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SPATIAL PATTERNS IN PUBLIC SPENDING AND TAXATION: A TEST OF HORIZONTAL INTERACTION AMONG LOCAL GOVERNMENTS

Federico Revelli
Department of Economics, University of Torino

Società italiana di economia pubblica

Dipartimento di economia pubblica e territoriale – Università di Pavia

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Spatial patterns in public spending and taxation:

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Federico Revelli*

Department of Economics

University of Torino

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* Mailing address: Department of Economics, University of Torino, Via Po 53, 10124 Torino (Italy). Tel: 0039 011 6702708. Fax: 0039 011 6702762. Email: federico.revelli@unito.it.

Abstract

Spatial interaction among local governments in tax setting and public spending decisions is receiving increasing attention in the applied public economics literature. Spatial interaction models rely on the presence of an externality from local budget making: in traditional public finance models, external effects originate either from inter-jurisdictional resource flows due to tax competition for a mobile base, or from local public expenditure spill-overs into neighbouring jurisdictions. However, the recent political agency - yardstick competition literature has stressed the role of 'informational' externalities between neighbouring jurisdictions, and predicted tax mimicry at the local level. The actual relevance of the above hypotheses clearly needs to be assessed empirically. In this paper, I propose an empirical model that allows to discriminate between different sources of interaction, and test it on a data set of the English municipal authorities' budgets. While both public spending levels and local property tax rates exhibit considerable positive spatial auto-correlation, maximum likelihood and instrumental variables estimation results suggest that the interdependence among local governments can be attributed to mimicking behaviour in local property tax setting.

1. Introduction

In most empirical studies in the local public finance literature, the determinants of local government expenditures on public services are taken to be the traditional economic variables – grants from other levels of government, price of public services relative to private consumption, tax base availability and disposable income – as well as political and demographic characteristics of the jurisdiction (Foster *et al.*, 1980; Wildasin, 1986; Inman, 1988). In econometric work, public expenditure levels are regressed on those variables in a linear specification, where the error term (the unexplained component of local spending) is assumed to be independently and identically distributed across local governments, and the level of public expenditure in a jurisdiction is assumed not to be affected by the expenditures in neighbouring jurisdictions. However, both theoretical models and casual observation suggest that spatial interactions in local government expenditure decisions should not be assumed out.

On the one hand, a spatial pattern in public spending might simply be due to the fact that local governments are hit by spatially auto-correlated shocks. On the other hand, expenditures might show spatial auto-correlation because of true policy interdependence. By maintaining that local governments affect each other in their public spending decisions, the latter hypothesis has more serious consequences than the former on empirical analysis: not accounting for such strategic interaction would yield biased and inconsistent estimates of the parameters of an equation of public expenditure determination (Case *et al.*, 1993).

Three models have been offered in the public economics literature to justify the existence of spatial interaction among local governments, and have been tested on local government data in recent years.

The first one is the traditional 'spill-over' or 'externality' model, according to which expenditure on local public services in a jurisdiction can have beneficial or harmful effects onto residents in nearby jurisdictions (Gordon, 1983). One such example is local expenditure on police services: using US county data, Kelejian and Robinson (1993) find that police expenditures in a given county are significantly and positively influenced by neighbouring county police expenditures. Since counties inflict a negative externality on their neighbours by spending more on police services due to cross-overs between the borders, the need for police services in a given county tends to increase as such services in neighbouring counties increase.

Second, spatial interaction among local jurisdictions arises in tax competition models, where local governments fund public spending through a tax on mobile capital (Wildasin, 1986). Since the level of the tax base in a jurisdiction depends both on own and on other jurisdictions' tax rates, strategic interaction results. In spite of a large theoretical literature, only recently have spatial econometrics techniques been applied to test tax competition models empirically. Brueckner (1998) finds evidence of policy interdependence in the adoption of growth control measures among California cities. By restricting the amount of developable land, a city government raises land rent both in its own and in nearby cities, thereby generating an externality and strategic interaction in growth control decisions. By using a panel data set of the US states, Figlio *et al*. (1999) find that decentralised welfare benefit setting exacerbates interstate competition and might induce states to respond to changes in their neighbours' policies asymmetrically.

Finally, a recent justification for the existence of interaction at the local level is the political agency - yardstick competition model, by which imperfectly informed voters in a local jurisdiction use other governments' performance as a yardstick to evaluate their own government (Salmon, 1987). Politicians are therefore sensitive to their fiscal performance relative to similarly situated states, and try not to get too far out of line with policies in those jurisdictions. The result is local authorities mimicking each other's behaviour. The extent to which geographic proximity or other similarity criteria matter, though, is an empirical question that has attracted some interest by applied economists in recent years. Case *et al*. (1993) estimate a public expenditure equation using a panel data set of the US states' budgets, where spatial correlation in both the dependent variable and in the errors is allowed for. While they can reject the hypothesis of expenditure spill-overs among geographic neighbours, they find strong empirical evidence in support of the mimicry hypothesis: state expenditures are affected by the expenditures of states that, regardless of geographic proximity, are similar in terms of demographic composition. Besley and Case (1995) present a political agency model where voters and politicians are sensitive to events outside their boundaries and test their yardstick competition hypothesis on US states' income taxes from 1960 to 1988. They find that geographic neighbours' tax changes have a positive and significant effect on a given state's tax change. Heyndels and Vuchelen (1998) test the tax mimicking hypothesis at the level of Belgian municipalities, and find strong positive spatial correlation in local income tax rates between neighbouring authorities. Bivand and Szymanski (1997; 2000) show that there is spatial dependence in the costs of domestic garbage collection in the UK districts, due to contracts based on performance comparison, and that spatial interactions are substantially reduced after the introduction of CCT (Compulsive Competitive Tendering), that imposes standard contracting rules and reduces the scope for local authorities to pursue idiosyncratic policies.

The aim of the analysis that follows is twofold. First, it tests whether the observed spatial auto-correlation in UK districts' expenditure patterns is simply attributable to the presence of common shocks, or instead it can be given a substantive interpretation of policy interdependence. Second, it presents an empirical approach aimed at ascertaining whether policy interdependence is due to the existence of a fiscal externality, or rather to mimicking behaviour originating from an informational externality. In order to do so, section **2** develops the basic theoretical framework on which the empirical analysis is based. Section **3** performs a number of tests for spatial dependence and tackles the problem of estimating equations of tax setting and local public spending determination, in the presence of spatial auto-correlation. Section **4** describes the results of the estimation on a cross-section of the English local governments, and section **5** concludes.

2. Local public spending and spatial auto-correlation

A standard empirical model of local public expenditure determination is usually expressed, in a linear specification, as:

$$y = X\beta + \varepsilon \qquad (1)$$

where y is a vector of (per capita) public spending levels of N local governments, X is a ($N \times K$) matrix of explanatory variables, β is a vector of parameters to be estimated, and ε is an error term that is assumed to be identically and independently distributed across the observations.

First, the above empirical model may not be correctly specified due to spatial auto-correlation in the error term. Any spatially auto-correlated variable that has an influence on y and is omitted from the model (reflecting either preferences for public services or actual spending needs) will lead to spatial dependence in the residuals. Furthermore, local jurisdictions may be subject to shocks that affect their expenditure decisions, and are spatially auto-correlated – such as common shocks to income and tax base, that may result from central government regional policies or intermediate level of government fiscal policies (Revelli, 2000b). The presence of common shocks can be allowed for by appropriately modelling a spatial process in the unobservable part of the local public spending equation, such as the following first-order spatial auto-regressive specification (Anselin, 1988a):

$$\varepsilon = \lambda W \varepsilon + \xi \qquad (2)$$

where λ is a scalar measuring spatial dependence in the errors, with $|\lambda|<1$, ξ is i.i.d. over space, and W is the ($N \times N$) spatial matrix containing the information on the location of the observations. The element corresponding to row r and column c in matrix W (w_{rc}) is different from zero if spatial sites r and c are, according to some geographic criterion, neighbours, and zero otherwise. Clearly, $w_{rc}=0$ if $r=c$. The simplest neighbourhood criterion states that two districts are neighbours if they share a border. In this case, w_{rc} is equal to one if they do, and is equal to zero otherwise. The matrix W is usually standardised such that the elements of a row sum to one.

Apart from spatial dependence in the errors, a second and more serious problem might arise from empirical specification (1) if policy making in a local jurisdiction is affected by the behaviour of public officials in other jurisdictions, that is if local decisions are truly interdependent. One possible explanation of local interaction is that public expenditure in a jurisdiction has spill-over effects into neighbouring jurisdictions. Benefit cross-overs may occur for expenditure on police and transport services, education, environment and welfare payments (Case *et al*., 1993; Revelli, 2000a). The presence of spill-overs requires explicit modelling of the spatial interdependence, by taking into account that local jurisdictions make their decisions simultaneously, and each authority takes its neighbours' behaviour into account when setting its own policy. Consequently, the equation of local public expenditure determination should be rewritten as a first-order spatial auto-regression:

$$y = \rho Wy + X\beta + \xi \tag{3}$$

where ρ ($|\rho|<1$) is the coefficient that identifies a 'substantive' spatial dependence process, in the sense that for each observation y is determined simultaneously with the y variables in the locations identified as neighbours through the spatial weights matrix W.

Clearly, though, the presence of expenditure spill-overs is not the only possible source of policy interdependence at the local level. The observed spatial pattern in public spending levels might be due to interactions that originate from the *revenue* side of the budget. In other words, local governments might choose local tax rates strategically, and affect each other in their tax setting policies. Two main motivations for such mimicry behaviour in tax setting policies have been put forward in the public economics literature. First, if local governments' own revenues depend on a mobile tax base, the availability of tax base in a jurisdiction depends both on own and on neighbours' taxes, and lowering tax rates can – under certain conditions – increase tax revenues. Consequently, tax competition can arise that makes local taxation behaviour interdependent and tax rates spatially auto-correlated. Second, in the presence of asymmetric information between taxpayers and public officials, the former can use other local governments' performance as a yardstick to evaluate their own government. Since politicians aim at being re-elected, they will try not to get too far out of line with tax rates in neighbouring jurisdictions, and tax mimicry will result.

Clearly, we would like to be able to discriminate among the interaction due to tax mimicry and the one due to expenditure spill-overs. Unfortunately, though, in several circumstances the two processes will tend to mimic each other. In particular, copycatting of local tax rates might engender a spatial dependence process in public spending levels that could wrongly be attributed to public expenditure spill-overs. Assume that the level of local public spending can be split into two components. The first one, y^*, is determined by variables reflecting local spending needs. In the UK grant distribution system, it is the level of standard spending determined by central government based on assessed spending needs, that can be achieved by adopting the standard revenue-raising effort (τ^*). The second one, y_τ, is the component of public spending reflecting local preferences for public services, that can be achieved by varying the local tax effort τ. By raising the revenue-raising effort above τ^*, a local jurisdiction can set an higher than standard expenditure level. The variables that capture the pattern of preferences for public services and that, consequently, affect the expenditure level through changes in local tax revenues will, in most instances, be the same as the ones reflecting actual spending needs, the ($N \times K$) matrix X:

$$y = y^*(X) + y_\tau(\tau(X)) = X\psi + \phi\tau(X) \qquad (4)$$

ψ is a ($K \times 1$) vector of parameters measuring the impact in terms of spending needs of the variables in X on y. ϕ is a scalar relating the level of the local tax effort with the level of spending.

Assume that there are no expenditure spill-overs (municipal services are purely local), municipalities have own revenues represented by a property tax at a locally varying rate t, and local property tax rates are imitated among neighbours. This can be expressed, in a linear specification, as:

$$t = \theta Wt + X\gamma + \mu \qquad (5)$$

Besides the matrix of exogenous variables X and a random term μ, the right hand side of equation (5) includes a spatially weighted average of the tax rates of neighbouring governments (Wt). Parameter θ measures the size of spatial interaction in local property tax setting.

Denoting the ($N \times N$) identity matrix by I, equation (5) can be inverted and rewritten as:

$$t = (I - \theta W)^{-1}(X\gamma + \mu) \tag{5'}$$

Substituting (5') into (4) and rearranging yields the following expenditure determination equation:

$$y = \theta Wy + X\delta + \nu \tag{6}$$

where: $\delta = \psi + \phi\gamma$, and $\nu = \phi\mu - \theta WX\psi$. Equation (6) is only apparently the same as equation (3). The crucial difference consists in the non random structure of the error term, that contains a spatial lag of X (WX). As a result, estimation of equation (6) yields biased parameter estimates, for two reasons. First, the spatial coefficient θ will be underestimated because the spatially lagged dependent variable (Wy) is negatively correlated with the error term ν. Second, since close-by authorities share common neighbours, the presence of the neighbourhood variable WX in the error term will give rise to positive spatial auto-correlation in the error term ν.

In other words, even though strategic interaction occurs on the tax rate t – as expressed by equation (5) through the parameter θ – it turns out that also local spending levels will show some spatial auto-correlation. In particular, estimation of an equation of local public spending determination such as (6) will yield a downward biased estimate of the coefficient on the spatially lagged dependent variable (θ), and a test for spatial dependence in the residuals will detect positive spatial auto-correlation.

The above considerations provide us with a rather simple and intuitive empirical test, that should be able to discriminate between the two alternative spatial processes described by equations (3) and (5). If spatial interaction is really due to expenditure spill-overs, model (3) is the correct specification and maximum likelihood (ML) estimation should yield a significant estimate of the coefficient ρ, pointing towards the presence of substantive spatial dependence and the absence of spatial error dependence. On the other hand, if model (5) is the correct specification of the spatial process, we will get a significant estimate of θ from equation (5), and spatial dependence in the residuals of equation (3).

3. Testing for strategic interaction among English local governments

In this and the next section, we will study the spatial pattern of public spending and taxation levels of the 296 English non-metropolitan districts in 1990. English districts – the lower tier of government in non-metropolitan England, the upper tier being represented by 39 counties – are responsible for a number of specifically local services, such as housing, refuse collection, building regulations and environmental health.[1] Until 1990, the most part of districts' revenues came from central government grants and local property tax revenues.[2] Due to the features of the grant distribution system, a district could afford a standard level of spending – the so-called *grea* (grant

[1] Due to the asymmetric structure of UK local government, with a one-tier structure in metropolitan areas and a two-tier structure in non metropolitan areas (districts and counties), pooling of urban and rural districts is not possible and we concentrate on the latter.

[2] The local property tax was replaced in 1990 by a flat rate tax (the community charge, or poll tax), later replaced (in 1993, due to huge discontent with the poll tax) by a renovated property tax, the council tax.

related expenditure assessment), determined by central government based on assessed spending needs – by setting a standard uniform property tax rate, irrespective of the level of the local tax base (value of property).

From a spatial view point, the striking feature of the UK municipal tier of government is that while districts' assessed expenditure levels do not show any spatial pattern, both actual spending levels and property tax rates show considerable positive spatial auto-correlation. This point emerges clearly from table 1, where a traditional measure of spatial dependence – the Moran spatial statistic (Cliff and Ord, 1981), a measure of the similarity between association in value (correlation) and association in space (contiguity) – has been computed for the assessed levels of spending per capita, the actual levels of spending per capita, and the property tax rates in 1990.[3] While the *grea* does not show any spatial auto-correlation (the Moran statistic is not significantly different from zero), the actual spending level and, more strongly, the property tax rates, clearly point towards a spatial pattern of positive auto-correlation.

By itself, however, the results of the Moran test cannot say what is driving the spatial pattern. As the analysis in section **2** suggests, there are two possible forms of spatial correlation. The first is usually referred to as 'substantive spatial dependence' or 'spatial lag dependence' (Anselin, 1988), and it is expressed by parameters ρ and θ for public spending and tax rates respectively in a mixed regressive-spatial autoregressive specification – equations (3) and (5). The second is referred to as 'spatial error dependence,' and is identified by parameter λ in equation (2).

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[3] Data are from the Chartered Institute of Public Finance and Accountancy (CIPFA).

The most widely applied diagnostic for spatial dependence in a regression model is an application of the Moran spatial statistic to the residuals of an OLS regression of the variable of interest on its explanatory variables. For a row-standardised spatial weights matrix, the Moran's statistic on the OLS residuals is defined as:

$$I(e) = \frac{e'\,We}{e'\,e} \tag{7}$$

where e are the OLS regression residuals of equation (1). An alternative to the Moran's I(e) is the use of two tests based on the Lagrange Multiplier (LM) principle. The first is an LM test for spatial error dependence – a scaled Moran's I(e) that was originally proposed in Burridge (1980):

$$LM\,(err) = \frac{\left(\dfrac{e'We}{(e'e)/N}\right)^2}{tr(W'W + W^2)} \tag{8}$$

with tr as the matrix trace operator. The second is an LM test for spatial lag dependence (Anselin, 1988b; Anselin and Rey, 1991):

$$LM\,(lag) = \frac{\left(\dfrac{e'Wy}{(e'e)/N}\right)^2}{\dfrac{(WXb)'M\,(WXb)}{(e'e)/N} + tr(W'W + W^2)} \tag{9}$$

where: $M=I-X(X'X)^{-1}X'$, and b is the OLS estimate of β in equation (1).

However, neither the Moran's I(e) test nor the LM tests are able to discriminate properly between spatial error dependence and spatial lag dependence (Anselin and Florax, 1995). Consequently, Anselin *et al*. (1996) have recently proposed two modified tests based on the LM principle, that can give a clearer indication of what is the most likely source of spatial dependence in the expenditure equation. The first is the adjusted Lagrange Multiplier test for spatial auto-correlation in the error term, that is robust to the presence of misspecification due to spatial auto-correlation in the dependent variable:

$$ALM(err) = \frac{\left[\frac{e'We}{(e'e)/N} - tr\left(\frac{(WXb)'M(WXb)}{(e'e)/N} + tr \right)^{-1} \frac{e'Wy}{(e'e)/N} \right]^2}{tr - tr^2 \left(\frac{(WXb)'M(WXb)}{(e'e)/N} + tr \right)^{-1}} \qquad (8')$$

The second is the counterpart of the first, that is a test for spatial auto-correlation in the dependent variable that is robust to misspecification due to a spatial process in the error term:

$$ALM(lag) = \frac{\left[\frac{e'Wy}{(e'e)/N} - \frac{e'We}{(e'e)/N} \right]^2}{\frac{(WXb)'M(WXb)}{(e'e)/N} + tr} \qquad (9')$$

Table 2 reports the results of the above tests on the residuals of the public spending equation (1), while table 3 reports the same tests on the residuals of the local tax rate equation (5), where parameter θ has been set to zero. The matrix of explanatory variables X includes grants from central government, population size, a dummy for closeness to metropolitan areas to control for the presence of externalities from the (excluded) urban areas, and a political control dummy to allow for systematic ideological differences. Finally, preferences for public services should be reflected in a set of socio-demographic characteristics (described in detail in section **5**).

The Moran's I(e) statistic definitely points towards some form of spatial auto-correlation in both equations, but it is unable to discriminate properly between lag and error dependence. The two LM tests in (8) and (9) do not give a clear-cut response either. Since the two LM tests are distributed as χ^2 with one degree of freedom, they both lead us to reject the null hypothesis of absence of spatial dependence. On the other hand, the two robust LM tests in (8') and (9') point towards substantially different patterns of spatial dependence for local public spending and property tax rates respectively. When controlling for a spatially lagged dependent variable, the robust test for error dependence supports the thesis of spatially auto-correlated errors in actual spending levels, while the robust test for lag dependence confirms the presence of substantive interaction only as far as local property tax rates are concerned.

The above results suggest that local authorities tend to imitate each other in local property tax rate setting, and that such strategic interaction gives rise to spatial interaction in local public spending. Consequently, the equation of public expenditure determination should have a spatial structure in the error term:

$$y = X\beta + \varepsilon \tag{1}$$

$$\varepsilon = \lambda W\varepsilon + \xi \tag{2}$$

On the other hand, the regression model for local tax rate setting should have a spatial structure in the dependent variable:

$$t = \theta Wt + X\gamma + \mu \tag{5}$$

Models (1)-(2) and (5) must be estimated by ML methods (Anselin, 1988). Alternatively, a reduced form of the spatial lag dependence model can be estimated with a two-stage least squares (2SLS) or an equivalent instrumental variables (IV) approach (Besley and Case, 1995; Heyndels and Vuchelen, 1998; Figlio *et al*., 1999; Revelli, 2000b). In the first stage, neighbours' tax rates are regressed on their own explanatory variables (WX), while in the second stage the fitted values of Wt are used in (5) to obtain an estimate of θ. If neighbours' tax rates are properly instrumented (that is if the instruments are correlated with Wt, but are not correlated with the error terms), the spatial correlation that is left and that identifies the substantive spatial parameter θ is not attributable to spatially correlated shocks, that is it is not a spurious correlation that is really due to spatial error dependence. The problem with this kind of estimation is that the choice of instruments must be done with some caution. However, there is no convincing reason why one should not try also this estimation procedure and compare the results with the ones obtained with the ML estimation. Strangely enough, to my knowledge no empirical analysis presents and compares the results of both estimation approaches.

4. Results

In the first set of estimates, we use as dependent variable the current public expenditure per head (capital expenditures are excluded) of the English non-metropolitan districts in the financial year 1989/1990. The means and data sources of all variables used in the analysis are shown in tables 8 and 9.

In table 4, the ML estimates of a conventional linear model of public spending determination with no spatial components (first column) are compared to ML estimates of both spatial specifications. The results for the spatial lag dependence model – equation (3) – are shown in column 2, while the results for the spatial error dependence model – equations (1)-(2) – are in column 3.

Both models achieve a significant increase in likelihood and both spatial coefficients are positive and highly statistically significant. Consequently, they can be used to reject a null hypothesis of absence of spatial interactions. Estimates of the spatial lag dependence model (second column, equation (3)) yield a significant estimate of ρ=0.225, while estimates of the spatial error dependence model (third column, equations (1)-(2)) yield a large significant estimate of λ=0.370. The fact that spatial effects really matter in the specification of the local public expenditure determination model is confirmed by the results of the likelihood ratio (LR) test. Twice the difference in log-likelihood of the restricted (no spatial effects) and unrestricted (either the spatial lag dependence model, or the spatial error dependence model) model is distributed as χ^2 with one degree of freedom (Bivand, 1984). In both cases the LR test statistic – conditional on the other parameter being zero – exceeds by a wide margin the $\chi^2(1)$ value at p=.99 of 6.63, as shown in table 4.

Since the two spatial processes tend to mimic each other, the best way of discriminating among the two is to evaluate and compare their explanatory power (Brueckner, 1998). Since the size of the likelihood is substantially higher for the spatial error dependence model, we take these results as a confirmation of the LM tests in section **3**, that is of the superiority of a model with spatial auto-correlation in the residuals to explain the process of local public expenditure determination.

As for the other coefficients, the lump-sum grant has a positive, though rather small, impact on the level of spending. The estimated coefficients on the two dummy variables suggest that Labour controlled authorities, as well as the ones that are located close to metropolitan areas, tend to have substantially higher spending levels. All socio-demographic variables – intended to be a measure of high spending needs – have the expected positive impact on spending, except for the rate of long-term unemployment. It should be taken into account, though, that if spatial interaction in public spending really depends upon tax mimicry, the very structure of the parameter vector δ in equation (6) does not make it possible to disentangle the impact of the explanatory variables on expenditure through actual spending needs (ψ) and through preferences for public services ($\phi\gamma$).

As regards the tax setting model, the results are shown in table 5. Column 1 presents the estimates of a non-spatial model, column 2 reports the estimates of the spatial lag dependence model – equation (5) – and column 3 reports the estimates of a tax setting model with a spatial structure in the error term:

$$t = X\gamma + \mu \tag{10}$$

$$\mu = \lambda W\mu + \eta \tag{11}$$

While both specifications lead to a substantial increase in likelihood, which according to the LR test is significant, the likelihood increase is higher for the lag dependence model, which confirms the LM test results of section **3**.

In order to convince ourselves of the robustness of the results obtained so far, tables 6 and 7 present IV estimates of the spatial lag dependence model for our two crucial policy variables – equations (3) and (5). The first column presents, by comparison, the OLS estimates of a model with a spatially lagged dependent variable. In the IV specification, neighbours' explanatory variables (*WX*) are used as instruments for the endogenous variables on the right hand side of the equation (*Wy* and *Wt*).

As far as local public spending is concerned, OLS yields an estimate of ρ of about 0.3. When controlling for potential spatial error dependence through instrumental variables, though, the size of ρ is substantially reduced. This result lends support to the thesis that spatial dependence in public spending is in large part due to correlation in the residuals, whose effect is controlled for in the IV estimation (but not in the OLS estimation). On the other hand, the IV estimate of θ in the tax setting equation is a large and highly significant coefficient of about 0.6 (t=5.2), an even higher value than the OLS estimate. As for the estimates of the coefficients on the other explanatory variables, they hardly differ from the respective ones in tables 4 and 5.

In sum, the IV estimation results thoroughly confirm the ML estimation results. While behavioural significance can be attached to the spatial process in the local property tax rate, the same does not appear to be true for public spending levels, whose spatial pattern is mostly driven by auto-correlation in the residuals. In both IV estimations, though, the size of the estimated spatial coefficients is larger than the analogous ML ones. This is most likely due to residual spatial error auto-correlation, that is still spuriously captured in the ρ and θ coefficients.

5. Conclusions

By using data on the English local governments, this paper has explored the source of spatial auto-correlation in local public expenditure. The results of the estimation of the spatial lag model (with spatial interaction in the dependent variable) and spatial error model (with spatial interaction in the error term) suggest that spatial auto-correlation is an important feature of local governments' expenditure decisions. Both models can be used to reject a null hypothesis of absence of spatial interactions, *i.e.*, both models are superior to a model that arbitrarily constrains the two spatial coefficients to be zero. Furthermore, the results suggest that local property tax mimicry brings about spatial auto-correlation in the residuals of a local public expenditure determination equation.

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References

Anselin, L., 1988a. Spatial econometrics: methods and models. Klower Academic Publishers, Dordrecht.

Anselin, L., 1988b. Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. Geographical Analysis 20, 1-17.

Anselin, L., Bera, K., Florax, R., Yoon, M., 1996, Simple diagnostic tests for spatial dependence. Regional Science and Urban Economics 26, 77-104.

Anselin, L., Florax, R., 1995. Small sample properties of tests for spatial dependence in regression models: some further results. In: Anselin, L., Florax, R. (Eds.), New directions in spatial econometrics. Springler-Verlog, Heidelberg, 21-74.

Anselin, L., Rey, S., 1991. Properties of tests for spatial dependence in linear regression models. Geographical Analysis 23, 112-131.

Besley, T., Case, A., 1995. Incumbent behavior: vote seeking, tax setting and yardstick competition. American Economic Review 85, 25-45.

Bivand, R., 1984. Regression modeling with spatial dependence: an application of some class selection and estimation methods. Geographical Analysis 16, 25-37.

Bivand, R., Szymanski, S., 1997. Spatial dependence through local yardstick competition: theory and testing. Economics Letters 55, 257-265.

Bivand, R., Szymanski, S., 2000. Modelling the spatial impact of the introduction of Compulsive Competitive Tendering. Regional Science and Urban Economics 30, 203-219.

Brueckner, J., 1998. Testing for strategic interaction among local governments: the case of growth controls. Journal of Urban Economics 44, 438-467.

Burridge, P., 1980. On the Cliff-Ord test for spatial correlation. Journal of the Royal Statistical Society B 42, 107-108.

Case, A., 1991. Spatial patterns in household demand. Econometrica 59, 953-965.

Case, A., Hines, J., Rosen, H., 1993. Budget spillovers and fiscal policy interdependence. Journal of Public Economics 52, 285-307.

Cliff, A., Ord, J., 1981. Spatial processes. Models and applications. Pion, London.

Figlio, D., Kolpin, V., Reid, W., 1999. Do states play welfare games? Journal of Urban Economics 46, 437-454.

Foster, C., Jackman, R., Perlman, M. 1980. Local government finance in a unitary state, London: George Allen & Unwin.

Gordon, R., 1983. An optimal taxation approach to fiscal federalism. Quarterly Journal of Economics 98, 567-587.

Heyndels, B., Vuchelen, J., 1998. Tax mimicking among Belgian municipalities. National Tax Journal 60, 89-101.

Inman, R., 1988. Markets, government and the ‘new’ political economy. In: A. Auerbach, A., Feldstein, M. (Eds.), Handbook of Public Economics. North-Holland, Amsterdam.

Kelejian, H., Robinson, D., 1993. A suggested method of estimation for spatial interdependent models with autocorrelated errors, and an application to a county expenditure model. Papers in Regional Science 72, 297-312.

Revelli, F., 2000a. Spatial patterns in local public expenditures in the UK: do spillovers matter? Working Paper 1-2000, Department of Economics “Cognetti de Martiis,” University of Torino.

Revelli, F., 2000b. Spatial patterns in local taxation: tax mimicking or error mimicking? *Applied Economics* (forthcoming).

Salmon, P., 1987, Decentralization as an incentive scheme. Oxford Review of Economic Policy 3, 24-43.

Wildasin, D., 1986. Urban public finance. Harwood Academic Publishers, New York.

Table 1 Moran spatial statistic

	Assessed spending level	Actual spending level	Property tax rate
Moran I statistic	0.01 (0.21)	0.139* (3.56)	0.271* (6.85)

Table 2 Tests for spatial auto-correlation in local public expenditures per head

Moran spatial statistic on estimated residuals: I(*e*)	0.203* (5.44)
Lagrange Multiplier test for spatial lag dependence: *LM*(*lag*)	17.84*
Robust Lagrange Multiplier test for spatial lag dependence: *ALM*(*lag*)	0.53
Lagrange Multiplier test for spatial error dependence: *LM*(*err*)	25.37*
Robust Lagrange Multiplier test for spatial error dependence: *ALM*(*err*)	8.05*

Table 3 Tests for spatial auto-correlation in local property tax rates

Moran spatial statistic on estimated residuals: I(*e*)	0.135* (3.73)
Lagrange Multiplier test for spatial lag dependence: *LM*(*lag*)	21.03*
Robust Lagrange Multiplier test for spatial lag dependence: *ALM*(*lag*)	11.82*
Lagrange Multiplier test for spatial error dependence: *LM*(*err*)	11.27*
Robust Lagrange Multiplier test for spatial error dependence: *ALM*(*err*)	2.05

Notes:
I) the spatial weights matrix is row-standardised, and is based on the criterion that two districts are neighbours if they have a common border;
II) the I(*e*) statistic is computed under the null hypothesis that the errors are normally distributed;
III) I(*e*) is distributed as a standard normal $z(0,1)$; the LM tests are distributed as χ^2 with one degree of freedom;
IV) *=significant at the 1% level;
V) number of observations = 296. Data are from 1990.

Table 4 ML estimates of the public expenditure determination equation

	Non-spatial model ML estimates	Spatial lag dependence ML estimates	Spatial error dependence ML estimates
ρ	-	0.225 (3.92)	-
λ	-	-	0.370 (4.68)
grant (lump-sum)	0.156 (2.11)	0.115 (1.60)	0.115 (1.56)
Labour dummy	11.779 (3.93)	11.051 (3.81)	12.307 (4.22)
metropolitan dummy	6.954 (2.99)	5.321 (2.32)	5.444 (2.19)
population (,000)	0.028 (1.19)	0.034 (1.48)	0.037 (1.62)
urbanisation rate (%)	0.117 (3.42)	0.099 (2.96)	0.067 (1.83)
ethnic minority (%)	0.739 (1.41)	1.233 (2.36)	1.047 (1.89)
elderly people (%)	1.153 (4.50)	1.080 (4.33)	1.106 (4.00)
housing benefits (%)	3.226 (3.28)	3.538 (3.70)	3.466 (3.30)
lone parents (%)	3.593 (2.83)	3.552 (2.87)	3.820 (2.90)
long term unemployed (%)	-0.462 (-1.62)	-0.516 (-1.85)	-0.392 (-1.33)
Log likelihood	-1210.51	-1203.22	-1201.31
LR test - χ^2	-	14.57 (1)	18.40 (1)
observations	296	296	296

Notes:
I) dependent variable = local public expenditure per head;
II) *t* values in parentheses;
III) Labour dummy=1 if the local authority is Labour controlled, and 0 otherwise;
IV) Metropolitan dummy=1 if the local authority has a common border with a metropolitan area.

Table 5 ML estimates of the tax setting equation

	Non-spatial model ML estimates	Spatial lag dependence ML estimates	Spatial error dependence ML estimates
θ	-	0.315 (4.77)	-
λ	-	-	0.408 (4.91)
grant (lump-sum)	-0.179 (-3.40)	-0.224 (-4.48)	-0.279 (-5.05)
Labour dummy	12.701 (6.05)	11.476 (5.68)	11.453 (5.59)
metropolitan dummy	6.017 (3.70)	4.188 (2.62)	3.882 (2.10)
population (,000)	0.011 (0.67)	0.021 (1.32)	0.027 (1.60)
urbanisation rate (%)	-0.033 (-1.35)	-0.037 (-1.61)	-0.043 (-1.71)
ethnic minority (%)	-0.762 (-2.05)	-0.345 (-0.96)	-0.332 (-0.74)
elderly people (%)	0.359 (2.01)	0.387 (2.27)	0.310 (1.31)
housing benefits (%)	0.989 (1.41)	1.050 (1.68)	1.331 (1.58)
lone parents (%)	2.771 (3.09)	2.986 (3.54)	2.932 (3.10)
long term unemployed (%)	0.097 (0.42)	-0.014 (-0.20)	0.078 (0.34)
Log likelihood	-1104.73	-1094.46	-1095.15
LR test - χ^2	-	20.54 (1)	19.16 (1)
observations	296	296	296

Notes:
I) dependent variable = local property tax rate;
II) *t* values in parentheses;
III) Labour dummy=1 if the local authority is Labour controlled, and 0 otherwise;
IV) Metropolitan dummy=1 if the local authority has a common border with a metropolitan area.

Table 6 IV estimates of the public expenditure determination equation

	OLS estimates	IV estimates
ρ	0.295 (5.03)	0.188 (2.60)
grant (lump-sum)	0.103 (0.73)	0.122 (0.87)
Labour dummy	10.830 (3.75)	11.170 (3.81)
metropolitan dummy	4.822 (2.39)	5.587 (2.40)
population (,000)	0.036 (1.18)	0.033 (1.09)
urbanisation rate (%)	0.094 (2.62)	0.102 (2.74)
ethnic minority (%)	1.384 (1.64)	1.152 (1.34)
elderly people (%)	1.058 (5.22)	1.091 (5.39)
housing benefits (%)	3.634 (2.07)	3.487 (1.98)
lone parents (%)	3.539 (1.87)	3.558 (1.84)
long term unemployed (%)	-0.533 (-1.86)	-0.507 (-1.77)
R^2	0.69	-
observations	296	296

Notes:
I) dependent variable = local public expenditure per head;
II) *t* values in parentheses;
III) Labour dummy=1 if the local authority is Labour controlled, and 0 otherwise;
IV) Metropolitan dummy=1 if the local authority has a common border with a metropolitan area.

Table 7 IV estimates of the tax setting equation

	OLS estimates	IV estimates
θ	0.474 (5.59)	0.586 (5.25)
grant (lump-sum)	-0.247 (-3.13)	-0.263 (-3.19)
Labour dummy	10.856 (5.04)	10.420 (4.77)
metropolitan dummy	3.264 (1.97)	2.614 (1.53)
population (,000)	0.025 (1.24)	0.029 (1.38)
urbanisation rate (%)	-0.039 (-1.56)	-0.040 (-1.61)
ethnic minority (%)	-0.136 (-0.23)	0.012 (0.02)
elderly people (%)	0.400 (2.51)	0.410 (2.50)
housing benefits (%)	1.082 (1.07)	1.104 (1.09)
lone parents (%)	3.093 (2.41)	3.169 (2.47)
long term unemployed (%)	-0.071 (-0.38)	-0.110 (-0.60)
R^2	0.51	-
observations	296	296

Notes:
I) dependent variable = local property tax rate;
II) *t* values in parentheses;
III) Labour dummy=1 if the local authority is Labour controlled, and 0 otherwise;
IV) Metropolitan dummy=1 if the local authority has a common border with a metropolitan area.

Table 8 Summary statistics of the variables used in the analysis

variable	Mean	Std. Dev.	Min.	Max.
local property tax rate (pence per £)	31.2	13.2	0	97.5
expenditure per head (£)	63.2	24.9	14.3	197.7
expenditure assessment per head - *grea* (£)	58.4	14.4	39.5	120.0
grant per head (£)	28.9	14.5	9.9	90.5
population (,000)	101	42	24	384
urbanisation rate	57.4	34.1	0	100
% elderly people	21.7	4.1	13.0	37.8
% ethnic minority	2.4	1.9	0.4	17.5
% long term unemployment	23.3	4.1	11.7	39.5
% housing benefit cases	5.7	2.1	2.0	13.3
% lone parents	4.9	1.5	2.8	11.1

Table 9 Data sources

data	source
property tax rate, public expenditure, grants	Chartered Institute of Public Finance and Accountancy *Finance and general statistics* (1990)
population, urbanisation rate	Chartered Institute of Public Finance and Accountancy *Local government comparative statistics* (1990)
socio-demographic data	Census of Population (1991)
political control	University of Plymouth: *Local Government Chronicle Elections Centre* (1993)