specifications. More specifically, the joint LM test confirms that at least one element, such as spatial error autocorrelation and/or random individual effects, exists in the error term. Likewise, these elements are tested individually through the marginal LM tests. The results of the tests reject the null hypothesis for both no spatial autocorrelation and no random effects, respectively. Furthermore, to validate the existence of spatial dependence, I also consider the conditional LM tests.[10] Test results reject the null hypothesis once more, disclosing the existence of both spatial correlation and random effects.

Lastly, the remaining group of tests proposed by Baltagi et al. (2007) verify spatial, serial correlation, and random effects jointly and conditionally. The joint LM test considers the existence of serial correlation left out in Baltagi et al. (2003), while the conditional LM tests permit me to assess the presence of each of them singly, under the assumption that the other two are non-null. The tests reject the null hypothesis, thus exhibiting the presence of serial correlation, and once again reaffirming the existence of spatial autocorrelation and random effects.[11]

The aforementioned diagnostic tests are connected to the spatial weighting matrix taken into account. Thus, as a robustness check for the co-movement among panel units, I also executed the Cross-sectional Dependence (CD) tests proposed by Pesaran (2004, 2015), following Sarafidis and Wansbeek (2012), Millo (2017), Yang (2020), and Elhorst et al. (2020). These tests control for strong and weak cross-sectional dependence, respectively; namely, as underlined by Chudik et al. (2011) and Vega and Elhorst (2016), they control for unobserved common factors (strong cross-sectional dependence) and spatial dependence (weak cross-sectional dependence). Table 5.5 presents the results of the tests, and shows the existence of both strong and weak cross-sectional dependence.

The evidence regarding the presence of spatial dependence calls for a particular

[10] More particularly, spatial autocorrelation is verified, permitting the presence of random effects, and random effects are verified, permitting the existence of spatial autocorrelation.

[11] All the LM statistical tests are estimated using the splm package built by Millo and Piras (2012). The results of the tests shown in Table 5.4 were obtained by using the spatial matrix $\boldsymbol{W}$ with the minimum bandwidth; however, the tests were also calculated utilizing the remaining two weighting matrices. Given that the results point to the same evidence, I do not repeat them to save space, but they can be provided on request.

Table 5.5: Testing for cross-sectional dependence

Test	Pesaran (2004)	Pesaran (2015)
CD	80.28	61.85
P-value	0.000	0.000

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

analytical methodology, such as spatial econometrics.

5.4.2 Estimation results

The empirical GMM estimates of the TSD model specified in Equation (5.4) are illustrated in Table 5.6, along with the outcomes of the dynamic panel data model.[12]

Table 5.6: Estimation results of TSD model for NPL

Variable	Dynamic Model	Spatial Dynamic Models		
		λ_{min}	λ_{01p}	λ_{02p}
	(1)	(2)	(3)	(4)
NPL_{t-1}	0.7524*** (0.047)	0.7681*** (0.038)	0.7547*** (0.039)	0.7366*** (0.039)
$Lerner_{t-1}$	0.1338*** (0.040)	0.0927*** (0.035)	0.0910*** (0.034)	0.0939*** (0.031)
$Debt_{t-1}$	-0.3026*** (0.094)	-0.2407*** (0.089)	-0.2227*** (0.084)	-0.2141*** (0.078)
$Z-Score_{t-1}$	-0.0164*** (0.005)	-0.0129*** (0.004)	-0.0130*** (0.004)	-0.0143*** (0.004)
FA_{t-1}	-0.0844 (0.452)	-0.2762 (0.362)	-0.1720 (0.339)	-0.1294 (0.283)
$\boldsymbol{W} \times NPL_t$		0.4799*** (0.081)	0.6357*** (0.088)	0.7476*** (0.104)
$\boldsymbol{W} \times NPL_{t-1}$		-0.3534*** (0.073)	-0.4661*** (0.081)	-0.5415*** (0.094)
No. Observations	1,813	1,813	1,813	1,813
No. Groups	259	259	259	259
No. Instruments	74	107	107	107
Years effects	Yes	Yes	Yes	Yes
AR(1)	0.1249	0.1253	0.1254	0.1205
AR(2)	0.5427	0.6643	0.8036	0.5645
Hansen test	0.1347	0.1634	0.3477	0.3353

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. 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.

[12] It should be underlined that all the GMM estimates were obtained using xtabond2 in Stata (Roodman, 2009a).

The instruments (107) are equal for all the SDPD specifications and there are fewer instruments than groups. The Hansen test result points out that the choice of instrumental variables is effective and the overidentifying restrictions are valid for all the SYS-GMM estimators. Furthermore, the Arellano-Bond first and second-order autocorrelation tests of the residuals (AR(1) and AR(2) tests) denote the non-rejection of the null hypothesis.[13] Together, these test results confirm that the estimates are dependable.

The parameters of the terms incorporating serial dependence, spatial dependence, and spatial-temporal dependence satisfy the assumption of global stationarity, i.e., the sum of the three coefficients is less than one along all the specification models. In line with previous studies (Tajik et al., 2015; Gulati et al., 2019), the NPLs present high persistence, as the coefficients associated with time-lagged terms are positive and statistically significant. Moreover, the magnitude of these coefficients is higher for all my TSD models (with just one exception).

Turning to the two spatial coefficients, they are highly statistically significant for all distances considered, and interestingly they present different signs for the contemporaneous and lagged term. In detail, the present NPL ratios of the neighboring local banks positively affect the same ratio of the i_{th} bank. This effect is not surprising and can be ascribed to exogenous macroeconomic effects which, in the short run, induce homogeneous variations of bad loan levels among the local banks, with little wiggle room to implement strategies for dealing with them. The negative signs associated with the space-time autoregressive coefficients mean that the higher (lower) NPL ratios of neighboring banks are, the lower (greater) the same ratio for the i_{th} bank is. This effect could mean that the recovery strategy of the local banks weakens the nearby banks' ability to recover their impaired loans. For example, an overhang of foreclosure sales reduces the house values in the same area, causing a negative spillover effect for nearby banks in collecting their impaired loans (Campbell et al., 2011).

From a different perspective, this result may reflect reputation issues arising from high NPL stock in bank balance sheets. Indeed, the literature shows that high NPLs, by impairing bank capital and increasing its costs, reduces a bank's ability to provide loans (recently, Chiesa and Mansilla-Fernández, 2020). For the local banks, this dynamic can trigger specific effects on the demand-loan side. Bearing in mind that local banks compete mainly among themselves (Coccorese et al., 2016), concerns regarding future credit tightening induces more creditworthy firms to require credit for local banks owning

[13] Roodman (2009a) emphasized that AR(1) exists by construction; thus, the absence or existence of autocorrelation needs to be tested at the AR(2) level.

low NPLs. This behavior induces more riskiness in the loan portfolio of local banks with high NPLs and in turn increases them.

The coefficients of the $Lerner$ variable are always statistically significant, taking a positive sign in the four specifications. Therefore, my evidence supports the competition-stability view hypothesis, as more bank market power implies more NPLs for the local banks. An interesting insight comes from comparing the magnitude of the $Lerner$ coefficient estimated in the model without the spatial lagged variables to the ones with the same coefficients estimated in the remaining three models. The first one is greater than the others, since it also captures the spatial autocorrelation present in data that the other models handle appropriately, resizing the bank market power on NPLs.

The remaining control variables take the expected sign along all the specifications and are statistically significant, except for FA_{t-1}.

5.4.3 Test for cross sectional independence

The existence of co-movement in the data, discussed in Section 5.4.1, calls attention to the effects of spatial relationships in the dynamic GMM model. The incorporation of spatial operators permits me to control for spatial dependence (weak cross-sectional dependence) among panel units. Nevertheless, common factors causing strong cross-sectional dependence could still exist even after the employment of spatial models.

To check this out, I conduct a post-estimation test using the CD test suggested by Pesaran (2004), in order to provide evidence regarding the presence of strong cross-sectional independence in the errors of SDPD specifications- namely, whether the inclusion of spatial terms treats the cross-sectional dependence. If the test results reject the latter hypothesis, the estimations show a different bias problem (Andrews, 2005; Bai and Ng, 2010).

Table 5.7: Testing for cross-sectional independence

Test	Time-Space Dynamic Models		
	λ_{min}	λ_{01p}	λ_{02p}
CD	0.925	-0.082	0.082
P-value	0.355	0.9344	0.9344

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

Table 5.7 summarizes the outcomes of the test, showing that the hypothesis of cross-sectional independence is not rejected for all the SDPD models, thereby giving evidence relating to the absence of unobserved common factors. The error term of all the spatial model specifications are unaffected by strong cross-sectional dependence. Thus, the spatial econometrics techniques employed in my empirical research address the issues tied to the interactions among spatial units.

5.5 Conclusions

This study uses a spatial econometrics approach to examine the neighbor effects on local banks' impaired loans ratios. I performed an empirical investigation employing a large sample of Italian cooperative banks over the years 2011-2018. Indeed, the NPL ratios for the BCCs, according to the preliminary LM and CD tests, are affected by spatial dependence that causes bias issues on the coefficients of the econometric models adopting NPLs as the dependent variable. In addition, the BCCs present a high degree of heterogeneity in terms of territorial coverage across the Italian regions.

I calculated three Gaussian kernel matrices by considering three different distance-decay parameters (3.6, 13.37, and 26.73 km), which I have used to determine six spatial variables to evaluate both the dependent and the lagged dependent variable. Hence, I estimated three SDPD models, through SYSGMM estimators, together with a model without spatial operators. Lastly, I checked for strong cross-sectional independence to ensure the robustness of the estimates.

My findings strongly support the existence of spatial autocorrelation in the NPLs of small cooperative banks, but surprisingly the neighbor effect is different for the contemporaneous and serially lagged spatial lags. In more detail, while the instantaneous spatial effect positively impacts the NPL ratios, namely an increase of neighbors' NPLs leads to an increase in the ith NPLs and vice versa, on the contrary the non-contemporaneous spatial effects are negative.

Whereas the positive simultaneous spatial spillover effect is the consequence of variations in the economic cycle that cause homogeneous movements in NPLs, the negative spatio-temporal spillover effect should be interpreted in terms of the recovery strategies of local banks. Specifically, the banks that maintain their recovery policies, throughout foreclosures, bankruptcies, and so on, increase their payback but determine the reduction in the house prices, which in turn harms collateral value and thus the capacity for recovering NPLs of nearby banks.

Likewise, reputation reasons can explain the negative signs of the time-lagged spatial terms. Specifically, high NPLs for a specific bank suggests possible credit rationing, which in turn induces highly creditworthy customers to switch credit providers by applying for loans at nearby banks. The outcome of this process is an enhancement of the loan portfolio of BCCs with low NPLs in the previous period, which ends up reducing their NPL ratios. My specification model also controls for the market competition effect via the Lerner Index. The results support the competition stability view, i.e., more bank competition enhances the soundness of small banks.

This investigation constitutes the first attempt to study the effects of simultaneous and non-simultaneous spatial dependence in the bad loans of small cooperative banks. My intriguing results about the different effects of the spatial and spatial-temporal terms on local banks' loan portfolio quality would benefit form a stress test, perhaps by using specific measures to control for the effects of recovery strategies as well as reputation indicators. Similarly, this study opens avenues for further research in other countries.

Chapter 6

Conclusion

6.1 Concluding Remarks

The present dissertation attempts to contribute to the literature by dealing with spatial dependence in the main risk, performance, and tax management indicators of local banks.

My work relies on a spatial econometric methodology and highlights the important role played by geographical spillover effects in cooperative banks' policies, as well as the ability to enhance the performance of econometric models. To sum up, more accurate estimates have been found when considering spatial interdependencies.

More precisely, I considered several spatial models that can be used to study other banking systems, for instance, in emerging countries with different development levels and diverse ownership structures. I decided to consider a spatial approach based on the punctual distance between spatial units in a particular system of cooperative banks such as Italy.

Relative to the existing literature, I contribute to the debate by pointing out the existence and significance of spatial dependence effects on managerial and policy choices of cooperative banks, a model of local banking. The estimation of all the spatial models has required the definition of several spatial weighting matrices for achieving the accuracy of the results.

To the best of my knowledge, this thesis extends the literature in several ways. In particular, the study conducted in Chapter 2 on the small-cooperative banks' risk performance contributes to the literature as follows. First, it supports the hypothesis that the inclusion of spatial operators enhances the small bank soundness models. Second, since this investigation controls for the banks' market power, it expands the literature concerning the relationship between bank risk and market competitive pressure, supporting the competition fragility view- namely, the bank monopolistic power enhances small bank soundness. Third, this study finds empirical evidence that the bank size does not affect the financial standing of the small banks. Finally, as this study proxies bank soundness with the *Z-Score* index, it indirectly tests the impacts on small firms of the relationship lending, a classic tool adopted by the small banks to assess the creditworthiness of small firms. Overall, these finding strongly support the hypothesis that risk-performance bank models are enhanced with spatial variables and that relationship lending makes small firm loan demand low price-elastic. In order to point out potential limitations, I am aware that subsequent studies are required to clarify a number of points that remain in the shadows of this research due to lack of data, for instance whether the relationship holds considering the effect of unconventional monetary policies.

The study carried out in Chapter 3, according to the literature that highlights how local banks tend to serve specific niche markets (small and micro enterprises and households) from which large banks are usually barred, leads to the discovery that spatial dependence has a positive effect on both the input and the output technical efficiency of local banks for three spatial specifications based on smaller distance. In contrast, for greater distances, the spatial lag parameter was not more statistically significant. Such results posited that local banks mainly compete among themselves and that the market discipline creates efficiency in this scenario. Furthermore, in some cases, the study shows that spatial covariates had the opposite effect on a bank's technical efficiency compared to the same variables when considered alone. This result highlights that the level of a bank's strategy can contradict the effect of general market tendencies on a bank's performance in terms of efficiency. In view of these evidences, supervisors should be aware that local bank efficiency also depends by the neighboring effects, and therefore this effect should be considered to promote the competition among local banks. This analysis did not control for different kinds of local bank borrowers, such as households and small and micro enterprises. Due to possible differences in the demand elasticity of these kinds of bank customers, a different weight of one of the other categories in the banks' loan portfolio could affect the efficiency of local banks. A lack of data prevented from overcoming this limitation.

Again, the study presented in Chapter 4 consists in the evaluation of the spatial dependence effects in an empirical model measuring local banks' tax aggressiveness, assessing the interdependence between geographical units and the related spillover effects. The results strongly support the existence of co-movements among banks' tax avoidance policies. The findings indicate that local banks compete mainly among themselves, even on the funding side, and that certain tax behavior can trigger loss of customers, which limits banks' tax avoidance activities. However, neighbors' adoption of aggressive tax strategies can remove the competition hurdle in pursuing tax avoidance policies. In addition, the study finds that greater bank market power increases spatial spillover effects, showing that neighbors' tax management strategies matter in planning a local bank's tax policies. These outcomes point out a virtuous effect of customer pressure, which could take effect in other areas of bank management. Overall, the empirical results in this study, highlighting the importance of considering the spatial co-movements of local banks for their tax planning activities, open avenues for further research in a cross-country context. Moreover, the availability of infra-annual data could strongly improve the accuracy of local banks' tax aggressiveness.

Lastly, the study shown in Chapter 5 investigates the existence of spatial dependence in the Non-Performing Loans ratio of Italian small cooperative banks. Since these banks operate in a delimited area, their recovery strategies for bad loans can produce spatial spillover effects in neighboring banks' ability to recover credit. Findings provide strong evidence that both spatial and spatial-temporal variables improve the analytical model by identifying the drivers of impaired loans for local banks. Specifically, the empirical results underline a different effect of the spatial terms, highlighting a direct impact of the contemporaneous spatial lag variable and a negative effect of the space-time autoregressive coefficient. Whereas the former effects can be ascribed to changes in the macroeconomic cycle, the latter confirms the insight that neighboring credit recovery policies can harm local banks' recovery abilities. Moreover, such study also controls for market power at the bank level, providing evidence supporting the competition-stability view. This investigation constitutes the first attempt to study the effects of simultaneous and non-simultaneous spatial dependence in the bad loans of small cooperative banks. The results about the different effects of the spatial and spatial-temporal terms on local banks' loan portfolio quality would benefit form a stress test, perhaps by using specific measures to control for the effects of recovery strategies as well as reputation indicators. Similarly, this study opens avenues for further research in other countries.

The central message here is that building a model analyzing banking indicators requires an intensive effort to verify whether spatial dependence is present in the data;

neglecting it leads to misleading estimates.

In term of managerial implications, the empirical research and the findings presented in this dissertation provide an important stimulus for the discussion and development of complex issues related to the local banks. Specifically, it was demonstrated that the management of local banks is not entirely independent and autonomous, as it suffers from the effects and behavior of the neighboring banks' managerial choices, or generally from the strategic decisions of the nearby competitors. Supervisors should consider the role of spatial interdependence during their supervisory activities in order to enhance a homogeneous regulation across EU members.

In conclusion, the specification models considered in the different empirical investigations could be improved, but they occurred suitable for my goals.

APPENDIX

A

APPENDIX - SYSTEM GMM MODEL

A.1 The asymptotic properties of system GMM estimator for SDPD models

SYS-GMM estimator, compared to Diff-GMM, considers additional moment restrictions to enhance the efficiency of the estimates (Blundell and Bond, 1998). Thus, endogenous variables in levels are instrumented with lags of their own fist differences ($\Delta y_{i,t-1}$).

The instrument matrix, which includes all the equations in first-differences ($T-2$) and the equations in levels ($T-2$) for period $t = 3, 4, \ldots, T$, can be written as follows:

$$Z = \begin{bmatrix} z_i & & & & & & & \\ 0 & \Delta y_{i,2} & 0 & 0 & \ldots & 0 & \ldots & 0 \\ 0 & 0 & \Delta y_{i,3} & 0 & \ldots & 0 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ldots & \vdots \\ 0 & 0 & 0 & 0 & \ldots & 0 & \ldots & \Delta y_{i,T-1} \end{bmatrix} \tag{A.1}$$

where

$$z_i = \begin{bmatrix} y_{i,1} & 0 & 0 & 0 & \ldots & 0 & \ldots & 0 \\ 0 & y_{i,1} & y_{i,2} & 0 & \ldots & 0 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ldots & \vdots \\ 0 & 0 & 0 & 0 & \ldots & y_{i,1} & \ldots & y_{i,T-1} \end{bmatrix} \tag{A.2}$$

The primary assumption is that covariance between η_i and $z_{i,t}$ is constant in the time. Mainly, the unobserved group effects are not related to shifts in the instrumenting variables. Therefore:

$$E(\eta_i \ \Delta z_{i,t}) = 0. \tag{A.3}$$

Consequently, the validity of the instruments ask the following moment conditions (Bond, 2002):

$$E[y_{i,s} \ \Delta(\eta_i + v_{i,t})] = 0 \text{ for i = 1, \dots, N; s = 2, \dots, t-1; t = 3, \dots, t} \tag{A.4}$$

$$E[x_{i,s} \ \Delta(\eta_i + v_{i,t})] = 0 \text{ for i = 1, \dots, N; s = 2, \dots, t-1; t = 3, \dots, t} \tag{A.5}$$

Since the spatially lagged variable is strictly endogenous, the instruments require that:

$$E[\mathbf{W} y_{i,t} \ \Delta(\eta_i + v_{i,t})] = 0 \text{ for i = 1, \dots, N; s = 2, \dots, t-1; t = 3, \dots, t} \tag{A.6}$$

SYS-GMM estimator is efficient and consistent on condition that the models do not present serial correlation of order two. To verify it, is considered a particular test proposed by Arellano and Bond (1991). In particular, it presents in the null hypothesis (H_0) the no second-order correlation in the disturbances. Formally:

$$Cov(\Delta\varepsilon_{i,t} \ \Delta\varepsilon_{i,t-2}) = 0. \tag{A.7}$$

Additionally, GMM models require that the instruments considered are valid. In this regard, is looked at the Hansen J test (Hansen, 1982) in which the null hypothesis is expressed as follows:[1]

- H_0: over-identifying moment conditions $E(Z_i' \Delta\varepsilon_i) = 0$ are valid.

The test statistic is given by:

$$J = NQ_N(\hat{\delta}) = N\Big(\frac{1}{N}\sum_{i=1}^{N} Z_i' \Delta\,\bar{\varepsilon}_i\Big)' \hat{W}_N^{opt}\Big(\frac{1}{N}\sum_{i=1}^{N} Z_i' \Delta\,\bar{\varepsilon}_i\Big), \tag{A.8}$$

[1] According to Roodman (2009b), a large quantity of instruments, especially due to growing periods of time, may overfit endogenous variables and conduct to a wrong inference, thus imposing that Hansen test should be interpreted attentively.

where

$$\hat{W}_N^{opt} = \left[\frac{1}{N}\sum_{i=1}^{N} Z_i' \Delta \hat{\varepsilon}_i^{os} \Delta \hat{\varepsilon}_i^{os\prime} Z_i\right]^{-1}. \tag{A.9}$$

More in detail, $\hat{W}_N^{opt}$ means the weight matrix is considered for computing the optimum two-step estimator. Additionally, $\Delta \hat{\varepsilon}_i^{os}$ and $\Delta \bar{\varepsilon}_i$ represent the one step residuals and the two-step residuals, respectively. When the value of the test is elevated, the null hypothesis is rejected. Therefore, the instruments are not valid and do not respect the orthogonality conditions, as either is not really exogenous or are wrongly excluded from the regression.

The statistical test is distributed as a chi-square (χ^2) with $R-K$ degrees of freedom under the null hypothesis. The latter is computed from the difference between the number of moment conditions (R columns in z_i) and the number of the parameter for included endogenous variables (K columns in ΔX_i).

APPENDIX

B

APPENDIX - SPATIAL DEPENDENCE TESTS

B.1 The lagrange multiplier test for spatial error correlation

Baltagi et al. (2003) implement a test to check for spatial error correlation and random effects in panel models. In detail, they expanded the Breusch and Pagan LM test to a spatial error component model. Take into account the following panel data model:

$$y = X'\beta + u$$
$$u = (I_N \otimes \iota_T)\mu + (B^{-1} \otimes I_T)\nu, \tag{B.1}$$

where $B = I_N - \rho W$, I_N, and I_T are identity matrices of dimension N and T.

Equation B.1 shows a model with a spatially correlated error in a random-effects context. The vector $(N \times 1)$ μ encloses the individual effects (fixed or random), while ν represents the vector $(NT \times 1)$ of residuals.

In the first place, these authors implement the joint LM test for verifying the existence of spatial autocorrelation and random effects. The null hypothesis in question is the following:

$$H_0 = \rho = \sigma^2 = 0,$$

which is tested against the alternative hypothesis (H_1), where at least one component is non-zero. The levels of significance of this test can be computed in an easy way since it follows a weighted chi-square (χ^2) distribution. Formally, the joint statistical test is computed as follows:

$$LM_{\rho,\sigma_\mu^2} = \frac{NT}{2(T-1)}\left(\frac{\tilde{u}'_{ols}(J_T \otimes I_N)\tilde{u}_{ols}}{\tilde{u}'_{ols}\tilde{u}_{ols}}\right)^2 + \frac{N^2T}{tr(W^2 + W'W)}\left(\frac{\tilde{u}'_{ols}(I_T \otimes I_N)\tilde{u}_{ols}}{\tilde{u}'_{ols}\tilde{u}_{ols}}\right)^2. \quad (B.2)$$

Secondly, the conditional LM test is developed. This statistical test is relevant because the model is studied for observing the presence of spatial autocorrelation regardless of whether random effects can be presented or not. The null hypothesis is:

$$H_0 = \rho = \sigma^2 \geq 0.$$

Formally, the conditional test is obtained in the following way:

$$LM_{\rho|\sigma_\mu^2 \geq 0} = \frac{\tilde{D}(\rho)}{\sqrt{\left((T-1) + \frac{\tilde{\sigma}_v^4}{\tilde{\sigma}_1^4}\right) b}}, \quad (B.3)$$

which is distributed as a standard normal $N(0,1)$, where

$$\tilde{D}(\rho) = \frac{1}{2}\tilde{u}'\left[\frac{\tilde{\sigma}_v^4}{\tilde{\sigma}_{1v}^4}((W'+W)\otimes(\frac{1}{T}J_T)) + \frac{1}{\tilde{\sigma}^2((W'+W)}\otimes(I_T - \frac{1}{T}J_T))\right]\tilde{u}, \quad (B.4)$$

and with

$$\tilde{\sigma}_v^2 = \frac{1}{N(T-1)}\tilde{u}'\left(I_N \otimes (I_T - \frac{1}{T}J_T)\right)\tilde{u}$$
$$\tilde{\sigma}_1^2 = \frac{1}{N}\tilde{u}'\left(I_N \otimes \frac{1}{T}J_T\right)\tilde{u}. \quad (B.5)$$

Furthermore, another conditional LM test is suggested for observing the existence of random effects, assuming the presence or not of spatial error correlation. The test statistic is:

$$LM_{\sigma_\mu^2|\rho \geq 0} = \frac{\tilde{D}_\mu\sqrt{(2\frac{\tilde{\sigma}_v^4}{T})(N\tilde{\sigma}_v^4 c - \tilde{\sigma}_v^4 g^2)}}{\sqrt{TN\tilde{\sigma}_v^4 ec - N\tilde{\sigma}_v^4 d^2 - T\tilde{\sigma}_v^4 g^2 e + 2\tilde{\sigma}_v^4 ghd - \tilde{\sigma}_v^4 h^2 c}}, \quad (B.6)$$

where $g = tr[(W'\tilde{B} + \tilde{B}'W)(\tilde{B}'\tilde{B})^{-1}]$, $h = tr[\tilde{B}\tilde{B}']$, $c = tr[((W'\tilde{B} + W\tilde{B}'(\tilde{B}'\tilde{B})^{-1})^2]$, $d = tr[(W'\tilde{B} + W\tilde{B}']$ and, finally, $e = tr[(\tilde{B}'\tilde{B})^2]$.

B.2 The lagrange multiplier test for spatial and serial error correlation

Let the model:

$$y_{i,t} = X'\beta + u_{i,t}, \tag{B.7}$$

where

$$u_t = \mu + \varepsilon_t, \tag{B.8}$$

with $\varepsilon_t = \lambda W + \nu_t$, and $\nu_t = \rho\nu_t + \epsilon_t$.

Baltagi et al. (2007) propose a test to check for serial, spatial correlation and random effects in panel models. Considering the model B.1, the joint LM test for testing the null hypothesis ($H_0 : \lambda = \rho = \sigma^2_\mu = 0$) is expressed as follows:

$$LM_J = \frac{NT^2}{2(T-1)(T-2)}[A^2 - 4AF + 2TF^2] + \frac{N^2T}{b}H^2, \tag{B.9}$$

where $A = \tilde{u}'(J_T \otimes I_N)\tilde{u}/(\tilde{u}'\tilde{u}) - 1$, $F = \frac{1}{2}(\tilde{u}'(G \otimes I_N)\tilde{u}/\tilde{u}'\tilde{u})$, $H = \frac{1}{2}(\tilde{u}'(I_T \otimes (W' + W))\tilde{u}/\tilde{u}'\tilde{u})$, $b = tr(W^2 + W'W)$ with $\tilde{u}$ indicating the OLS residuals and G denoting the bidiagonal matrix with bidiagonal elements all equal to one.

The LM test is asymptotically distributed as χ^2_3, in addition, the restricted likelihood function (LR) test statistic for the null hypothesis is computed by:

$$LR_J = 2(L_U - L_R), \tag{B.10}$$

where

$$\begin{aligned} L_U = Const. + \frac{N}{2}\, ln(1-\rho^2) - \frac{1}{2}\, ln\, |d^2(1-\rho)^2\phi I_N + (B'B)^{-1}| \\ - \frac{NT}{2}\, ln(\sigma^2_e) + (T-1)\, ln\, |B| - \frac{1}{2}u'\Omega^{-1}u, \end{aligned} \tag{B.11}$$

and

$$L_R = Const. - \frac{NT}{2} ln\, \tilde{\sigma}^2_e - \frac{NT}{2\tilde{\sigma}^2_e}\tilde{u}'\tilde{u}, \tag{B.12}$$

with $\phi = \sigma_\mu^2/\sigma_e^2$, $d^2 = \alpha^2 + (T-1)$ and $\alpha = \sqrt{(1+\rho)/(1-\rho)}$.

Nevertheless, Baltagi et al. (2007) also present one-dimensional conditional tests to solve possible misspecification. In particular, C.1, C.2, and C.3 have been developed.

The C.1 test statistics is a one-dimensional conditional test for no spatial error correlation permitting serial correlation and random effects. The null hypothesis is:

$$H_0 : \lambda = 0 \mid \rho \neq 0 \mid \sigma_\mu^2 > 0.$$

Formally, the LM conditional test statistic is asymptotically distributed as χ_1^2 under H_0 and, it is expressed as follows:

$$LM_{\lambda|\rho\mu} = \frac{\tilde{D}(\lambda)^2}{b(T - 2cg + c^2g^2)}, \tag{B.13}$$

where

$$\tilde{D}(\lambda) = \frac{1}{2}\,\tilde{u}'\,[V^{-1} - 2CV^{-1} + c^2(V^{-1}\,J_T)^2V^{-1}] \otimes (W' + W)\,\tilde{u}, \tag{B.14}$$

and $c = \sigma_e^2\sigma_\mu^2/d^2(1-\rho)^2\sigma_\mu^2 + \sigma_e^2$, b is defined above, J_T is a matrix of ones of dimension T and $g = tr(V^{-1}J_T) = 1/\sigma_e^2(1-\rho)\,[2 + (T-2)(1-\rho)]$. Finally, $V = \sigma_e^2(1/(1-\rho^2))V_1$, where

$$V_1 = \begin{bmatrix} 1 & \rho & \rho^2 & \dots & \rho^{T-1} \\ \rho & 1 & \rho & \dots & \rho^{T-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{T-1} & \rho^{T-2} & \rho^{T-3} & \dots & 1 \end{bmatrix} \tag{B.15}$$

and

$$C = \begin{bmatrix} (1-\rho^2)^{1/2} & 0 & 0 & \dots & 0 & 0 & 0 \\ -\rho & 1 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 0 & -\rho & 1 \end{bmatrix} \tag{B.16}$$

In turn, C.2 is a one-dimensional conditional test for no serial correlation permitting the existence of both spatial error correlation and random effects. The null hypothesis is:

$$H_0 : \rho = 0 \mid \lambda \neq 0 \mid \sigma_\mu^2 > 0.$$

In this case, the LM test statistic is given by:

$$LM_{\rho|\lambda\mu} = \tilde{D}(\rho)\; J_{33}^{-1}. \tag{B.17}$$

Specifically, the first component of the formula is given by:

$$\begin{aligned}\tilde{D}(\rho) = &-\frac{T-1}{T}(\hat{\sigma}_e^2\, tr(Z_0(B'B)^{-1} - N) + \frac{\hat{\sigma}_e^2}{2}\,\tilde{u}'\left(\frac{1}{\hat{\sigma}_e^4}(E_T G E_T)\otimes(B'B)\right.\\ &\left.+\frac{1}{\hat{\sigma}_e^2}(\bar{J}\,GE_T)\otimes Z_0 + \frac{1}{\hat{\sigma}_e^2}(E_T G\bar{J})\otimes Z_0 + (\bar{J}G\bar{J})\otimes Z_0(B'B)^{-1}Z_0\right)\tilde{u}\end{aligned} \tag{B.18}$$

where $B = I_N - \lambda W$ and $Z_0 = [T\sigma_\mu^2 I_N + \sigma_e^2(B'B)^{-1}]^{-1}$.

Additionally, the second component is the B.11 element of $\bar{J}_\theta$ (inverse of the information matrix) under the null hypothesis. This matrix is expressed as follows:

$$\bar{J}_\theta = \begin{bmatrix} \frac{1}{2}\left(\frac{N(T-1)}{\hat{\sigma}_e^4} + d_1\right) & \frac{T}{2}d_2 & \frac{(T-1)}{T}\left(\hat{\sigma}_e^2\, d_1 - \frac{N}{\hat{\sigma}_e^2}\right) & \frac{1}{2}\left[\frac{(T-1)}{\hat{\sigma}_e^2}d_3 + \hat{\sigma}_e^2\, d_4\right] \\ \frac{T}{2}d_2 & \frac{T^2}{2}tr[Z_0]^2 & (T-1)\,\hat{\sigma}_e^2\, d_2 & \frac{T\hat{\sigma}_e^2}{2}d_5 \\ \frac{(T-1)}{T}\left(\hat{\sigma}_e^2\, d_1 - \frac{N}{\hat{\sigma}_e^2}\right) & \frac{(T-1)}{T}\left(\hat{\sigma}_e^2\, d_1 - \frac{N}{\hat{\sigma}_e^2}\right) & J_{pp} & \frac{(T-1)}{T}(\hat{\sigma}_e^2\, d_4 - d_3) \\ \frac{1}{2}\left[\frac{(T-1)}{\hat{\sigma}_e^2}d_3 + \hat{\sigma}_e^2\, d_4\right] & \frac{T\hat{\sigma}_e^2}{2}d_5 & \frac{(T-1)}{T}(\hat{\sigma}_e^2\, d_4 - d_3) & \frac{1}{2}[(T-1d_6 + \hat{\sigma}_e^4\, d_7] \end{bmatrix} \tag{B.19}$$

where $\hat{\sigma}_e^2$ represents the restricted maximum likelihood of σ_e^2 and with

- $J_{pp} = \frac{N}{T^2}(T^3 - 3T^2 + 2T + 2) + \left(\frac{2(T-1)\hat{\sigma}_e^4}{T^2}\right) d_1$;
- $d_1 = tr[Z_0(B'B)^{-1}]^2$;
- $d_2 = tr[Z_0(B'B)^{-1}Z_0]$;
- $d_3 = tr[(W'B + B'W)(B'B)^{-1}]$;
- $d_4 = tr[Z_0(B'B)^{-1}(W'B + B'W)(B'B)^{-1}Z_0(B'B)^{-1}]$;
- $d_5 = tr[Z_0(B'B)^{-1}(W'B + B'W)(B'B)^{-1}Z_0]$;
- $d_6 = tr[(W'B + B'W)(B'B)^{-1}]^2$;
- $d_7 = tr[Z_0(B'B)^{-1}(W'B + B'W)(B'B)^{-1}]^2$.

This LM conditional test is asymptotically distributed as χ_1^2 under H_0. Furthermore, respect to the joint LM test, the restricted likelihood function under the null hypothesis is:

$$L_R = Const. - \frac{NT}{2} ln\, \tilde{\sigma}_e^2 - \frac{1}{2} ln[|T\, \tilde{\phi}\, I_N + (B'B)^{-1}|] + (T-1) ln|B| - \frac{1}{2}\, \tilde{u}'\, \Omega^{-1}\, \tilde{u}, \quad \text{(B.20)}$$

where $\Omega = \sigma_e^2 I_{NT}$ and L_U equal to B.11.

Finally, C.3 is a one-dimensional conditional test for no random effects permitting the existence of both serial and spatial error correlation. The null hypothesis is:

$$H_0 : \sigma_\mu^2 = 0\ |\rho \neq 0\ |\ \lambda \neq 0.$$

In this circumstance, the LM conditional test statistic is computed as:

$$LM_{\mu|\lambda\rho} = \tilde{D}(\sigma_\mu^2)\ J_{22}^{-1}, \quad \text{(B.21)}$$

where

$$\tilde{D}(\sigma_\mu^2) = -\frac{g}{2} tr(B'B) + \frac{1}{2\sigma_e^4}\, \tilde{u}'\, [V_P^{-1} J_T V_P^{-1} \otimes (B'B)^2]\, \tilde{u}, \quad \text{(B.22)}$$

and J_{22}^{-1}, which represents the B.8 of $\bar{J}_\theta$ (inverse of the information matrix) under the null hypothesis. The matrix is structured as follows:

$$C = \begin{bmatrix} \frac{NT}{2\sigma_e^4} & \frac{gtr[B'B]}{2\sigma_e^2} & \frac{N\rho}{\sigma_e^2(1-\rho^2)} & \frac{Td_3}{2\sigma_e^2} \\ \frac{gtr[B'B]}{2\sigma_e^2} & \frac{g^2 tr[B'B]^2}{2} & \Theta_{pp} & \frac{g}{2} tr[W'B + B'W] \\ \frac{N\rho}{\sigma_e^2(1-\rho^2)} & \Theta_{pp} & \Upsilon_{kk} & \frac{\rho d_3}{1-\rho^2} \\ \frac{Td_3}{2\sigma_e^2} & \frac{g}{2} tr[W'B + B'W] & \frac{\rho d_3}{1-\rho^2} & \frac{Td_6}{2} \end{bmatrix} \quad \text{(B.23)}$$

where

- $\Theta_{pp} = \frac{tr[B'B]}{\sigma_e^2(1-\rho)}[(2-T)\rho^2 + (T-1) + \rho)]$;
- $\Upsilon_{kk} = \frac{N}{\sigma_e^2(1-\rho^2)^2}(3\rho^2 - \rho^2 T + T - 1)$.

Also in this case, this test statistic is asymptotically distributed as χ_1^2 under H_0. Whereas, the restricted likelihood function is given by:

$$L_R = Const. + \frac{N}{2} ln(1-\rho^2) - \frac{Nt}{2} ln\, \tilde{\sigma}_e^2 + T ln|B| - \frac{1}{2}\, \tilde{u}'\, \Omega^{-1}\, \tilde{u}, \quad \text{(B.24)}$$

and L_U is equal to B.11.

B.3 Cross-sectional dependence tests

Consider the following model:

$$y_{it} = \mathbf{x}_{it}\beta + \epsilon_{it}, \text{ for } i = 1,2,\ldots,N; \ t = 1,2,\ldots,T, \tag{B.25}$$

in which i is the cross section dimension and t the time series dimension, $\mathbf{x}_{it}$ is the $k \times 1$ vector of covariates, and ϵ_{it} the residual vector. If there exist common components and/or spatial autocorrelation in the errors $(\hat{\epsilon})$, they determine cross-sectional dependence (CD) in the regression model. To test it, Pesaran (2004, 2015) proposes two several CD tests.

Pesaran (2004)'s test can be used to detect the unobserved common factors (strong CD test), especially when N is large and T is small. The statistic test is computed as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right), \tag{B.26}$$

where $\hat{\rho}_{ij}$ is the pairwise correlation of the error terms. In particular,

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} \epsilon_{it}\epsilon_{jt}}{(\sum_{t=1}^{T} \epsilon_{it}^2)^{1/2} (\sum_{t=1}^{T} \epsilon_{jt}^2)^{1/2}}, \tag{B.27}$$

and ϵ_{it} is the residuals of equation (B.25). Under the null hypothesis of no cross-sectional dependence, the CD test is asymptotically distributed:

$$CD \sim N(0,1). \tag{B.28}$$

Concurrently, Pesaran (2015) suggests a test for weak cross-sectional dependence (spatial autocorrelation). The CD statistic is given by:

$$CD = \sqrt{\frac{TN(N-1)}{2}} \; \hat{\bar{\rho}}_N, \tag{B.29}$$

with $\hat{\bar{\rho}}_N$ that is given by the following formula:

$$\hat{\bar{\rho}}_N = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \hat{\rho}_{ij}, \tag{B.30}$$

where $\hat{\rho}_{ij}$ is determined by (B.27). Under the null (absence of cross-section dependence), the CD test asymptotically follows a normal distribution with mean zero and unit variance.

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