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SPATIAL EFFECTS ON LOCAL GOVERNMENT EFFICIENCY

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Abstract

Little attention has been paid to the spatial pattern in local governments' efficiency. This paper intends to fill this gap by conducting an empirical analysis on a sample of 246 Italian municipalities over the decade 1998-2008. The efficiency of the municipal government is measured in terms of the speed of payments for different categories of public spending. Estimation results reveal the presence of spatial interdependence in the speed of payments among the geographically close municipalities, with a greater magnitude for the speed of current outlays. Thus, municipalities mimic the speed with which public spending is carried out by their neighbors.

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Spatial effects on local government efficiency*

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1 Introduction

Spatial interdependence in fiscal policy decisions of local governments has received increasing attention over the last 15 years. There exist a large number of studies that empirically investigate the presence of spatial patterns in the levels of local public expenditure and taxation (for reviews, see Brueckner (2003) and Revelli (2005, 2015)). Only a few studies have analyzed whether the efficiency of local governments in the provision of public goods and services also depend on neighborhood decisions (Geys, 2006; Revelli and Tovmo, 2007; Bollino et al., 2012). They share the view that yardstick competition (Salmon, 1987; Besley and Case, 1995) due to citizens' benchmarking could be one of the plausible determinants of mimicking behavior in local governments efficiency. Citizens do not have complete knowledge about the fiscal performance of their politician incumbents, and they fill this information gap by comparing it with those of neighboring jurisdictions. Thus, the incumbent politician sets his/her own fiscal decisions in line with those of neighboring administrations, also avoiding punishment at the polls. Also emphasized has been the role played by local governments in copying best administrative practices from each other to improve efficiency, involving spatial interdependence through the diffusion of knowledge among neighboring jurisdictions (Bollino et al., 2012).

Getting into the specifics of these studies, Geys (2006) finds that the abilities of Flemish municipalities to spend money on public goods efficiently is affected by neighborhood effects. He uses 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. Revelli and Tovmo (2007) test the existence of yardstick competition in production efficiency of 205 Norwegian municipalities. As a measure of local administrations' efficiency, they use an indicator developed by Borge et al. (2005) based on the ratio between an aggregate measure of the production of services provided by local governments and

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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 compare 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 neighboring municipalities for reasons compatible with yardstick competition. Finally, 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 of the Italian region 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.

The current paper contributes to investigating the presence of the spatial patterns in local governments' 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 et al., 2014). This measure deals with the speed with which local governments transform spending commitments into actual payments into local public goods. Higher payment speed involves greater government efficiency because a larger share of spending commitments is realized, involving a greater share of public goods provided. The speed of payments is calculated for several categories of public spending such as current expenditure, capital expenditure, expenses to third-parties and total expenditure.

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). In this strand of the literature, the current paper represents the first contribution that uses the Bayesian method to investigate the nature of spatial dependence. The selection model conducted by this approach points to the static spatial Durbin model for the speed of total payments and the static spatial autoregressive model for the other indicators of spending efficiency.

Estimation results reveal the presence of spatial interdependence in the speed of payments among the geographically close municipalities. Hence, they highlight that municipalities mimic not only the levels of public expenditure, as shown by past empirical studies, especially on the Italian context (Ermini and Santolini, 2010; Bartolini and Santolini, 2012; Ferraresi et al., 2018), but also the speed with which they made payments for providing public goods and services. Estimates also show that a municipality reacts more to changes in the speed of current spending of neighboring municipalities than in changes in the speed of payments of other categories of public expenditure. One reason for this result may be the rigidity of some components of current expenditure (such as wages and salaries of public employees) that could artificially inflate the spatial effect in current spending efficiency, resulting in a more pronounced reactivity of municipality to changes in the speed of current outlays of its neighbors. On the other hand, time and costs for public works construction are subject to greater uncertainty, making capital spending efficiency less spatially correlated. Overall, the results

The rest of the paper is structured as follows. Section 2 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 3. Selection of both spatial models and spatial weight matrices by the Bayesian method is illustrated in Section 4. Estimation results are discussed in Section 5, and Section 6 concludes.

2 Data and variables

The empirical analysis has been conducted on a sample of 246 Italian municipalities over the decade 1998-2008. The municipalities are located in the Marche Region[1], where evidence on fiscal policy interdependence has been documented (Santolini, 2008; Ermini and Santolini, 2010; Bartolini and Santolini, 2012). The Marche Region is located in the center of Italy, and 14% of its municipalities face onto the Adriatic Sea, while the remainder extend up to the Umbro-Marche Apennine mountains. The region is characterized by a large number of municipalities with populations of fewer than 3,000 inhabitants (56% in 2014) and a population density smaller than 150 inhabitants per square kilometer (64% in 2014).

In Italy, the municipality is the lowest level of government, which deals with many important activities affecting citizens' lives, such as primary schooling, public finance, urban planning, public order, among others. 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 voters for policies implemented as well as for the administrative control of the municipality activities.

The budget of a municipality furnishes evidence of these policies and makes it possible to assess government efficiency through budget indicators such as the speed of payments (Drago et al., 2014). This measure of spending efficiency is calculated for total public expenditure (*totexp speed*) as the ratio between the total public expenditure paid and the total public expenditure committed by the municipality. Additional indicators of the speed of payments are computed in the same manner for the main budget items of the municipal public expenditure such as current (*currexp speed*) and capital (*capexp*

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

speed) expenditure and expenditure to third-parties (*tprexp speed*).[2] Each indicator assumes values between 0 and 1 (inclusive). A value equal to 1 indicates that expenses committed by the municipality are fully paid within the budget year. Hence, increasing the value of the ratio implies that municipality shows a better budget performance.[3] The speed of payments indicators are built using data on local public finance released by the Ministry of Interior.[4]

In the panel regression analysis, control variables on demographics, economic and political characteristics are included. As regards the municipal demographic aspects, population size (*pop*) and *density*, measured in terms of inhabitants per square kilometer of land area, are employed.[5] The effects of population on 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. Population enters the spatial panel data regressions in logarithmic form. The demographic structure is controlled by the percentage of *young people* (aged 0-14 years old) and *elderly people* (aged 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 et al., 2008).

On the side of economic controls, *income* enters the panel regression analysis in terms of the logarithm of per-capita income tax base.[6] Rich households demand a better quality of local public services and greater efficiency in their provision. Thus, a positive correlation between income and government efficiency should be expected.

Political characteristics like the size of mayor's majority and political ideology can significantly affect the municipal government's efficiency.[7] Mayors who received large share of votes during elections have greater political strength to impose hard budget constraints for pursuing budget consolidation policies (Borge et al., 2008). Accordingly,

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

[3]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.

[4]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 have been filled by the data of the year 1999.

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

[6]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.

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

it can be expected that the mayors' *votes share* is positively correlated with government efficiency. Political ideology is also taken into account by a dummy variable named *left-wing* that assumes value 1 when the municipality is ruled by a left-wing coalition, and zero otherwise. The size of public expenditure is commonly higher in municipalities ruled by left-wing coalitions because they support stronger government intervention in the economy by promoting extensive social welfare programs. Hence, they are more inclined to set a soft budget constraint because they face higher costs increases due to the supply of a wide range of public services. Thus, it is expected that municipalities ruled by left-wing coalitions have less government efficiency (Borge et al., 2008).

The literature has shown that incumbent politicians increase expenditure in pre-electoral periods to gain larger voter consensus for reappointment in office (Rogoff and Sibert, 1988; Rogoff, 1990). 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 electoral cycle, a dummy variable named *election* is used as control. It assumes value one in the election year and zero otherwise.[8]

Politicians' competencies can make a difference in implementing fiscal policies efficiently. A highly competent politician adapts better to changes (Welch, 1970), revealing a better government performance (Besley et al., 2011). A dummy variable *education* enters among the regressors to capture mayor's competence. It assumes value 1 if the elected mayor has a university degree, and zero otherwise.[9]

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.

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

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

[9]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
dens	2706	180.853	253.271	3.962	1888.229
young	2706	12.940	1.879	4.850	18.930
elderly	2706	23.689	4.763	11.390	43.780
income (log)	2706	9.003	0.210	8.309	9.611
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
election year	2706	0.191	0.393	0.000	1.000

3 Models and estimation methodology

A general empirical specification for investigating the presence of spatial dependence in municipal spending efficiency is the dynamic general nesting spatial (GNS) model (Elhorst, 2014; Yesilyurt and Elhorst, 2017) illustrated in equation (1).

$$\begin{aligned} GNS: \quad y_t =& \delta y_{t-1} + \rho W y_t + \eta W y_{t-1} + X_t \beta + W X_t \phi + f + \tau_t + c + \epsilon_t \\ \epsilon_t =& \lambda W \epsilon_t + \upsilon_{it} \quad \upsilon \sim \left(0, \rho_\epsilon^2 I_N\right) \end{aligned} \tag{1}$$

The dependent variable y_t is a $N \times 1$ vector containing the indicator of the speed of payments in the *i-th* 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 y_{t-1} is included on the right-side of (1).

Spatial interdependence among neighboring municipalities is described by the $N \times N$ spatial weight matrix W. Adopting the spatial weight matrix with the geographical distance has the advantage of making W exogenous, permitting the identification of the spatial process.[10] If only first order neighbors 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 (W_1) and the second (W_2) order contiguity matrix are considered.[11]

Alternative distance measures are used to better identify the geographical neighborhood. Accordingly, use is made of a spatial weight matrix $W_{d<20km}$ with elements based

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

[11] The W_2 matrix includes the first order contiguous neighbors and neighbors that share a border with them.

on kilometers (km) distance 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 $W_{d<20km}$ are zero. Finally, the spatial matrix W_k with *k*-nearest neighbours weights is employed, where *k* is a positive integer set equal to 4, 6 and 8 as in other empirical studies (Bocci et al., 2017). The off-diagonal elements of W_k are set 1 for the k closest spatial units to the *i-th* municipality and zero otherwise. The diagonal elements of W_k are zero.

The coefficient ρ associated with 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 one-period lag in the spatially dependent variable (Wy_{t-1}) is also included in the GNS model, as well as the $1 \times K$ vector X of control variables and the spatially lagged explanatory variables (WX). Fixed-effects (f) are added in order to control for the omission of unobserved heterogeneity of municipalities and year dummies to check for common shocks across them. A constant term *c* and spatially autocorrelated errors ϵ_t are included in the GNS model with υ independently and identically distributed with zero mean and constant variance.[12].

A drawback of the dynamic GNS model is that the inclusion of WX prevents the identification of the interaction effects in the dependent variable and the error terms (Anselin et al., 2008; Elhorst, 2014). Therefore, the removal of one of the two spatial interaction effects is necessary when WX is included in the empirical model for achieving the goal of identification. This also leads to obtaining other spatial specifications. In particular, the removal of errors spatially distributed ($\lambda = 0$) transforms the GNS model into a dynamic spatial Durbin model (SDM), whereas the absence of the interaction effects in the dependent variable ($\rho = \eta = 0$) transforms it into a dynamic spatial Durbin error model (SDEM), as shown by (2) and (3).

$$\begin{aligned} SDM: \quad y_t =& \delta y_{t-1} + \rho W y_t + \eta W y_{t-1} + X_t\beta + WX_t\phi + f + \tau_t + c + \epsilon_t \\ & \epsilon \sim \left(0, \rho_\epsilon^2 I_N\right) \end{aligned} \tag{2}$$

$$\begin{aligned} SDEM: \quad y_t =& \delta y_{t-1} + X_t\beta + WX_t\phi + f + \tau_t + c + \epsilon_t \quad \epsilon_t = \lambda W \epsilon_t + \upsilon_t \\ & \upsilon \sim \left(0, \rho_\epsilon^2 I_N\right) \end{aligned} \tag{3}$$

The two Durbin spatial nested-models involve spatial spillovers occurring when the outcome of the *i-th* jurisdiction is affected by the characteristics and/or actions of the *j-th* jurisdiction neighbor to *i*. However, the nature of spillovers differs among them. The

[12]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 W matrix (LeSage, 2008; Elhorst, 2010).

SDEM implies *local spillovers*, involving only jurisdiction *i* and neighbors of *j*. The SDM involves *global spillovers* among the *i-th* jurisdiction and neighbors of neighbors of neighbors (and so on) of *j* (LeSage and Pace, 2009).

Two further spatial model specifications can be easily derived from the SDM and the SDEM by assuming ϕ=0. In particular, the dynamic SDM is transformed in the dynamic spatial autoregressive (SAR) model displayed in (4), whereas the dynamic SDEM turns into the dynamic spatial error model (SEM) illustrated in (5). 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 and Pace, 2009) and the true-data generation process coincides with the SAR and the 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 specification to investigate spatial dependence more attractive than other model specification (Elhorst, 2010).

$$SAR: \quad y_t = \delta y_{t-1} + \rho W y_t + \eta W y_{t-1} + X_t\beta + f + \tau_t + c + \epsilon_t \qquad \epsilon \sim \left(0, \rho_\epsilon^2 I_N\right) \tag{4}$$

$$SEM: \quad y_t = \delta y_{t-1} + X_t\beta + f + \tau_t + c + \epsilon_t \qquad \epsilon_t = \lambda W \epsilon_t + \upsilon_t \quad \upsilon \sim \left(0, \rho_\epsilon^2 I_N\right) \tag{5}$$

Since the 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 $y_i = \beta \sum_{r=1}^{k} x_{i,r} + \epsilon_i$, the *direct effects* coincide with the 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 neighbor *j* is given by $\partial y_i / \partial x_{jr} = 0$ for $j \neq i$ and $\forall$ *r* (LeSage, 2008).

The (in)direct effects differ among spatial econometric models (Elhorst, 2010). Considering, for simplicity, their static versions, the (in)direct effects of the SDM are given by the (off-)diagonal elements of $(I - \rho W)^{-1}(\beta_k + W\phi_k)$. The (in)direct effects of the static SAR model correspond to the (off-)diagonal elements of $(I - \rho W)^{-1}\beta_k$. The coefficients β and ϕ of the SDEM specification can be directly interpreted as direct and indirect effects, respectively. The SEM has the same effects as the linear regression model (Elhorst and Vega, 2013). The summation of direct and indirect effects determines the *total effects*.[13]

The inclusion of Wy makes the ordinary least squares (OLS) estimator inconsistent (Cliff and Ord, 1973; Anselin, 1988). Thus, other methods, such as the maximum likelihood (ML) and the quasi-ML (QML) estimator, can be used to estimate the spatial panel data models (Yu et al., 2008; Lee and Yu, 2010b). The ML estimator provides consistent

[13]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 (LeSage and Pace, 2009; Golgher and Voss, 2016).

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 these problems. The two estimators have common drawbacks. They provide consistent estimates only if the estimated spatial econometric model is the true data-generating process (Lee, 2004). Thus, the model selection is crucial when the ML-based estimators are used, since the wrong specification makes them inconsistent. Moreover, they do not rely on endogenous variables.

The instrumental variables (IVs) estimator can be used to address endogeneity problems. It also remains consistent with non-normal heteroscedastic errors and even in the presence of spatial auto-correlated shocks among jurisdictions (Anselin, 1988; Kelejian and Prucha, 1998). One disadvantage is that estimated coefficients ρ and λ may be outside parameters space. Moreover, the traditional instruments based on neighbors' characteristics Wx (Kelejian and Prucha, 1998) used for the spatially lagged dependent variable could be invalid or almost weak. Gibbons and Overman (2012) have made some criticisms about identification problems raised by using neighbors' characteristics as instruments. Indeed, if the exclusion of Wx from spatial econometric models is invalid, it and its higher order lags (W^2x, W^3x, etc.) are unsuitable instruments for the identification of the causal effect of Wy on y in a spatial instrumental variable setting. By contrast, if the exclusion restrictions are valid and W is known, 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.

4 Models selection

Identification problems occur because of the difficulty in distinguishing among different spatial econometric models, incurring erroneous economic interpretations of spatial effects (Gibbons and Overman, 2012). LeSage (2014) argues that practitioners can select between the SDM or the SDEM specification by providing convincing theoretical argumentations in favor of local or global spillovers. However, Gibbons and Overman (2012) are rather skeptical about using only theoretical motivations to selecting 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 et al., 1996) as well as additional test procedures to select among alternative spatial specifications. More recently, LeSage (2014, 2015) has encouraged the adoption of a Bayesian approach of model uncertainty to select spatial models with different definitions of the neighborhood. One advantage in using this approach is that it enables practitioners to focus only on the SDM and the SDEM specification because other specifications can be easily derived from them (LeSage, 2015).

The Bayesian approach is used to select both spatial models and distance-based spatial weight matrices as made by other ones (Yesilyurt and Elhorst, 2017; Costa da Silva et al., 2017). Table 2 displays the values of both the log marginal likelihood (divided by 1,000) and the Bayesian posterior-model probabilities for the static spatial panel data models ($\phi = \eta = 0$) with different definitions of W.[14] Comparing the probabilities of all 24 combinations,[15] it results that the SAR model with $W_{d<20km}$ shows the largest posterior-probabilities for the speed of payments of current and capital component of expenditure. It is noteworthy that the SAR model is only slightly superior to the SEM for $capexp\ speed$ since the posterior-probabilities and the log marginal values of both spatial models are close to each other. Clear-cut indications are provided by the Bayesian posterior model probability for the other two indicators of the municipal spending efficiency. Indeed, it points to the SDM with $W_d < 20km$ matrix for $totexp\ speed$ and to the SAR model with $W_{k=6}$ matrix for $tpexp\ speed$.

A similar picture is shown in Table 3 by comparing the Bayesian posterior probabilities of the dynamic spatial panel data models with different distance-based spatial weight matrices. One remarkable difference is observed for $tptexp\ speed$. For this indicator, the Bayesian testing procedure points to the dynamic SAR panel data model with no clear indications on which geographical distance to select for the spatial weight matrix. In fact, the posterior-probabilities and the log-marginal likelihood values of the dynamic SAR model performed with $W_{k=6}$ and $W_{d<20km}$ matrix are close to each other, making the matrix selection for this kind of spatial model difficult.

5 Results

The static specification with $\phi = \eta = 0$ is estimated because the log marginal values in Table 2 are higher than those in Table 3, suggesting a better performance of the static specification compared with the dynamic one. The estimates set out in Table 4 are performed with the QLM estimator with data transformation proposed by Lee and Yu (2010a) to eliminate fixed individual effects from the spatial model.[16] Indeed, the variance parameter estimated with the direct approach, not transforming data according to Lee and Yu's method, is inconsistent when *T* is small, whereas the coefficients of the spatial and control variables estimated remain consistent with small *T* and large *N* (Lee and Yu, 2010a).

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

[15] The probabilities are normalized so that the sum of the probabilities of all 24 combinations is 1. This can be easily verified by summing the probabilities displayed in the column "Raw tot".

[16] The Stata command *xsmle* realized by Belotti et al. (2017) is used to perform the QLM estimates.

The static SDM is estimated with regard to $totexp\ speed$, whereas the static SAR model is estimated for the remaining indicators of spending efficiency. The panel data regressions are performed with $W_d < 20km$ matrix, except for $tpexp\ speed$, of which W is based on 6 nearest neighbors.

The estimation results displayed in Table 4 show that the spatial parameter ρ is statistically significant at 1% level, indicating that a municipality interacts significantly with its geographical neighbors in terms of spending efficiency by mimicking neighbors' speed of payments. Municipalities are also more inclined to mimic the efficiency of neighboring municipalities in the payments of current and total expenditure. In this regard, it should be noted that ρ is twice as large in the estimates with the speed of current and total outlays (see columns 1 and 13) compared to the estimates with the speed of capital outlays and the speed of payments to third-parties (see columns 5 and 9). The higher reaction to neighbors' 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. On the other hand, public investment decisions are subject to greater uncertainty about the time and the costs of public works which could result in less intense spatial correlation in spending efficiency.

The estimates also show that population size significantly affects the indicators of municipal spending efficiency, except for the speed of capital outlays, increasing government inefficiency due to congestion effects. However, when the territories of neighboring jurisdictions are densely populated, municipal efficiency improves significantly (see column 14). Also the demographic structure of population impacts significantly on the municipal spending efficiency, especially on $tpexp\ speed$ and $totexp\ speed$. A one percentage point increase of *elderly* in the municipal area reduces $tpexp\ speed$ by 0.008 percentage points in that area. The direct effect on $tpexp\ speed$ is of small magnitude and weakly significant at 10% level. The *elderly* variable produces both direct and indirect effects on $totexp\ speed$ but of opposite signs.

Further significant determinants of municipal spending efficiency are *income* and the *DSP*. The richer is the municipal area and its surroundings, the higher is the municipal speed of payments except for the speed of current outlays, which is not significantly affected by *income*. The adoption of the *DSP* produces negative direct and indirect effects on both $capexp\ speed$ and $tpexp\ speed$, significant at 1% level. The negative effects suggest that the municipality and its neighborhood reduce the annual growth of public spending for complying with fiscal rule dispositions by slowing down the speed of capital outlays and payments with which they pay third-parties.

On the side of political determinants, all indicators of spending efficiency respond significantly to the electoral cycle, suggesting the presence of opportunistic behavior 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.

capexp speed increases by about 0.001 percentage points in the municipal area and its surroundings after a one percentage point increases in *majority size*, confirming the hypothesis that mayors supported by larger voter consensus implement fiscal policies efficiently. *Left-wing* coalition produces positive direct and indirect effects on *capexp speed*, where the direct effects (0.024) prevail in terms of magnitude to the spillover effects (0.007). However, the effect of leftist ideology is contrary to sign expectations based on the conjecture that left parties are more inclined to soften budget constraints in order to offer a wider range of public services, undermining the municipal efficiency. *totexp speed* is negatively correlated with *majority size* and *education* mainly through neighboring effects, contradicting the sign expectations.

Table 5 displays the QLM estimation results with both time and fixed individual effects included among the regressors. These estimates are performed using the direct approach that yields consistent QLM estimates for the coefficients of the spatial regressors and the control variables when both effects are introduced in the spatial models and N is large (Lee and Yu, 2010a). However, the coefficients estimated with this approach are biased because they are not properly centered (Lee and Yu, 2010a). Hence caution is necessary in comparing the parameters estimated with this approach with those estimated with the transformation approach used in the estimates displayed in Table 4. Keeping this caveat in mind, Table 5 shows that ρ remains statistically significant for each indicator of spending efficiency. However, its magnitude is smaller than that of the estimates in Table 4, especially for *capexp speed* and *totexp speed*. It is noteworthy that the speed of municipal payments remains particularly sensitive to electoral periods but less responsive to the adoption of fiscal rules and changes in disposable income.

6 Conclusions

The impact of spatial effects on local government efficiency has to date been neglected in the literature, although it is a fruitful area of research. In this respect, both knowledge diffusion and yardstick competition could be the main causes of spatial effects on local governments' efficiency. Indeed, local governments adopt innovative administrative practices developed in neighboring jurisdictions, resulting in a similar pattern of productivity costs efficiency. Citizens can use the production efficiency of neighboring 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 neighbors, creating spatial interdependences in local government efficiency.

This study has empirically explored spatial patterns in the spending efficiency of local governments on a sample of Italian municipalities. The estimation results, obtained with spatial econometric techniques, show a significant presence of spatial interdependences in the speed of payments used to measure municipal spending efficiency. The speed of current and total 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. The results of the empirical analysis suggest that municipalities mimic not only the levels of public expenditure, as shown by past empirical studies, but also the speed with which it is made.

Table 2: Comparison of static spatial panel data models and spatial weight matrices by the Bayesian posterior-model probabilities

	W_1		W_2		$W_{d<20km}$		$W_{k=4}$		$W_{k=6}$		$W_{k=8}$		*Raw tot*
	log marg.	*model prob.*	*log marg.*	*model prob.*	*log marg.*	*model prob.*	*log marg.*	*model prob.*	*log marg.*	*model prob.*	*log marg.*	*model prob.*	
currexp speed													
SAR	3.1862	0.0001	3.1806	0.0000	3.1959	0.8348	3.1853	0.0000	3.1887	0.0006	3.1886	0.0006	0.8361
SDM	3.1678	0.0000	3.1510	0.0000	3.1931	0.0508	3.1688	0.0000	3.1755	0.0000	3.1648	0.0000	0.0508
SEM	3.1846	0.0000	3.1795	0.0000	3.1938	0.1023	3.1839	0.0000	3.1871	0.0001	3.1875	0.0002	0.1026
SDEM	3.1677	0.0000	3.1509	0.0000	3.1915	0.0104	3.169	0.0000	3.1752	0.0000	3.1643	0.0000	0.0104
capexp speed													
SAR	0.1272	0.0989	0.1268	0.0629	0.1277	0.1578	0.1266	0.0532	0.1267	0.0615	0.1269	0.0729	0.5072
SDM	0.1158	0.0000	0.1081	0.0000	0.1215	0.0003	0.1087	0.0000	0.1096	0.0000	0.1119	0.0000	0.0003
SEM	0.1272	0.0960	0.1268	0.0621	0.1276	0.1500	0.1266	0.0513	0.1267	0.0609	0.1269	0.0719	0.4922
SDEM	0.1158	0.0000	0.1081	0.0000	0.1215	0.0003	0.1087	0.0000	0.1096	0.0000	0.1119	0.0000	0.0003
tpexp speed													
SAR	0.2360	0.0221	0.2371	0.0649	0.2379	0.1426	0.2363	0.0298	0.2388	0.3533	0.2369	0.0508	0.6635
SDM	0.2279	0.0000	0.2169	0.0000	0.2365	0.0337	0.2123	0.0000	0.2167	0.0000	0.2190	0.0000	0.0337
SEM	0.2343	0.0041	0.2364	0.0334	0.2360	0.0217	0.2358	0.0175	0.2377	0.1226	0.2357	0.0167	0.2160
SDEM	0.2283	0.0000	0.2171	0.0000	0.2374	0.0868	0.2126	0.0000	0.2171	0.0000	0.2193	0.0000	0.0868
totexp speed													
SAR	0.7649	0.0000	0.7577	0.0000	0.7752	0.0000	0.7505	0.0000	0.7531	0.0000	0.7588	0.0000	0.0000
SDM	0.7737	0.0000	0.7544	0.0000	0.7964	0.7602	0.7512	0.0000	0.7548	0.0000	0.7612	0.0000	0.7602
SEM	0.7614	0.0000	0.7549	0.0000	0.7722	0.0000	0.7474	0.0000	0.7497	0.0000	0.7549	0.0000	0.0000
SDEM	0.7726	0.0000	0.7529	0.0000	0.7952	0.2398	0.7499	0.0000	0.753	0.0000	0.7597	0.0000	0.2398

Table 3: Comparison of dynamic spatial panel data models and spatial weight matrices by the Bayesian posterior-model probabilities

	W_1		W_2		$W_{d<20km}$		$W_{k=4}$		$W_{k=6}$		$W_{k=8}$		*Raw tot*
	log marg.	*model prob.*	*log marg.*	*model prob.*	*log marg.*	*model prob.*	*log marg.*	*model prob.*	*log marg.*	*model prob.*	*log marg.*	*model prob.*	
currexp speed													
SAR	3.0720	0.0355	3.0708	0.0107	3.0746	0.4919	3.0717	0.0271	3.0730	0.1002	3.0739	0.2595	0.9249
SDM	3.0388	0.0000	3.0349	0.0000	3.0498	0.0000	3.0388	0.0000	3.0424	0.0000	3.0392	0.0000	0.0000
SEM	3.0702	0.0061	3.0691	0.0020	3.0713	0.0185	3.0703	0.0067	3.0710	0.0133	3.0717	0.0284	0.0750
SDEM	3.0394	0.0000	3.0352	0.0000	3.0502	0.0000	3.0392	0.0000	3.0427	0.0000	3.0394	0.0000	0.0000
capexp speed													
SAR	0.1070	0.0849	0.1069	0.0711	0.1074	0.1257	0.1068	0.0663	0.1069	0.0740	0.1069	0.0776	0.4996
SDM	0.0934	0.0000	0.0852	0.0000	0.1001	0.0001	0.0869	0.0000	0.0871	0.0000	0.0892	0.0000	0.0001
SEM	0.1070	0.0853	0.1069	0.0716	0.1074	0.1253	0.1068	0.0669	0.1069	0.0739	0.1069	0.0773	0.5003
SDEM	0.0934	0.0000	0.0852	0.0000	0.1000	0.0001	0.0868	0.0000	0.0870	0.0000	0.0891	0.0000	0.0001
tpexp speed													
SAR	0.2296	0.1015	0.2295	0.0931	0.2304	0.2128	0.2289	0.0478	0.2304	0.2169	0.2295	0.0869	0.7590
SDM	0.2188	0.0000	0.2102	0.0000	0.2233	0.0002	0.2067	0.0000	0.2113	0.0000	0.2132	0.0000	0.0002
SEM	0.2283	0.0260	0.2287	0.0384	0.229	0.0524	0.2283	0.0264	0.2292	0.0660	0.2285	0.0313	0.2405
SDEM	0.2191	0.0000	0.2103	0.0000	0.2238	0.0003	0.2069	0.0000	0.2116	0.0000	0.2134	0.0000	0.0003
totexp speed													
SAR	0.6904	0.0000	0.6821	0.0000	0.6977	0.0000	0.6746	0.0000	0.6775	0.0000	0.6827	0.0000	0.0000
SDM	0.7024	0.0000	0.6774	0.0000	0.7176	0.6158	0.6714	0.0000	0.6794	0.0000	0.6866	0.0000	0.6158
SEM	0.6863	0.0000	0.6789	0.0000	0.6941	0.0000	0.6715	0.0000	0.6735	0.0000	0.678	0.0000	0.0000
SDEM	0.7018	0.0000	0.6757	0.0000	0.7171	0.3842	0.6702	0.0000	0.6778	0.0000	0.6852	0.0000	0.3842

Table 4: The QLM estimation results of static spatial panel data model

	currexp speed				*capexp speed*			
	SAR coeff (1)	*SAR direct (2)*	*SAR indirect (3)*	*SAR total (4)*	*SAR coeff (5)*	*SAR direct (6)*	*SAR indirect (7)*	*SAR total (8)*
ρ	0.492***				0.227***			
	(7.211)				(4.753)			
pop (log)	-0.097*	-0.100*	-0.099	-0.199*	0.064	0.060	0.019	0.080
	(-1.794)	(-1.854)	(-1.630)	(-1.795)	(0.466)	(0.445)	(0.470)	(0.454)
dens	0.0002	0.0002	0.0002	0.0004	-0.0003	-0.0003	-0.0001	-0.0004
	(1.579)	(1.569)	(1.429)	(1.535)	(-0.945)	(-0.912)	(-0.853)	(-0.907)
young	0.001	0.001	0.001	0.002	0.007	0.007	0.002	0.009
	(0.232)	(0.285)	(0.358)	(0.327)	(0.965)	(1.067)	(0.992)	(1.063)
elderly	-0.001	-0.001	-0.001	-0.003	0.006	0.006	0.002	0.008
	(-0.812)	(-0.869)	(-0.787)	(-0.839)	(1.377)	(1.416)	(1.256)	(1.399)
income (log)	-0.022	-0.022	-0.019	-0.041	0.160***	0.161***	0.047***	0.208***
	(-1.630)	(-1.548)	(-1.562)	(-1.601)	(5.592)	(5.566)	(3.244)	(5.513)
DSP	-0.004	-0.004	-0.004	-0.008	-0.041***	-0.041***	-0.012***	-0.052***
	(-1.397)	(-1.385)	(-1.256)	(-1.350)	(-4.700)	(-4.721)	(-3.303)	(-4.919)
majority size	-0.0001	-0.00005	-0.00005	-0.0001	0.001**	0.001**	0.000*	0.001**
	(-0.357)	(-0.330)	(-0.323)	(-0.330)	(2.177)	(2.246)	(1.835)	(2.203)
left-wing	-0.0005	-0.001	-0.00001	-0.001	0.024**	0.024**	0.007*	0.031**
	(-0.069)	(-0.113)	(-0.001)	(-0.057)	(2.207)	(2.137)	(1.771)	(2.093)
education	-0.003	-0.003	-0.003	-0.006	0.011	0.011	0.003	0.014
	(-0.543)	(-0.579)	(-0.473)	(-0.534)	(1.326)	(1.387)	(1.277)	(1.385)
election year	0.004**	0.004**	0.004**	0.009**	0.026***	0.026***	0.008**	0.034***
	(2.336)	(2.324)	(2.084)	(2.316)	(3.351)	(3.382)	(2.306)	(3.207)
Log-pseudolik.	4107.2				1012.8			
Obs. No	2460				2460			
Fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes
Lee & Yu (2010a)	yes	yes	yes	yes	yes	yes	yes	yes
Time-effects	no	no	no	no	no	no	no	no

Table 4: *(continue)* The QLM estimation results of static spatial panel data model

	tpexp speed				*totexp speed*				
	SAR	*SAR*	*SAR*	*SAR*	*SDM*	*SDM*	*SDM*	*SDM*	*SDM*
	coeff	*direct*	*indirect*	*total*	*coeff*	*WX*	*direct*	*indirect*	*total*
	(9)	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*	*(17)*
ρ	0.213***				0.427***				
	(6.071)				(10.982)				
pop (log)	-0.307*	-0.314*	-0.084*	-0.398*	0.040	-1.372***	0.006	-2.329***	-2.323***
	(-1.867)	(-1.928)	(-1.734)	(-1.915)	(0.387)	(-3.128)	(0.059)	(-3.113)	(-3.072)
dens	-0.0002	-0.0002	-0.00004	-0.0002	-0.000	0.003**	-0.0001	0.006**	0.006**
	(-0.547)	(-0.519)	(-0.516)	(-0.520)	(-0.919)	(2.492)	(-0.570)	(2.490)	(2.376)
young	0.006	0.006	0.002	0.008	0.002	0.007	0.002	0.013	0.015
	(0.682)	(0.757)	(0.751)	(0.760)	(0.292)	(0.392)	(0.392)	(0.435)	(0.524)
elderly	-0.008*	-0.008*	-0.002	-0.010*	0.008*	-0.017**	0.008*	-0.024**	-0.017*
	(-1.741)	(-1.839)	(-1.606)	(-1.809)	(1.676)	(-2.375)	(1.696)	(-2.397)	(-1.909)
income (log)	0.191***	0.194***	0.052***	0.246***	0.044	0.167**	0.051	0.314***	0.365***
	(4.848)	(4.840)	(3.026)	(4.526)	(0.685)	(2.112)	(0.796)	(3.130)	(5.376)
DSP	-0.036***	-0.036***	-0.009***	-0.045***	-0.014	-0.005	-0.014	-0.020	-0.034**
	(-3.438)	(-3.438)	(-3.278)	(-3.568)	(-0.904)	(-0.293)	(-0.923)	(-0.917)	(-2.034)
majority size	0.0002	0.0002	0.0001	0.0003	0.000	-0.010***	-0.000	-0.016***	-0.016***
	(0.461)	(0.514)	(0.524)	(0.518)	(0.649)	(-6.106)	(-0.121)	(-5.896)	(-5.781)
left-wing	0.009	0.009	0.002	0.011	0.011	0.005	0.010	0.017	0.027
	(0.642)	(0.602)	(0.595)	(0.603)	(1.194)	(0.172)	(1.158)	(0.317)	(0.502)
education	0.003	0.003	0.001	0.004	-0.010	-0.151**	-0.013*	-0.266**	-0.279***
	(0.202)	(0.202)	(0.196)	(0.201)	(-1.279)	(-2.435)	(-1.731)	(-2.519)	(-2.589)
election year	0.034***	0.034***	0.009***	0.043***	0.035***	-0.026*	0.035***	-0.019	0.016
	(4.650)	(4.633)	(3.223)	(4.495)	(3.504)	(-1.852)	(3.449)	(-0.928)	(0.868)
Log-pseudolik.	1098.3				1698.7				
Obs. No	2460				2460				
Fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Lee & Yu (2010a)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time effects	no	no	no	no	no	no	no	no	no

Note: $W_{d<20km}$ in (1)-(8), (13)-(17); $W_{k=6}$ in (9)-(12); Lee & Yu (2010a)'s data transformation; z-statistics in parenthesis; standard errors robust to heterosckedasticity; *p<0.10, **p<0.05, ***p<0.01.

Table 5: The QLM estimation results of static spatial panel data model with both time and fixed-effects

	currexp speed				*capexp speed*			
	SAR	*SAR*	*SAR*	*SAR*	*SAR*	*SAR*	*SAR*	*SAR*
	coeff	*direct*	*indirect*	*total*	*coeff*	*direct*	*indirect*	*total*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
ρ	0.406***				0.096*			
	(5.093)				(1.827)			
pop (log)	-0.090	-0.093	-0.065	-0.157	-0.066	-0.070	-0.006	-0.076
	(-1.538)	(-1.595)	(-1.395)	(-1.565)	(-0.457)	(-0.494)	(-0.353)	(-0.488)
dens	0.0002*	0.0002*	0.0002	0.0004*	-0.000	-0.000	-0.000	-0.000
	(1.834)	(1.812)	(1.426)	(1.699)	(-1.103)	(-1.071)	(-0.813)	(-1.062)
young	0.001	0.001	0.001	0.002	0.009	0.010	0.001	0.011
	(0.202)	(0.255)	(0.340)	(0.296)	(1.337)	(1.463)	(1.029)	(1.459)
elderly	-0.001	-0.001	-0.001	-0.002	0.004	0.003	0.000	0.004
	(-0.395)	(-0.441)	(-0.361)	(-0.412)	(0.765)	(0.773)	(0.638)	(0.771)
income (log)	0.049	0.051	0.038	0.089	0.074	0.077	0.009	0.086
	(1.423)	(1.437)	(1.201)	(1.366)	(0.971)	(0.992)	(0.798)	(0.990)
DSP	-0.006	-0.006	-0.005	-0.010	-0.036**	-0.036**	-0.004	-0.039**
	(-0.599)	(-0.588)	(-0.593)	(-0.600)	(-2.085)	(-2.066)	(-1.248)	(-2.071)
majority size	-0.00005	-0.00004	-0.00003	-0.0001	0.001**	0.001**	0.0001	0.001**
	(-0.316)	(-0.281)	(-0.293)	(-0.291)	(2.339)	(2.399)	(1.308)	(2.340)
left-wing	-0.001	-0.001	-0.000	-0.002	0.029**	0.028**	0.003	0.031**
	(-0.158)	(-0.192)	(-0.078)	(-0.146)	(2.551)	(2.488)	(1.384)	(2.444)
education	-0.003	-0.003	-0.002	-0.005	0.010	0.011	0.001	0.012
	(-0.530)	(-0.545)	(-0.406)	(-0.495)	(1.222)	(1.282)	(0.941)	(1.277)
election year	-0.00003	0.000003	0.00003	0.00003	0.019**	0.019**	0.002	0.022*
	(-0.013)	(0.001)	(0.014)	(0.007)	(2.013)	(1.998)	(1.201)	(1.959)
Log-pseudolik.	4661.3				1257.6			
Obs. No	2706				2706			
Fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes
Lee & Yu (2010a)	no	no	no	no	no	no	no	no
Time-effects	yes	yes	yes	yes	yes	yes	yes	yes

Table 5: *(continue)* The QLM estimation results of static spatial panel data model with both time and fixed effects

	tpexp speed				*totexp speed*				
	SAR	*SAR*	*SAR*	*SAR*	*SDM*	*SDM*	*SDM*	*SDM*	*SDM*
	coeff	*direct*	*indirect*	*total*	*coeff*	*WX*	*direct*	*indirect*	*total*
	(9)	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*	*(17)*
ρ	0.133***				0.238***				
	(3.789)				(4.974)				
pop (log)	-0.538***	-0.545***	-0.083**	-0.628***	0.016	-2.713***	-0.016	-3.520***	-3.536***
	(-2.949)	(-3.029)	(-2.195)	(-3.019)	(0.152)	(-5.658)	(-0.160)	(-5.783)	(-5.815)
dens	-0.001	-0.001	-0.000	-0.001	-0.0002	0.006***	-0.0001	0.007***	0.007***
	(-1.532)	(-1.488)	(-1.268)	(-1.474)	(-0.646)	(3.629)	(-0.387)	(3.776)	(3.687)
young	0.009	0.010	0.002	0.011	0.003	0.051**	0.003	0.067**	0.070***
	(1.139)	(1.246)	(1.083)	(1.233)	(0.517)	(2.440)	(0.713)	(2.382)	(2.590)
elderly	-0.015***	-0.016***	-0.002**	-0.018***	0.008*	-0.034***	0.008*	-0.042***	-0.034**
	(-2.786)	(-2.942)	(-2.072)	(-2.894)	(1.887)	(-2.927)	(1.880)	(-2.912)	(-2.439)
income (log)	0.005	0.010	0.002	0.013	0.043	-0.026	0.045	-0.036	0.009
	(0.055)	(0.107)	(0.162)	(0.115)	(0.664)	(-0.168)	(0.699)	(-0.192)	(0.049)
DSP	0.013	0.013	0.002	0.015	-0.011	-0.021	-0.011	-0.033	-0.044
	(0.613)	(0.603)	(0.618)	(0.610)	(-0.745)	(-0.427)	(-0.764)	(-0.528)	(-0.746)
majority size	0.0003	0.0004	0.0001	0.0004	0.0002	-0.008***	0.0001	-0.010***	-0.010***
	(0.783)	(0.824)	(0.791)	(0.826)	(0.733)	(-4.413)	(0.468)	(-4.325)	(-4.198)
left-wing	0.017	0.016	0.002	0.018	0.012	0.065**	0.012	0.092**	0.104**
	(1.165)	(1.110)	(1.033)	(1.110)	(1.355)	(2.059)	(1.373)	(2.268)	(2.516)
education	0.003	0.003	0.000	0.004	-0.010	-0.134**	-0.011	-0.176**	-0.187**
	(0.212)	(0.209)	(0.207)	(0.210)	(-1.311)	(-2.229)	(-1.523)	(-2.340)	(-2.441)
election year	0.030***	0.030***	0.005**	0.035***	0.032***	-0.130***	0.031***	-0.158***	-0.127**
	(2.913)	(2.871)	(2.100)	(2.840)	(3.332)	(-2.989)	(3.150)	(-2.785)	(-2.250)
Log-pseudolik.	1381.2				2028.6				
Obs. No	2706				2706				
Fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Lee & Yu (2010a)	no	no	no	no	no	no	no	no	no
Time-effects	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: $W_{d<20km}$ in (1)-(8), (13)-(17); $W_{k=6}$ in (9)-(12); Lee & Yu (2010a)'s data transformation; z-statistics in parenthesis; standard errors robust to heterosckedasticity; *p<0.10, **p<0.05, ***p<0.01.

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