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FULL ARTICLE

Spatial effects on local government efficiency

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Abstract

Little attention has been paid to the spatial pattern of local government efficiency. This paper intends to fill this gap by conducting an empirical analysis of a sample of 246 Italian municipalities over the decade 1998–2008. Municipal government efficiency is measured in terms of the speed of payments. Estimation results reveal that municipalities mimic the speed with which public spending is carried out by their neighbours. Political yardstick competition is found to be the source of mimicking behaviour in the speed of payments.

KEYWORDS

Italian municipalities, neighbourhood effects, spatial econometrics, the speed of payments, yardstick competition

JEL CLASSIFICATION

C23; H72; H73

1 | INTRODUCTION

Spatial interdependence in fiscal policy decisions of local governments has received increasing attention over the last 25 years. Although the presence of spatial patterns in the levels of local public expenditure and taxation has been extensively investigated (for reviews, see Brueckner, 2003; Revelli, 2005, 2015), few studies have analysed whether the efficiency of local governments in the provision of public goods and services also depends on neighbourhood decisions (Balaguer-Coll, Brun-Martos, Márquez-Ramos, & Prior, 2019; Bollino, di Vaio, & Polinori, 2012; Geys, 2006; Revelli & Tovmo, 2007). Political "yardstick competition" (Besley & Case, 1995; Salmon, 1987), due to citizens' benchmarking, could be one of the plausible determinants of mimicking behaviour in local government efficiency. Further attention has been attached to the role played by local governments in copying best practices from each other to improve efficiency, involving spatial interdependence through the diffusion of knowledge among neighbouring jurisdictions (Bollino et al., 2012). The spread of best practices among jurisdictions can take place through a learning process whereby a jurisdiction learns from high-performing jurisdictions mainly to reduce its own costs in the provision of public goods and/or to compete for tax base (Ward & John, 2013).

The current paper investigates the presence of spatial patterns in local government spending efficiency by using a sample of 246 Italian municipalities over the period 1998–2008. Municipal efficiency is measured through the speed of payments, already used in other studies (Drago, Nannicini, & Sobbrio, 2014; Gagliarducci & Nannicini, 2013). This measure deals with the speed with which local governments transform spending commitments into actual payments for local public goods. Swifter payments mean greater government efficiency because a larger share of spending commitments is undertaken within the financial year. The speed of payments is computed for current expenditure since this category of public expenditure involves short-term budget decisions which could reflect a more intense spatial correlation among geographically neighbouring municipalities. Additional categories of public spending, such as capital expenditure, expenses to third parties and total expenditure, are also considered.

Spatial dependence in local government spending efficiency is investigated through spatial econometric models and geographical distance-based matrices selected by the Bayesian approach of model uncertainty (LeSage, 2014). This method has already been used by Rios, Pascual, and Cabases (2017) to investigate the presence of spatial patterns in local government expenditure by Spanish municipalities. The current paper employs the Bayesian method to investigate the presence and nature of spatial dependence in local government efficiency. The selection model adopted by this approach points to the spatial autoregressive model for the municipal speed of current outlays. The spatial Durbin (error) model is selected for municipal spending efficiency computed for the other categories of public expenditure.

Estimation results reveal the presence of spatial interdependence in the speed of payments among geographically neighbouring municipalities, showing that municipalities mimic not only levels of public expenditure, as shown by past empirical studies, especially in the Italian context (Bartolini & Santolini, 2012; Ermini & Santolini, 2010; Ferraresi, Migali, & Rizzo, 2018), but also the speed with which payments are made to provide public goods and services. Estimates also show that a municipality reacts more to changes in the speed of current spending of neighbouring municipalities than to changes in the speed of payments for other categories of public expenditure. One reason for this result may be the rigidity of some components of current expenditure (such as public employee wages and salaries) that could artificially inflate the spatial effect in current spending efficiency, resulting in more pronounced reactivity of municipality to changes in the speed of current outlays of its neighbours. On the other hand, time and costs for public works construction projects are subject to greater uncertainty, making capital spending efficiency less spatially correlated. Finally, estimates show that municipalities, governed by mayors supported by large majorities, do not react to changes in the speed of current outlays of the surrounding area. This result is consistent with the political yardstick competition hypothesis.

The rest of the paper is structured as follows. Section 2 illustrates the theoretical background that sheds light on the potential mechanisms whereby the efficiency of a local government is influenced by its neighbourhood, and the existing empirical evidence. Section 3 presents the indicators of public spending efficiency and the control variables used in empirical analysis. The spatial econometric models and estimation methodology are described in Section 4. Selection of both spatial models and spatial weight matrices by the Bayesian method is illustrated in Section 5. The baseline estimation results are discussed in Section 6. Empirical investigation of the political yardstick competition hypothesis is presented in Section 7. Section 8 concludes.

2 | THEORETICAL BACKGROUND AND EMPIRICAL EVIDENCE

Considerable attention has been paid to analysing the presence and the sources of spatial interdependence in the level of expenditure and tax rate of local governments by estimating the slope of reaction functions in their fiscal policy decisions (Brueckner, 2003; Revelli, 2005). By contrast, issues of spatial local government efficiency have been less widely treated. Indeed, there are few studies that theoretically explore the potential sources of spatial dependence on local government efficiency. Ward and John (2013) show that spatial interdependence in local government performance can be ascribed to “pure learning” and “competitive learning.” The “pure learning” process assumes that local governments copy good practices from high-performing jurisdictions to avoid high costs in the provision of public services associated with the failure of the ideas implemented. Behind the competitive learning process, there are jurisdictions which compete with each other to attract mobile taxpayers and investors from surrounding areas by implementing best practices from high-performing municipalities to the benefit of greater efficiency in providing public services to citizens and firms.

The performance comparison among jurisdictions could also be driven by electoral reasons, since the improvement of local government efficiency could lead to an increase in the chances of the incumbent politician being re-elected (Ward & John, 2013). According to the approach of “political yardstick competition” (Besley & Case, 1995; Salmon, 1987), citizen-voters do not have complete knowledge about the fiscal performance of their incumbent politician, and they fill this information gap by comparing his/her performance with those of neighbouring jurisdictions. Thus, incumbent politicians set their own fiscal policy decisions in line with those of neighbouring administrations, thereby also avoiding defeat being inflicted at the polls. From a theoretical standpoint, this generates a positive slope in the reaction function of fiscal policy decisions set by incumbents to fiscal policy decisions set by their neighbours (Solé Ollé, 2003).

Most of the studies that have analysed the political yardstick competition hypothesis have tested the presence of strategic complementarity in spending levels and tax rates of local governments as indicators of fiscal performance. However, evaluating the performance of local governments only with regard to the above indicators may restrict examination of the phenomenon of political yardstick competition. Such performance can also be assessed by citizen-voters in terms of the efficiency with which they are provided with public services (Geys, 2006; Revelli & Tovmo, 2007). Voters gauge the efficiency of their local government in responding to their needs and preferences by comparing the quality of local public services and their efficiency with those provided by neighbouring jurisdictions. This comparison may induce incumbent politicians to mimic efficiency in the provision of local public services of neighbouring jurisdictions for signalling good performance to voters and increasing their own electoral chances. In particular, incumbent politicians supported by small majorities could be more inclined to align their own fiscal policies (Allers & Elhorst, 2005; Solé Ollé, 2003), as well as government efficiency, to that of nearby jurisdictions. Because of the low electoral margin of victory, they risk being not re-elected if voters assess their government performance as poor overall.

Few studies have empirically investigated the presence of spatial interdependence in local government efficiency. Geys (2006) used cross-sectional data on 304 Flemish municipalities for the year 2000 and a stochastic parametric reference methodology to determine municipalities' efficiency ratings as proxies for the ratio of public spending to public goods provision. He found that the abilities of Flemish municipalities to spend money on public goods efficiently are affected by neighbourhood effects. Revelli and Tovmo (2007) tested the existence of yardstick competition in the production efficiency of 205 Norwegian municipalities. As a measure of local administrations' efficiency, they used an indicator developed by Borge, Falch, and Tovmo (2005) based on the ratio between an aggregate measure of the production of services provided by local governments and the total revenues of local governments. To verify that the spatial interdependencies that occurred in the government efficiency index depended on yardstick competition, they employed information from a survey on the attitude of local Norwegian politicians to comparing their own performance in the provision of public services with those of other jurisdictions. They found that the Norwegian municipalities mimic the production efficiency of the geographically neighbouring municipalities for reasons compatible with yardstick competition. Bollino et al. (2012) built an indicator of cost efficiency in the production of local public services with the non-parametric data envelopment analysis method on 341 municipalities in the Italian region of Emilia-Romagna. They then explored the presence of spatial interaction in cost efficiency scores with Moran's *I* scatter plot, showing that municipalities with high (low) degrees of efficiency are surrounded by municipalities with similar high (low) levels of efficiency. Ward and John (2013) tested the presence of “pure learning” and “competitive learning” on a sample of 148 English local authorities. They used a service performance score based on six services (education, social care for adults, housing, environment, and library and leisure facilities) as a measure of local government efficiency. They found significant evidence consistent with both the pure and the competitive learning process. More recently, Balaguer-Coll et al. (2019) investigated the existence of spatial patterns in the government efficiency of 524 municipalities of the Valencia region in Spain, using the robust order-m methodology for estimating a municipal efficiency index. Their empirical analysis highlights the crucial role played by spatial interaction in determining the local government efficiency of Valencian municipalities.

The above-mentioned studies used different indicators of local government efficiency obtained, in some cases, by non-parametric methods. In the current study, the speed of payments is used as a measure of the municipal administrative efficiency (Drago et al., 2014; Gagliarducci & Nannicini, 2013). It captures the municipality's ability to pay its commitments to private contractors within the financial year. Hence, the increased speed of payments means greater efficiency of the municipality in meeting its planned expenses. For the Italian context, the presence of spatial interdependence in the speed of municipal payments may be the result of both political "yardstick competition" and "pure learning." Indeed, "competitive learning" among neighbouring jurisdictions should be excluded from among the potential sources of spatial local government efficiency because of the scant tax base mobility across Italian municipalities. Recent empirical evidence (Buso, Greco, & Moretti, 2017) has shown that a politician is more efficient at respecting his/her spending commitments during electoral years. This means that voters are sensitive to changes in the speed of payments and are prone to punish their incumbent if it is too slow. In this perspective, voters can also assess the incumbent's administrative performance by comparing the efficiency with which they are provided with local public services and goods with respect to neighbouring jurisdictions. In line with the political yardstick competition approach, the incumbent politician may be tempted to align efficiency in the provision of public services, hence in the speed of payments, with that of his/her neighbouring jurisdictions, signalling good administrative performance to voters in order to increase his/her re-election chances.

The diffusion of administrative innovations in municipal budget procedures could be one major source of spatial dependence in the speed of payments made by Italian municipalities since 2012. The new accounting standards introduced by Legislative Decree 118/2011 (with amendments under Legislative Decree 126/2014) have imposed the harmonization of municipal budgeting processes, with the result of increasing the speed of payments by Italian municipalities in the years 2013–2015, as documented by the Italian Court of Auditors (2017). Other important budgetary innovations, such as electronic invoicing (Laws 244/2007, 89/2014) and the split payment of VAT (Law 190/2014), have revolutionized the system of payments of all Italian public administrations, enhancing municipal payment performance in recent years (Bassetti, 2017). Moreover, e-public procurement (Laws 94/2012, 135/2012) has made the simplification of public administration procurement possible, reducing its administrative costs and procurement times to the benefit of greater budget transparency and administrative efficiency. The above innovations are the result of national reforms rather than the result of single initiatives taken by local administrations. Thus, their diffusion across municipalities is not due to mimicking behaviour caused by "pure learning"; rather, it is due to their adaptation to national prescriptions.

3 | DATA AND VARIABLES

Our empirical analysis was conducted on a sample of 246 municipalities located in the Marche region[1] over the decade 1998–2008[2] and where evidence on fiscal policy interdependence has been documented (Bartolini & Santolini, 2012; Ermini & Santolini, 2010; Santolini, 2008).[3] The Marche region is located in central Italy, and 14% of its municipalities give onto the Adriatic Sea, while the remainder extend up to the Umbro-Marche Apennine

[1]Focusing on the empirical analysis of municipalities belonging to the same region has the advantage of strengthening the effect of fiscal interdependence as they share a similar economic and social context and are subject to the same regional administrative rules. Thus, they mimic each other more, rather than municipalities of neighbouring regions.

[2]Since seven municipalities (Casteldelci, Maiolo, Novafeltria, Pennabilli, San Leo, Sant'Agata Feltria and Talamello) located in the north of the Marche left it in the year 2009 to join neighbouring Emilia-Romagna (Law 117/2009), the time period of the analysis ends in the year 2008.

[3]Data on this region are considered because its socio-economic indicators are in line with the Italian indicators. Thus, they are representative of the country as a whole (Bartolini & Santolini, 2012). Moreover, it has been shown empirically (Bartolini & Santolini, 2012; Ermini & Santolini, 2010) that the Marche municipalities tend to react significantly to changes in neighbouring spending policies. Therefore, also in terms of spending efficiency, they are very likely to show similar spatial patterns.

mountains. The region has a large number of municipalities with fewer than 3,000 inhabitants (56% in 2014) and a population density lower than 150 inhabitants per square kilometre (64% in 2014).

In Italy, the municipality is the lowest level of government, dealing with many important activities affecting citizens' lives, such as primary schooling, public finance, urban planning and public order. The political and administrative structure of municipalities consists in the mayor (*sindaco*), the executive body (*giunta comunale*) and the municipal council (*consiglio comunale*). Since 1993, the mayor has been directly elected and has the power to appoint and remove members of the executive board (Law 81/1993). These changes have made the mayor politically and directly accountable to the electorate for policies implemented as well as for the administrative control of the municipality activities. The budget of a municipality provides evidence of such policies and makes it possible to assess government efficiency through budget indicators such as the speed of payments (Drago et al., 2014; Gagliarducci & Nannicini, 2013). This measure of spending efficiency is calculated for current expenditure since it involves budget decisions less subject to uncertainty about the time and costs of implementation which could result in more intense spatial correlation. Moreover, it is the largest component of municipal public expenditure.[4] The indicator, called *currexp speed*, is computed as the ratio between the total public current expenditure paid and the total public current expenditure committed by the municipality. Additional indicators of the speed of payments are also considered in order to investigate the presence of spatial patterns. They are computed in the same manner for the main aggregate budget items of the municipal public expenditure such as capital expenditure (*capexp speed*), expenditure to third parties (*tprexp speed*) and total public expenditure (*totexp speed*). Each indicator assumes values between 0 and 1 (inclusive). A value of 1 indicates that expenses committed by the municipality are fully paid within the budget year. Hence, an increasing ratio means that the municipality is performing better budget-wise.[5] The speed of payments indicators are built using data on local public finance released by the Ministry of the Interior.[6]

The speed of payments is an indicator commonly used by Italian political actors (e.g., Ministry of the Interior), researchers (Drago et al., 2014; Gagliarducci & Nannicini, 2013) and other institutions (e.g., ANCI,[7] the Italian Court of Auditors) to measure the degree of administrative efficiency at the Italian municipal level. Basically, the indicator captures the efficiency of municipal budget management because it measures the municipality's ability to pay its commitments within the financial year. The better able the municipality is to keep its payment promises, the more efficient the municipality is in managing public spending.

The panel regression analysis includes control variables on demographics, economic and political characteristics. As regards demographic aspects, population size[8] (*pop*) is employed.[9] The effects of population on local government performance can be ambiguous. A positive correlation signals the presence of government efficiency due to economies of scale in the provision of local public services, while a negative correlation denotes government inefficiency due to congestion effects. The demographic structure is controlled by the percentage of *young people* (0–14 years old) and *elderly people* (65 years old or above). Municipalities with a large share of vulnerable groups in the population have a low fiscal capacity that leads to enhancing government efficiency (Borge, Falch, & Tovmo, 2008).

On the side of economic controls, *income* enters the panel regression analysis in terms of the logarithm of the per-capita income tax base.[10] Rich households demand a better quality of local public services and greater efficiency in

[4]The capital component of public expenditure in Italian municipalities is generally lower than the current component. The sample based on the Marche fully confirms this trend. In the year 2008, the share of current public expenditure on total public expenditure of the Marche municipalities was on average 70%, while the share of public capital expenditure represented only 6%. Payments to third parties accounted for about 12% of the total.

[5]In the few cases in which the numerator and the denominator of the speed of payments are jointly zero, it is assumed that the spending efficiency indicator is equal to 1.

[6]When missing values are found, they are filled by interpolating them with the data computed as the inter-temporal average of the year immediately before and after. Missing values for the initial year 1998 were filled by data for the year 1999.

[7]ANCI (*Associazione Nazionale Comuni Italiani*) is the official association of Italian municipalities.

[8]Population enters the spatial panel data regressions in logarithmic form.

[9]Data on population are collected from the database *Atlante Statistico dei Comuni* released by the National Institute of Statistics (ISTAT).

[10]Since data on disposable income are not available for Italian municipalities, the income tax base (*Imposta sul Reddito delle Persone Fisiche*) is used as its proxy. They are extracted from the database released by Ministry of Economy and Finance.

their provision. Thus, a positive correlation between income and government efficiency should be expected. Since *income* may be endogenous and affect the estimate of ρ and its significance, its fitted value is used in the spatial regressions.[11]

Political characteristics like the size of the mayor's majority and political ideology can significantly affect municipal government efficiency.[12] Mayors elected with substantial majorities have greater political strength to impose hard budget constraints for pursuing budget consolidation policies (Borge et al., 2008). Accordingly, it can be expected that the control variable *majority size*, which represents the share of the mayors' votes, is positively correlated with government efficiency. Political ideology is also taken into account by a dummy variable called *leftwing* that assumes value 1 when the municipality is governed by a left-wing coalition, and zero otherwise. The size of public expenditure is commonly higher in municipalities governed by left-wing coalitions because they support stronger government intervention in the economy by promoting extensive social welfare programmes. Hence, they are more inclined to set a soft budget constraint because they face higher cost increases due to the supply of a wide range of public services. Thus, municipalities governed by left-wing coalitions are expected to be less administratively efficient (Borge et al., 2008).

The literature has shown that incumbent politicians increase expenditure in pre-electoral periods to gain a larger voter consensus for reappointment in office (Rogoff, 1990; Rogoff & Sibert, 1988). In line with this theoretical view, the incumbent should increase the speed of payments in pre-electoral periods to inflate public expenditure to please voters (Buso et al., 2017). To control for the electoral cycle, a dummy variable termed *election* is used as control. It assumes value one in the election year and zero otherwise.[13]

Politicians' competence can make a difference in implementing fiscal policies efficiently. A highly competent politician adapts better to changes (Welch, 1970), revealing better government performance (Besley, Montalvo, & Reynal-Querol, 2011). A dummy variable *education* enters among the regressors to capture the mayor's competence. It assumes value 1 if the elected mayor has a university degree, and zero otherwise.[14]

Ambiguous effects on spending efficiency are expected after the imposition of stringent fiscal rules at the local level of government. Fiscal rules determined at the central level impose hard budget constraints on sub-central governments in order to consolidate their budgets and increase local government efficiency (Borge et al., 2008). On the other hand, national fiscal rules that limit the growth of local spending by imposing "expenditure caps" could contribute to slowing down the speed of payments of local administrators to respect fiscal constraints at the expense of local government efficiency. Since the year 1999, Italian municipalities have been subject to a national fiscal discipline rule to constrain budgets. From 1999 to 2000 all municipalities were subjected to the domestic stability pact (DSP hereafter), whereas from 2001 to 2012 only municipalities with a population higher than 5,000 inhabitants were affected. The effects of the *DSP* are checked by including a dummy variable that assumes value one when the municipality is subjected to the DSP, and zero otherwise.

Finally, a dummy variable termed *crisis*, which assumes value one in the year 2008 and zero otherwise, is added to capture the effects of the 2008 global financial crisis. It is expected that municipalities increased their efficiency in payments to firms and households to alleviate the recessionary effects of the global liquidity crisis that occurred in 2008–2009.

Table 1 displays the summary statistics for both the dependent and the aforementioned control variables.

4 | MODELS AND ESTIMATION METHODOLOGY

As suggested by LeSage (2014), practitioners should only choose between the spatial Durbin model (SDM) and the spatial Durbin error model (SDEM) because it is easy to derive other model specifications from them. Both models

[11]The fitted value of *income* is obtained by regressing it on $\mathbf{X}$, $\mathbf{WX}$ and $\mathbf{W^2X}$.

[12]Data are collected from the Historical Archives of elections provided by the Italian Ministry of Internal Affairs.

[13]Italian municipal elections do not suffer from endogeneity problems because the election date is fixed by national law.

[14]Data on politicians' educations are extracted from a database on locally elected administrators provided by the Italian Ministry of Internal Affairs.

TABLE 1 Summary statistics

Variable	Obs	Mean	Std.dev.	Min	Max
Currexp speed	2706	0.786	0.063	0.290	0.968
Capexp speed	2706	0.177	0.175	0.000	1.000
Tpexp speed	2706	0.827	0.191	0.010	1.000
Totexp speed	2706	0.601	0.150	0.042	0.905
Pop (log)	2706	7.889	1.195	4.787	11.533
Young	2706	12.940	1.879	4.850	18.930
Elderly	2706	23.689	4.763	11.390	43.780
Income (fitted values, log)	2706	9.016	0.138	8.260	9.411
DSP	2706	0.382	0.486	0.000	1.000
Majority size	2706	60.415	12.761	32.100	100.000
Left-wing	2706	0.261	0.439	0.000	1.000
Education	2706	0.456	0.498	0.000	1.000
Crisis	2706	0.090	0.287	0.000	1.000
Election year	2706	0.192	0.394	0.000	1.000

capture spatial spillovers that occur when the outcome of the *i*th jurisdiction is affected by the characteristics and/or actions of the *j*th jurisdiction neighbour to *i*. However, the nature of spillovers differs between the models. The SDM involves global spillovers among the *i*th jurisdiction and neighbours of neighbours (and so on) of *j*. The SDEM implies local spillovers between jurisdiction *i* and neighbours of *j* (LeSage & Pace, 2009).

The dynamic version of the SDM is illustrated in (1), where the dependent variable $\boldsymbol{y_t}$ is a $N \times 1$ vector containing the indicator of the speed of payments in the *ith* municipality (for $i = 1,...,N$) at time period t (for $t = 1,...,T$). Since the pattern of government efficiency may depend on the past, the first order lag of the dependent variable $\boldsymbol{y_{t-1}}$ is included on the right-side of (1):

$$DSDM\colon \boldsymbol{y}_t = \delta \boldsymbol{y_{t-1}} + \rho \boldsymbol{W y_t} + \boldsymbol{X}_t \beta + \boldsymbol{W X}_t \phi + \boldsymbol{f} + \boldsymbol{c} + \boldsymbol{\varepsilon}_t. \tag{1}$$

Spatial interdependence among neighbouring municipalities is described by the $N \times N$ spatial weight matrix $\boldsymbol{W}$. Adopting the spatial weight matrix with the geographical distance has the advantage of making $\boldsymbol{W}$ exogenous, permitting identification of the spatial process.[15] If only first order neighbours are included in the spatial weight matrix, element w_{ij} assumes value 1 for $i \neq j$ when the *j*th municipality shares a border with the *i*th municipality, and 0 otherwise. The diagonal elements of the first order binary contiguity matrix are zero, that is, $w_{ij} = 0$ when $i = j$ (Anselin, 1988). In the empirical analysis, the first ($\boldsymbol{W_1}$) and the second ($\boldsymbol{W_2}$) order contiguity matrix are considered.[16]

Alternative distance measures are used to better identify the geographical neighbourhood. Accordingly, use is made of a spatial weight matrix $\boldsymbol{W_d}$ with elements based on distance (d) in kilometres (km) from the centroid of the *i*th municipality to the centroid of the *j*th municipality. If the distance between the two centroids is less than or equal to 20 km, the weight assigned is one, and zero otherwise. The diagonal elements of $\boldsymbol{W_d}$ are zero. Distance cut-offs at 35 km and 50 km are also used. Three spatial weight matrices $\boldsymbol{W_{1/d}}^{\boldsymbol{2}}$ with elements equal to the squared inverse distance between the two centroids are also employed at the cut-offs of 20, 35 and 50 km. If the distance exceeds 20 km (35 km or 50 km), the spatial weight elements are set to zero. Finally, the spatial matrix $\boldsymbol{W_k}$ with *k*-

[15]Corrado and Fingleton (2012) suggest alternative specifications of $\boldsymbol{W}$ based on economic distance. However, the main concern with this kind of matrix specification is its endogeneity, which undermines the identification process (Vega & Elhorst, 2015).

[16]The $\boldsymbol{W_2}$ matrix includes the first order contiguous neighbours and neighbours that share a border with them.

nearest neighbours weights is employed, where k is a positive integer set equal to 4, 5, 6, 7, 8, 9, 10, 12, 16 and 20 similarly to other empirical studies (Bocci, Ferretti, & Lattarulo, 2019; Rios et al., 2017; Rios & Gianmoena, 2018). The off-diagonal elements of $\boldsymbol{W_k}$ are set at 1 for the k closest spatial units to the *i-th* municipality and zero otherwise. The diagonal elements of $\boldsymbol{W_k}$ are zero. The coefficient ρ associated with $\boldsymbol{Wy_t}$ measures the strength of spatial dependence in the municipal speed of payments at time t, suggesting the presence of strategic complementarities when its sign is positive and substitution effects when its sign is negative.

The $N \times K$ matrix $\boldsymbol{X}$ of control variables and the spatially lagged explanatory variables $\boldsymbol{WX}$ are also included in the model. Municipal fixed-effects[17] ($\boldsymbol{f}$) are added in order to control for the omission of unobserved heterogeneity of municipalities. A constant term c and an error term ε, independently and identically distributed with zero mean and constant variance, are also included on the right-side of (1).

Assuming that errors are spatially autocorrelated and ρ equals zero in (1), the dynamic spatial Durbin error model (DSDEM) is easily derived from (1), as shown by the equation below[18]:

$$DSDEM\colon \boldsymbol{y_t} = \delta \boldsymbol{y_{t-1}} + \boldsymbol{X_t}\beta + \boldsymbol{WX_t}\phi + \boldsymbol{f} + \boldsymbol{c} + \boldsymbol{\varepsilon_t} \qquad \boldsymbol{\varepsilon_t} = \lambda \boldsymbol{W\varepsilon_t} + \boldsymbol{\upsilon_t}. \tag{2}$$

Two further spatial model specifications can be easily derived from the DSDM and the DSDEM by assuming $\phi = 0$. In particular, the DSDM is transformed into the dynamic spatial autoregressive (DSAR) model displayed in (3), whereas the DSDEM turns into the dynamic spatial error model (DSEM) illustrated in (4). One advantage of the SDM with respect to the other spatial regression specifications is that the parameter estimates are consistent, though inefficient, when errors are spatially dependent (LeSage & Pace, 2009) and the true-data generation process coincides with the SAR and SEM (Elhorst, 2010). A further advantage of the SDM is that it does not impose prior restrictions on the magnitude of the spatial effects, representing a more attractive specification to investigate spatial dependence than other model specifications (Elhorst, 2010):

$$DSAR\colon \boldsymbol{y_t} = \delta \boldsymbol{y_{t-1}} + \rho \boldsymbol{Wy_t} + \boldsymbol{X_t}\beta + \boldsymbol{f} + \boldsymbol{c} + \boldsymbol{\varepsilon_t}, \tag{3}$$

$$DSEM\colon \boldsymbol{y_t} = \delta \boldsymbol{y_{t-1}} + \boldsymbol{X_t}\beta + \boldsymbol{f} + \boldsymbol{c} + \boldsymbol{\varepsilon_t} \qquad \boldsymbol{\varepsilon_t} = \lambda \boldsymbol{W\varepsilon_t} + \boldsymbol{\upsilon_t}. \tag{4}$$

Since direct interpretation of the estimated coefficients of spatial regression models is not always possible, spatial direct and indirect effects should be considered. In a standard linear regression model $y_i = \beta \sum_{r=1}^{k} x_{i,r} + \varepsilon_i$, the *direct effects* coincide with parameter β_r due to changes in the *r-th* explanatory variable of jurisdiction i on outcome y_i as follows: $\partial y_i/\partial x_{ir}$. The *indirect effects* produced on y_i by changes in the characteristics of neighbour j are given by $\partial y_i/\partial x_{jr} = 0$ for $j = i$ and $\forall\, r$ (LeSage, 2008; LeSage & Pace, 2009). The (in)direct effects differ among spatial econometric models.[19]

Considering, for simplicity, the static versions of models (1)–(4) by assuming $\delta = 0$, the (in)direct effects of the static SDM are given by the (off)diagonal elements of $(\boldsymbol{I} - \rho\boldsymbol{W})^{-1}(\beta_k + \boldsymbol{W}\phi_k)$. The (in)direct effects of the static SAR model correspond to the (off-)diagonal elements of $(\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\beta_k$. Coefficients β and ϕ of the static SDEM specification can be directly interpreted as direct and indirect effects, respectively. The static SEM has the same effects as the linear regression model (Elhorst & Vega, 2013). The summation of direct and indirect effects generates the *total effects*.[20,21]

[17]Time-fixed effects are not included in the spatial models because control variables *election year* and *crisis* already capture time-varying components.

[18]If the rows of the spatial weight matrix are standardized, the parameters ρ and λ are defined between $1/w_{min}$ and 1, where w_{min} is the smallest eigenvalue of the $\boldsymbol{W}$ matrix (Elhorst, 2010; LeSage, 2008).

[19]Golgher and Voss (2016) showed for cross-section spatial regression models that the direct, indirect and total effect of the SDM exceed those of the SAR model because the SDM includes local effects by $\boldsymbol{WX}$. They are also greater than the effects of the SDEM due to the presence of spatial endogenous dependence captured by coefficient ρ.

[20]The average value is calculated across all jurisdictions for indirect, direct and total effects and used as a summary indicator for the interpretation of estimation results (Golgher & Voss, 2016; LeSage & Pace, 2009).

[21]For computation of the direct, indirect and total effect in dynamic space–time panel data models see Debarsy, Ertur, and LeSage (2012).

The inclusion of $\boldsymbol{Wy}$ makes the ordinary least squares (OLS) estimator inconsistent (Anselin, 1988; Cliff & Ord, 1973). The same drawback occurs because of the correlation between $\boldsymbol{y}_{t-1}$ and fixed-effects that make the lagged dependent variable correlated with error term (Baltagi, 2005). Thus, other methods, such as the Bayesian Markov chain Monte Carlo (MCMC) approach, the maximum likelihood (ML) and the quasiML (QML) estimator, can be used to estimate the spatial panel data models (Lee & Yu, 2010a; Lee & Yu, 2010b; Yu, Jong, & Lee, 2008). The ML estimator provides consistent and efficient estimates only when the errors are normally distributed and homoscedastic. In the presence of non-normal heteroscedastic errors, the QML can be used to cater for such problems. The two estimators have drawbacks in common. They provide consistent estimates only if the estimated spatial econometric model is the true data-generating process (Lee, 2004). Thus, model selection is crucial when ML-based estimators are used, since the wrong specification makes them inconsistent. Moreover, they do not rely on endogenous variables.

The instrumental variables (IVs) or generalized method of moments (GMM) estimators can be used to address endogeneity problems. Moreover, they remain consistent with non-normal heteroscedastic errors and even in the presence of spatial autocorrelated shocks among jurisdictions (Anselin, 1988; Kelejian & Prucha, 1998). One disadvantage is that estimated coefficients ρ and λ may lie outside parameter space. Moreover, the traditional instruments based on neighbours' characteristics $\boldsymbol{WX}$ (Kelejian & Prucha, 1998) used for the spatially lagged dependent variable could be invalid or weak. Gibbons and Overman (2012) have raised some criticisms about identification problems when using neighbours' characteristics as instruments. Indeed, if the exclusion of $\boldsymbol{WX}$ from spatial econometric models is invalid, then $\boldsymbol{WX}$ and its higher order lags ($\boldsymbol{W}^2\boldsymbol{X}$, $\boldsymbol{W}^3\boldsymbol{X}$, etc.) are unsuitable instruments for the identification of the causal effect of $\boldsymbol{Wy}$ on $\boldsymbol{y}$ in a spatial instrumental variable setting. By contrast, if the exclusion restrictions are valid and $\boldsymbol{W}$ is known, $\boldsymbol{WX}$ could be a set of weak instruments for the identification of the causal parameter ρ because they are highly correlated with each other. In this circumstance, Gibbons and Overman (2012) suggest the use of instruments based on institutional changes that provide exogenous variations useful for the identification of the causal effect in a spatial IV context.

5 | MODEL SELECTION

Identification problems occur because of the difficulty in distinguishing among different spatial econometric models, incurring erroneous economic interpretations of spatial effects (Gibbons & Overman, 2012). LeSage (2014) argues that practitioners can select between the SDM or SDEM specification by providing convincing theoretical argumentations in favour of local or global spillovers. However, Gibbons and Overman (2012) are rather sceptical about using only theoretical motivations to select the true data-generating process. They encourage researchers to consider exogenous institutional changes as “natural experiments” with which to identify causal effects in spatial models. Elhorst (2010) suggests adoption of the (robust) Lagrangian multiplier (LM) test (Anselin, 1988; Anselin, Bera, Florax, & Yoon, 1996) and Wald or likelihood ratio tests to select among alternative spatial specifications. More recently, LeSage (2014, 2015) encouraged the adoption of a Bayesian approach of model uncertainty to select spatial models with different definitions of the neighbourhood. One advantage in using this approach is that it enables practitioners to focus only on the SDM and SDEM specification since other specifications can be easily derived from them (LeSage, 2015).

The Bayesian approach is used to select spatial models and spatial weight matrices as done by other scholars (Costa da Silva, Elhorst, & da Mota Silveira Neto, 2017; Rios et al., 2017; Yesilyurt & Elhorst, 2017). Table 2 displays the values of the Bayesian posterior-model probabilities computed across different definitions of $\boldsymbol{W}$ for each spatial panel data model.[22] On comparing the probabilities of all 72 combinations,[23] the DSAR model with $\boldsymbol{W}_{d<20km}$ shows

[22]The Matlab code developed by Yesilyurt and Elhorst (2017) is rearranged for this purpose. Their code is available at https://spatial-panels.com/software/.

[23]The probabilities are normalized so that the sum of the probabilities of all 72 combinations is 1. This can be easily verified by summing the probabilities displayed in the column “Raw tot.”

TABLE 2 Bayesian posterior-model probabilities computed across dynamic spatial panel data models

	W_1	W_2	$W_{d<20km}$	$W_{d<35km}$	$W_{d<50km}$	$W_{1/d^2<20km}$	$W_{1/d^2<35km}$	$W_{1/d^2<50km}$
Currexp speed								
DSAR	0.0031	0.0007	0.2388	0.0049	0.0003	0.0262	0.0139	0.0067
DSDM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DSEM	0.0006	0.0004	0.0073	0.0010	0.0002	0.0015	0.0010	0.0006
DSDEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Capexp speed								
DSAR	0.0002	0.0003	0.0004	0.0004	0.0003	0.0002	0.0002	0.0002
DSDM	0.0000	0.0000	0.0000	0.3529	0.3486	0.0000	0.0000	0.0000
DSEM	0.0002	0.0002	0.0003	0.0003	0.0003	0.0002	0.0002	0.0002
DSDEM	0.0000	0.0000	0.0000	0.1633	0.1246	0.0000	0.0000	0.0000
Tpexp speed								
DSAR	0.0008	0.0002	0.0016	0.0009	0.0002	0.0003	0.0004	0.0004
DSDM	0.0000	0.0000	0.0000	0.0001	0.5743	0.0000	0.0000	0.0000
DSEM	0.0003	0.0001	0.0004	0.0002	0.0001	0.0001	0.0001	0.0002
DSDEM	0.0000	0.0000	0.0000	0.0001	0.3977	0.0000	0.0000	0.0000
Totexp speed								
DSAR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DSDM	0.0000	0.0000	0.0041	0.2967	0.0002	0.0000	0.0000	0.0000
DSEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DSDEM	0.0000	0.0000	0.0048	0.6784	0.0004	0.0000	0.0000	0.0000

	$W_{k=4}$	$W_{k=5}$	$W_{k=6}$	$W_{k=7}$	$W_{k=8}$	$W_{k=9}$	$W_{k=10}$	$W_{k=12}$	$W_{k=16}$	$W_{k=20}$	Raw tot
Currexp speed											
DSAR	0.0086	0.0496	0.0331	0.1044	0.0875	0.2147	0.0269	0.0165	0.0329	0.0693	0.9381
DSDM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DSEM	0.0022	0.0082	0.0047	0.0087	0.0085	0.0083	0.0022	0.0016	0.0023	0.0026	0.0619
DSDEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Capexp speed											
DSAR	0.0002	0.0002	0.0003	0.0003	0.0003	0.0003	0.0003	0.0004	0.0005	0.0005	0.0055
DSDM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.7015
DSEM	0.0002	0.0002	0.0003	0.0003	0.0003	0.0003	0.0003	0.0004	0.0005	0.0004	0.0051
DSDEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2879
Tpexp speed											
DSAR	0.0004	0.0020	0.0017	0.0007	0.0006	0.0004	0.0004	0.0006	0.0031	0.0077	0.0224
DSDM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5744
DSEM	0.0002	0.0007	0.0005	0.0003	0.0002	0.0002	0.0001	0.0002	0.0005	0.0010	0.0054
DSDEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3978
Totexp speed											
DSAR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

(Continues)

TABLE 2 (Continued)

	$W_{k=4}$	$W_{k=5}$	$W_{k=6}$	$W_{k=7}$	$W_{k=8}$	$W_{k=9}$	$W_{k=10}$	$W_{k=12}$	$W_{k=16}$	$W_{k=20}$	Raw tot
DSDM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0021	0.0015	0.3047
DSEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DSDEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0040	0.0074	0.6952

the largest posterior probabilities for the speed of payments of the current component of expenditure. The Bayesian posterior-model probabilities comparison points to the DSDM for both *capexp speed* and *tpexp speed* with $\boldsymbol{W}_{d\,<\,35km}$ and $\boldsymbol{W}_{d\,<\,50km}$ matrix, respectively. Interestingly, the $\boldsymbol{W}_{d\,<\,35km}$ matrix is only slightly superior to the $\boldsymbol{W}_{d\,<\,50km}$ matrix for *capexp speed* since the posterior probabilities are close to each other. The comparison of spatial regression models also indicates that the DSDEM with $\boldsymbol{W}_{d\,<\,35km}$ matrix is the best choice for *totexp speed*.[24]

6 | BASELINE RESULTS

The estimates set out in Tables 3 and 4 are performed with the bias-corrected QLM (BCQML) estimator[25] developed by Yu et al. (2008),[26] who rigorously demonstrated that the QML estimator for the spatial dynamic panel data models with fixed effects is biased when both the number of units (N) and the number of time periods (T) tend to infinity, such that the limit of N/T is bounded between 0 and infinite. They have proposed a bias correction that yields T consistent QML estimates when N/T tends to infinity. Moreover, they have shown that the correction eliminates the bias and yields a centred confidence interval when T grows faster than $N^{1/3}$. The sample used in the empirical analysis consists of 246 units that grow faster than T (= 10), providing for consistent estimates. Moreover, T is greater than $N^{1/3}$ = 6.26, suggesting that the bias is eliminated. Thus, the estimator proposed by Yu et al. (2008) is properly used.

The DSAR model is estimated for the speed of current outlays with the $\boldsymbol{W}_{d\,<\,20km}$ matrix. The estimation results displayed in Table 3 show that the spatial parameter ρ is statistically significant at the 1% level, indicating that a municipality interacts significantly with its geographical neighbours in terms of spending efficiency by mimicking neighbours' speed of current outlays. However, interpretation of the coefficients of the spatially lagged variables is more complex in the SDM, where both exogenous and endogenous components of spatial dependence are included. Information obtained through the computation of both the direct and indirect effects makes it possible to clarify the magnitude of neighbourhood effects. Since spatial dynamic model specifications are estimated, direct and indirect effects are computed for both the short-run and the long-run period (Bellotti et al., 2017; Elhorst, 2014).

The DSP produces negative effects on the municipal speed of current outlays, significant at the 5% level. However, its impact is scant because in the short-run period the estimated direct and indirect effects of the *DSP* on *currexp speed* are −0.008 and − 0.003, respectively, while the long-run direct effect is −0.016. The negative effects suggest that the municipality and its neighbourhood reduce the annual growth of public spending to comply with fiscal regulations by slowing down the speed of current outlays.

The electoral cycle is another significant determinant of the municipal speed of current outlays, suggesting the presence of opportunistic behaviour by the incumbent politician, who signals to voters a better budget performance during the election year in order to capture more voter consensus for re-election in office. When an election takes place in a given municipality, the speed of current outlays in the short term increases by 0.006 points in that municipal area and by 0.003 points in its surroundings. This suggests that when an election takes place in a given municipality, rumours on election results spread among neighbouring jurisdictions, influencing their administrative

[24]The log-marginal likelihood values computed for each spatial regression model with different spatial weight matrices provide the same indications. They are available from the author upon request.

[25]The Stata command *xsmle* realized by Belotti, Hughes, and Mortari (2017) is used to perform the QLM estimates.

[26]The bias-adjusted QML estimator of Yu et al. (2008) is also used by Elhorst, Zandberg, and De Haan (2013).

TABLE 3 Estimation results of the spatial dynamic panel data model for the municipal speed of current outlays

	Currexp speed						
	DSAR	DSAR	DSAR	DSAR	DSAR	DSAR	DSAR
	Main	SR_direct	SR_indirect	SR_total	LR_direct	LR_indirect	LR_total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ρ	0.29^{7***} (4.62)						
y_{t-1}	0.514*** (8.28)						
Pop (log)	−0.020 (−0.75)	−0.020 (−0.75)	−0.009 (−0.72)	−0.030 (−0.75)	−0.043 (−0.75)	−0.102 (−0.25)	−0.146 (−0.33)
Young	−0.001 (−0.24)	−0.001 (−0.22)	−0.0001 (−0.12)	−0.001 (−0.19)	−0.001 (−0.22)	−0.002 (−0.04)	−0.003 (−0.06)
Elderly	0.001 (0.92)	0.001 (0.92)	0.0005 (0.85)	0.002 (0.91)	0.002 (0.91)	0.004 (0.24)	0.006 (0.37)
Income (log)	−0.047 (−1.36)	−0.045 (−1.35)	−0.019 (−1.21)	−0.065 (−1.34)	−0.096 (−1.35)	−0.111 (−0.06)	−0.207 (−0.11)
DSP	−0.008** (−1.99)	−0.008** (−2.02)	−0.003* (−1.65)	−0.011** (−1.96)	−0.016** (−2.00)	−0.020 (−0.06)	−0.036 (−0.10)
Majority size	0.000002 (0.02)	0.00001 (0.05)	0.000001 (0.03)	0.00001 (0.04)	0.00001 (0.05)	0.0002 (0.05)	0.0002 (0.06)
Left-wing	−0.003 (−0.54)	−0.003 (−0.56)	−0.001 (−0.44)	−0.004 (−0.53)	−0.007 (−0.56)	−0.018 (−0.08)	−0.025 (−0.10)
Education	−0.001 (−0.15)	−0.001 (−0.15)	−0.0001 (−0.07)	−0.001 (−0.13)	−0.001 (−0.15)	−0.008 (−0.04)	−0.009 (−0.05)
Election year	0.006** (2.25)	0.006** (2.37)	0.003* (1.95)	0.009** (2.36)	0.013** (2.37)	0.020 (0.16)	0.032 (0.27)
Crisis	0.009** (2.49)	0.009*** (2.61)	0.004** (2.09)	0.013** (2.57)	0.020*** (2.60)	0.035 (0.20)	0.055 (0.31)
Log-pseudolikelihood	4415.5						
R^2	0.210						

Notes: z-statistics in parenthesis; standard errors robust to heteroscedasticity. *p < 0.10, **p < 0.05, ***p < 0.01.

TABLE 4 Estimation results of the spatial dynamic panel data models with alternative indicators of the municipal spending efficiency

	Capexp speed	*Tpexp speed*	*Totexp speed*
	DSDM	**DSDM**	**DSDEM**
	(1)	**(2)**	**(3)**
ρ	0.135 (1.61)	0.225** (2.15)	
λ			0.483*** (6.55)
y_{t-1}	0.142*** (4.72)	0.254*** (8.48)	0.122*** (4.83)
Log-pseudolikelihood	1137.58	1269.31	1666.04
R^2	0.033	0.004	0.022

Notes: z-statistics in parenthesis; standard errors robust to heteroscedasticity. *p < 0.10, **p < 0.05, ***p < 0.01.

performance. In the long term, *election year* in a given municipal area generates only an increase in the speed of current outlays of the municipality in question, without any indirect effect on nearby municipalities.

Municipalities responded significantly to the 2008 global financial crisis by increasing their speed of current outlays to alleviate its harmful effects on local economic development. In the short term, *crisis* produces a significant and positive direct effect on the municipal speed of current outlays, but also a significant spillover effect that is slightly lower than the direct effect in terms of magnitude. More specifically, the occurrence of *crisis* in a municipal area significantly increases the speed of current outlays in the short term, by 0.009 points in that area itself and by 0.004 points in neighbouring municipalities. This suggests that the financial *crisis* occurring in a given area spreads its effects with a similar intensity among nearby jurisdictions. Moreover, it produces a long-term direct effect on the municipal area of about 0.020, which is statistically significant at the 1% level.

Interestingly, the absence of spillovers impacts on *currexp speed* in the long run, where changes in a given municipal area are driven only by changes experienced in that area itself. Thus spillovers affect *currexp speed* only in the short term.

The estimated values of the spatial parameters for the other indicators of administrative efficiency are summarized in Table 4. The municipality's speed of payments to third parties is significantly spatially correlated with that of neighbouring municipalities. As displayed by column (2), ρ is statistically significantly at the 5% level. By contrast, spatial dependence is not a relevant determinant of the municipal speed of capital outlays. This is hardly surprising because public investment decisions are subject to greater uncertainty about the time and costs of public works which may result in less intense spatial correlation.

Interestingly, the magnitude of ρ of the speed of municipal current outlays exceeds the magnitude of the speed of capital outlays and the speed of payments to third parties. The higher reaction to neighbours' changes in the speed of current payments may be due to the rigidity of certain components of current expenditure that could inflate the spatial effect. Indeed, the speed with which the salaries of public employees are paid is on average high and similar among municipalities.

The municipal speed of total public expenditure is significantly spatially correlated through the error term structure, where the estimated parameter λ is 0.48. Moreover, the variables related to spatial spillovers $\boldsymbol{WX}$ are statistically significant among the other regressors.[27] The estimated coefficient of $\boldsymbol{y_{t-1}}$ is statistically significant in each regression, suggesting the validity of the spatial dynamic specification.

Overall, the estimates indicate that all indicators of municipal administrative efficiency are found to grow faster when elections are coming. Population size significantly affects the indicators of municipal spending efficiency,

[27]The full estimation results are available from the author upon request.

[28]As a robustness check, it was verified whether the population has non-linear effects (Bosch & Solé Ollé, 2005) on the indicators of the municipal speed of payments. The estimated parameter of the squared population is not statistically significant and the inclusion of this variable in the spatial regression analyses does not change the main results.

TABLE 5 A test of the political yardstick competition hypothesis on the municipal speed of current outlays

	40%	**45%**	**50%**	**55%**	**60%**	**65%**	**70%**	**75%**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ρ	0.005 (0.30)	−0.054 (−1.49)	0.080* (1.67)	0.228*** (3.42)	0.274*** (4.35)	0.307*** (4.76)	0.319*** (5.07)	0.307*** (4.76)
ρ*maj%	0.401*** (4.01)	0.500*** (4.84)	0.340*** (3.38)	0.179 (1.60)	0.093 (0.76)	−0.070 (−0.56)	−0.226 (−1.50)	−0.171 (−1.28)
Maj%	−0.317*** (−4.03)	−0.398*** (−4.89)	−0.270*** (−3.39)	−0.141 (−1.60)	−0.073 (−0.76)	0.053 (0.54)	0.177 (1.52)	0.136 (1.30)
y_{t-1}	0.508*** (7.99)	0.506*** (7.94)	0.509*** (8.00)	0.511*** (8.26)	0.513*** (8.27)	0.515*** (8.28)	0.515*** (8.31)	0.515 (8.30)
Likelihood ratio-test	0.0001	0.000	0.0001	0.0001	0.000	0.000	0.000	0.000
Log-pseudolikelihood	4424.3	4428.8	4423.7	4419.1	4416.7	4415.7	4416.3	4415.8
R^2	0.279	0.287	0.249	0.225	0.216	0.206	0.216	0.220

Notes: z-statistics in parenthesis; standard errors robust to heteroscedasticity. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

except for the municipal speed of current and capital outlays, increasing government inefficiency due to congestion effects.[28] Moreover, the demographic structure of the population impacts significantly on municipal spending efficiency. A one percentage point increase in *young* in the municipal area is accompanied by a reduction in *tpexp speed* in the surrounding area by −0.272 points and − 0.409 points in the short and long term, respectively. The municipal speed of capital outlays increases in both the short and long run by about 0.001 points in the municipal area after a one percentage point increase in the *majority size*, confirming the hypothesis that mayors supported by larger voter consensus implement fiscal policies efficiently. The municipal speed of payments to third parties is also positively and significantly affected by *majority size* through spillover effects in both the short and long term.

7 | A TEST OF POLITICAL YARDSTICK COMPETITION

One source of spatial dependence in local government efficiency is political yardstick competition. However, few empirical studies have investigated this issue (Borge et al., 2005; Revelli & Tovmo, 2007). According to the political yardstick competition approach, mayors who are supported by small majorities are more prone to align their own fiscal policy decisions with those of nearby jurisdictions to please voters (Allers & Elhorst, 2005; Solé Ollé, 2003). Similarly, they might be expected to mimic the government efficiency of neighbouring municipality to a greater extent in order to obtain greater voter consensus for being re-elected in office. This hypothesis is tested by estimating the dynamic SAR model in (5) with the $\boldsymbol{W}_{d\,<\,20km}$ matrix, where the spatially lagged dependent variable is interacted with a dummy variable ***mv*** that assumes value 1 if the share of the mayor's votes exceeds a threshold z set at different critical values, and zero otherwise.[29] This approach to testing the sources of spatial dependence in fiscal policy decisions by local governments was already used in other empirical analyses (Ferraresi et al., 2018; Rizzo, 2008). The hypothesis of political yardstick competition is verified when η assumes significantly positive values for a mayor's lower voting share and/or significantly negative values for a larger share of the mayor's voting margin. Mayors who are supported by large majorities are also expected to be insensitive to changes in the administrative efficiency of neighbouring jurisdictions, determining statistically insignificant values of parameter η:

$$\boldsymbol{y_t} = \delta \boldsymbol{y_{t-1}} + \rho \boldsymbol{W} \boldsymbol{y_t} + \eta \boldsymbol{W} \boldsymbol{y_t} \cdot \boldsymbol{mv_t} + \gamma \boldsymbol{mv_t} + \boldsymbol{X_t} \beta + \boldsymbol{f} + \boldsymbol{c} + \boldsymbol{\varepsilon_t}. \tag{5}$$

The estimation results displayed in Table 5 show that, for the mayor's share of votes of 40%, 45% and 50%, municipalities tend to react more to changes in the speed of current outlays of neighbouring jurisdictions. In columns (1)–(3) the coefficient η of the interaction term is statistically significant at the 1% level, assuming values between 0.30–0.50. The F-test in columns (1)–(3) indicates that the estimated parameters ρ, η and γ are jointly statistically significant different from zero at the 1% level. Upon increasing the threshold of the share of the mayor's votes, coefficient γ proves to be statistically insignificant and becomes negative for the mayor's share of votes over 65%. These results are in line with the political yardstick competition hypothesis, suggesting that it could be a potential source of spatial interdependence detected in the speed of current outlays.

8 | CONCLUSIONS

The impact of spatial effects on local government efficiency is a fruitful area of research, albeit largely neglected in the literature. Both knowledge diffusion and yardstick competition could be the main causes of spatial effects on such efficiency. Indeed, local governments adopt innovative administrative practices developed in neighbouring

[28]As a robustness check, it was verified whether the population has non-linear effects (Bosch & Solé Ollé, 2005) on the indicators of the municipal speed of payments. The estimated parameter of the squared population is not statistically significant and the inclusion of this variable in the spatial regression analyses does not change the main results.

[29]The variable *majority size* is not included in the set of control variables ***X***.

jurisdictions, resulting in a similar pattern of productive efficiency. Citizens can use the production efficiency of neighbouring jurisdictions as a benchmark with which to evaluate the fiscal performance of their incumbent politicians. This induces the incumbents to align their performance with that of their neighbours, creating spatial interdependence in local government efficiency.

This study empirically explored spatial patterns in the spending efficiency of local governments on a sample of Italian municipalities. The estimation results show a significant presence of spatial interdependence in the speed of payments used to measure municipal spending efficiency. Municipalities mimic not only levels of public expenditure, as shown by previous empirical studies, but also the speed with which payments are made. The speed of current outlays reveals a greater magnitude of spatial patterns with respect to both the speed of capital outlays and the speed of payments to third parties, which may reflect the rigidity of certain components of current expenditure. The source of the spatial dependence detected in the municipal speed of current outlays is ascribed to political yardstick competition, since municipalities governed by mayors supported by large majorities are insensitive to neighbouring changes in the municipal speed of current outlays.

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Resumen. Se ha prestado poca atención al patrón espacial de la eficiencia del gobierno local. El objetivo de este artículo es llenar esta laguna de conocimiento mediante un análisis empírico de una muestra de 246 municipios italianos durante la década 1998–2008. La eficiencia del gobierno municipal se mide en términos de la rapidez de los pagos. Los resultados de las estimaciones revelan que los municipios imitan la rapidez con la que sus vecinos llevan a cabo el gasto público. Se ha comprobado que la competencia por comparación en la política es la fuente del comportamiento imitador de la velocidad de los pagos.

抄録: これまで、地方政府の効率性の空間パターンにはほとんど関心が向けられてこなかった。本稿では、こうした不足を補うため、1998~2008年のイタリアの246の自治体を対象に実証分析を行う。自治体の効率性は、支払いのスピードで測定する。推計結果によると、地方自治体は近隣の自治体の公的支出のスピードを模倣していることが明らかになった。政治的なものさしによる競争 (political yardstick competition)は、支払いのスピードを模倣する行動の原因であることがわかっている。