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Modelling the spatial impact of the introduction of Compulsory Competitive Tendering ☆

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Abstract

This paper uses data on local authority garbage collection costs to measure the spatial impact of the shift from local in-house monopoly provision to Compulsory Competitive Tendering (CCT). The data shows that before CCT service costs were correlated across authorities after controlling for their characteristics. However, following CCT this spatial correlation disappears or is significantly attenuated. We associate this change with the way in which contracts were written before and after CCT. We also show that political factors were an important factor in determining costs both before and after CCT. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

In recent years economists have developed an interest in the effect of geography on economic processes. It is now fashionable to express the view that 'geography matters', but most of the work in this field has been theoretical. Empirical work is scarce, and where it exists, the econometric techniques employed do not often

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employ methods designed specifically for the analysis of spatial data. However, spatial analysts have over a number of years developed a sophisticated set of techniques for estimating the impact of geography, usually known as spatial econometrics. This paper uses these techniques to analyse the impact of location on the cost of garbage collection services.

Domestic garbage collection in the UK is a service organised by local government. Each local authority has a statutory duty to ensure that domestic garbage is removed and may hire their own staff or hire a contractor to provide the service. In another paper (Bivand and Szymanski, 1997), we have developed a principal-agent model which can account for spatial spillover effects between local authorities. In this paper we explore the econometrics in more detail, and examine the effect of political control on the geographic effects. We show that spatial dependence existed in garbage collection costs prior to the introduction of compulsory competitive tendering (CCT) in the sense that an authority's cost was likely to be higher (lower) if its neighbour's own cost was high (low), after controlling for relevant characteristics. However, once CCT was introduced, the degree of spatial dependence declined.

The next section briefly outlines the background to compulsory competitive tendering and Section 3 discusses our theoretical model. The subsequent two sections report on our modelling of expenditure on garbage collection, using spatial econometric methods. In conclusion we discuss the consequences of our findings for the analysis of geographical data, and in relation to the introduction of compulsory competitive tendering.

2. Background to Compulsory Competitive Tendering

Compulsory Competitive Tendering of blue collar services such as garbage collection and street cleaning was introduced in the UK by the Local Government Act 1988. This law, imposed by central government, obliged elected local authorities to expose specific services to competitive tendering at fixed intervals and subject to national guidelines. Prior to the 1988 Act, most local authorities operated garbage collection services through what is now known as the Direct Service Organisation (DSO), basically a department of the local authority operating under monopoly conditions. Despite the introduction of competitive tendering by a small number of local authorities (a purely voluntary act by those authorities) and the well documented cost reductions associated with such policies (whether contracts were won in house or were contracted out to private operators, q.v. Domberger et al., 1986 and Cubbin et al., 1987) the policy was not widely adopted.

The 1988 Act required that defined activities including garbage collection, street cleaning, building cleaning, schools and welfare catering, grounds maintenance and vehicle maintenance should be supplied under competitive conditions and laid down a timetable with dates by which specific services had to be subjected to competition.[1] Where the authority intended to allow the existing in-house team (the DSO) to compete, the Act laid down guidelines to ensure fair competition, including ring-fencing the DSO – denying it the right to bid in other districts – and a minimum rate of return on assets (initially 5%, since raised to 8%). The Act has frequently been supplemented by guidance from the Department of the Environment as to the conduct of competitive tendering. Each DSO was only allowed to bid for the contract in its own area. Because of its compulsory nature, and because of the antagonism between the Conservative central government and local authorities controlled by other political parties (particularly the Labour Party) CCT has been hugely controversial. Labour Party policy is to remove CCT, and many local authorities vigorously opposed its implementation.

Studies on the impact of CCT include Walsh (1991); Walsh and Davies (1993); Escott and Whitfield (1995); Audit Commission (1993); Shaw et al. (1994); Painter (1991); Szymanski (1996). Apart from the last of these, all the other studies were based on small sample case studies. The economic impact (for studies of the political impact, see Stewart, 1992) of CCT is usually measured by its impact on service costs. If CCT reduces costs, cost reductions can then be attributed to either lower service quality, poorer terms and conditions for the workforce or higher productivity. There is some consensus that CCT reduces costs at the expense of the workforce but not to the detriment of service standards (Walsh, 1995, provides a useful summary of the evidence).

Garbage collection is the only service where large sample statistical analysis is feasible. Garbage collection cost data is reported by each local authority to the Department of Environment. Units of output can be measured by the number of households from which garbage is collected. Whilst there are some variations in service standards, these are relatively small and do not account for the large variations in cost across authorities (see Szymanski, 1996, for a more detailed discussion). Despite this, there are large regional disparities in service costs as can be seen from Table 1. The data covers 324 of the 365 local authorities in England and compares expenditure in the last full year before CCT to first full year after. Districts where cost data was not available for both the pre-CCT and post-CCT years were omitted, in order to ensure that the data sets for the two years were fully comparable. As Szymanski (1996) shows, the missing 41 districts do not have clear regional or other patterning, and we feel that the possible impact on estimation is small, on the basis comparison of results for a smaller 314 district data set presented in Bivand and Szymanski (1997), and those given below.

Before CCT, costs per household varied between £15.90 per household in the West of England to £26.15 in Greater London. While there is evidence from a number of sources indicating that garbage collection costs have fallen significantly

[1] Some services had already been subjected to CCT by the 1980 Local Government Planning and Land Act, while the 1988 Act exempted services with an annual cost below £100 000.

Table 1
Descriptive measures of garbage collection cost by English standard region; A: £ per household pre-CCT, B: £ per household post-CCT, C: % cost reduction, D: % of contracts won by incumbents, E: % Labour controlled, F: % Conservative controlled, G: average size (000 households), H: number of authorities; source: see Szymanski (1996) for full details

	A	B	C	D	E	F	G	H
All England	19.53	16.11	17.5	70	27	36	54.7	324
West	15.90	13.91	12.5	69	5	28	44.6	39
East Anglia	16.39	13.89	15.3	55	15	45	44.9	20
South East	18.78	15.75	16.1	66	12	60	45.8	92
West Midlands	18.85	16.08	14.7	84	38	21	61.7	32
East Midlands	19.41	15.82	18.5	72	25	50	41.7	36
North West	20.67	16.35	20.9	74	45	23	69.9	31
Yorkshire	20.85	17.82	14.5	87	39	9	80.2	23
North	22.35	18.74	16.2	78	67	0	41.1	27
London	26.15	18.59	28.9	50	38	38	94.3	24

as a result of CCT (Walsh, 1991; Audit Commission, 1993; Szymanski, 1996), Table 1 also indicates widely differing impacts by region. Whilst all regions reduced costs on average, the size of cost reductions ranged from 12.5 to 28.9%. Whilst there is a clear relationship between the rank of regions by cost pre-CCT and the size of cost reductions, the pattern is not uniform. For example, before CCT the North had 20% higher costs per household than the South-East, and yet both regions registered the same percentage cost reduction. Clearly, however, the extent of regional variation fell after CCT. Regional variations may in part be explained by systematic characteristics of the regions. However, the pattern of relationships are not entirely clear from the table.

3. Competitive tendering in theory

A service subject to CCT such as garbage collection can be thought of as a standard principal-agent problem, where the agent is either an in-house team or a private contractor and the principal is the elected authority. It is a standard intuition of economics that auctioning monopoly franchises can enable the public sector to obtain a given service at a lower cost (see e.g. Demsetz, 1968, whose argument is formalised by Laffont and Tirole, 1987). In the UK, local authorities were compelled to hold auctions as a result of the CCT legislation, often against the will of elected local representatives. Compulsion can be justified if the principal is likely to collude with a particular agent at the expense either of local consumers or of other potential suppliers. For example, Laffont and Tirole (1993) analyse a model where principals are biased in favour of particular agents. In their model a higher jurisdiction may bias the tender process in the favour of some agents in order to counterbalance bias by the lower jurisdiction. A similar model has been analysed by Vagstad (1994).

In this paper we analyse the spatial dimension of procurement and find that costs tend to be correlated after controlling for observable characteristics before the introduction of CCT but that CCT attenuates or eliminates this spatial effect. The spatial effect can therefore be argued to arise from some unobservable characteristic of local authorities which is eliminated by CCT. Care does, however, need to be shown in attributing the disappearance of spatial dependence to the introduction of CCT alone, because of the possible instability of spatial dependence patterns over time. Our approach can be compared to that of Brueckner (1998), who provides empirical evidence of strategic interaction among local governments in terms of policy interdependence.

In Bivand and Szymanski (1997) we outline the structure of a model which can account for this effect. Most local authorities evaluate service and cost levels by comparison with their local neighbours, a form of local yardstick competition. In such a world an authority with an extremely high average might lead neighbouring authorities to believe that their own costs are relatively low, even though they are in fact above average. Thus, in a world without competition spatial patterns in costs will be generated. However, following the introduction of competition, local comparisons will no longer be relevant if competition arises from private contractors who compare themselves with best practice on a nationwide basis.

The results of the model can be summarised as follows:

1. If there are economic shocks which can be observed by agents but not principals, and these shocks are locally correlated, then the optimal contract may involve comparison with costs of neighbouring authorities (local yardstick contracts).
2. If specific policies relating to variables such as wages paid by one authority are unobservable to neighbouring principals and agents, then there may be spillover effects from one authority to another, inducing local correlation in costs.
3. To the extent that a national policy such as CCT imposes standard rules on the way contracts are let and therefore removes the scope for an individual authority to pursue an idiosyncratic (and unobservable) policy, spillovers and local correlation will be attenuated or disappear altogether.
4. Standardisation of contracts under a policy such as CCT will tend to reduce idiosyncratic variance in the relationship between costs and variables such as market wage rates and population density, thereby increasing the significance of these variables in regression analysis.

4. Modelling garbage collection expenditure

Our data covers local government expenditure on garbage collection for 324 English districts out of 365 in total. Taking into account the different years in which the contracts were entered into, the expenditure and wage variables have been deflated to a common base across the data set. The dependent variable is here measured as the logarithm of real expenditure net of income. It could be argued that our model should be written in terms of expenditure per property, as in the data presented in Table 1. On the other hand, such a specification would diverge from current practice in the area, and might well raise substantial difficulties related to economies of scale.

The initial set of explanatory variables includes the number of properties from which garbage is collected, the percentage of dwellings among these properties, the density of the properties per unit area, dummy variables for London and other metropolitan districts (all of which have the same values before and after CCT) and regional male manual wage rates (pre-CCT and post-CCT real wages have a correlation coefficient of 0.91).[2] Since only the real wage variable differs between the two time periods, no attempt was made to construct a pooled pre-post model, within which parameter stability could have been examined formally.

'Entitation' (establishing the boundaries of entities) is an issue of some substance in the analysis of data collected from spatial or 'areal' units. Where the underlying process held to be generating the dependent variable or variables cannot be assumed to be well-bounded by the areal units of observation, the so-called modifiable areal unit problem may hinder identification and modelling. This is because an arbitrary redefinition of the boundaries, either by aggregation or zoning, could lead to very different estimation results (see Fotheringham and Wong, 1991). However, we can be confident that district boundaries accurately capture the behaviour of local government, because the boundaries of each jurisdiction are fixed by law and did not change over the period covered by our data. This is because the district boundaries strictly define the sphere of reference of our principals, and in the vast majority of cases of our agents as well.

We are interested in investigating the correlation between the costs, here measured as the logarithm of real expenditure net of income, of local authorities with the costs of their neighbours. Further, we are interested in exploring how this correlation, which we expect to fall in influence post-CCT, affects models accounting for costs, if at all. Using Moran's I, it is quite clear that the cost variable is spatially dependent: for pre-CCT costs, the observed $I = 0.311$, and testing under randomisation yields a standard deviate of 8.49. For post-CCT costs,

[2] These are the standard explanatory variables used in the literature (see e.g. Domberger et al., 1986). Endogeneity of our independent variables is not a problem given that the characteristics of each authority are fixed and the local market wage rate is unlikely to be significantly affected by the wage setting of the garbage collection service.

$I = 0.258$, with a standard deviate of 7.05, also highly significant. Moran's I is the standard measure of dependence among observations taken at the nodes of a lattice, where the edges of the lattice are used to describe neighbourhood; a recent use in economics is by Aten (1996, 1997), who employs the statistic to demonstrate spatial autocorrelation in international prices, and who provides a summary of its features. In essence, the statistic measures the correlation between the observed values at lattice nodes i, and the average values of nodes linked by edges to i, termed by analogy with time series 'lagged' values. With an adequate choice of explanatory variables, this spatial dependence may be readily drawn into a model, and cease to be a nuisance. Spatial dependence is not necessarily just a nuisance, but may help us to capture important facets of the realities of economic processes (cf. Hendry and Mizon, 1978).

Spatial data are usually divided into three kinds: spatially continuous data typical of environmental sciences, area or lattice data most often found in economics and the social sciences, and point data commonly occurring in ecology and epidemiology (see Cressie, 1993, for a comprehensive presentation). Methods used for analysing these data vary substantially but, as Anselin and Hudak (1992) show, it is possible to use standard econometric software to estimate spatial statistics and models. The literature on spatial statistics for lattice data is substantial (see Cliff and Ord, 1973, 1981; Upton and Fingleton, 1985; Anselin, 1988; Haining, 1990). Estimation methods for models using lattice data and taking spatial dependence into account are equally mature (Ord, 1975; Hepple, 1976). Examples of the application of these methods by economists are Dubin's estimation of a hedonic regression with cross-section data (1988), an analysis of spatial patterns in household demand by Case (1991) (see also Case et al., 1993; Besley and Case, 1995; Pinkse and Slade, 1998).[3]

We will now present briefly the methods to be used in analysing the garbage collection cost data. Assuming that the variance of the disturbance term is constant, we start from the standard linear regression model:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \qquad \boldsymbol{\varepsilon} \sim N(0,\sigma^2) \tag{1}$$

where $\mathbf{y}$ is an $(N \times 1)$ vector of observations on a dependent variable taken at each of N locations, $\mathbf{X}$ is an $(N \times k)$ matrix of exogenous variables, $\boldsymbol{\beta}$ is an $(k \times 1)$ vector of parameters, and $\boldsymbol{\varepsilon}$ is an $(N \times 1)$ vector of disturbances. Two alternative forms of spatial dependence models are the spatial lag model:

$$\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{2}$$

[3] A recent line of research in analysing spatial data, mainly associated with Luc Anselin, has focused on how to establish the characteristics of the dependence between observations, whether dependence can be demonstrated and how it ought to be represented. See Anselin (1995) for a program package running under Gauss (SpaceStat 1.80) implementing chosen tests.

where **A** is an $(N \times N)$ matrix describing the relationships between the N locations; this is most commonly parameterised as $\rho\mathbf{W}$, where ρ is a scalar spatial lag parameter, and **W** is a row-standardised $(N \times N)$ matrix with elements:

$$w_{ij} = \frac{w'_{ij}}{\sum_{j=1}^{n} w'_{ij}} \tag{3}$$

where $w'_{ij} = 1$ if i is linked to j and $w'_{ij} = 0$ otherwise. The spatial lag model is then written:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}. \tag{4}$$

Using a similar parameterisation of the dependency process, the second form is the spatial error model:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}, \qquad \mathbf{u} = \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon}, \tag{5}$$

where λ is a scalar spatial error parameter, and **u** is a spatially autocorrelated disturbance vector. These two models can also be related through the Common Factor model (see Burridge, 1981 and Bivand, 1984). The use of Eq. (1) with spatial data is equivalent to assuming that $\mathbf{u} = \boldsymbol{\varepsilon}$, and that $\mathbf{A} = \mathbf{0}$, or in the parameterisation of Eqs. (4) and (5), that $\rho = \lambda = 0$. Models (4) and (5) can only be combined for estimation if the neighbourhood specifications, here the **W** matrices, of the lag and error components differ; for testing, however, the same matrix may be employed.

Three issues need to be resolved: how to specify the weights matrix **W**, how to test whether the spatial parameters can safely be taken as equal to zero, and how to estimate models (4) and (5), should the tests indicate that Eq. (1) is mis-specified. In a recent study, Griffith (1995) has demonstrated that a parsimonious specification of the weights matrix (such as Eq. (3)) is to be preferred to one making assumptions about say distance decay. In our case, a Voronoi tesselation was constructed from the points at which the observations were located, here the administrative centres of the 365 districts; this is shown as an edited Delaunay triangulation in Fig. 1 (for details of these geometrical transformations, see e.g. Okabe et al., 1992). The edges retained in Fig. 1 run between district nodes for the 324 observations; nodes with intervening missing neighbours were not joined together with the exception of Penwith and Kerrier in West Cornwall, which would otherwise have been isolated. In addition, edges crossing major estuaries were removed. A small number of districts with missing cost data in the pre-CCT period could have been added to the post-CCT data set and also to the weights matrix, but it was chosen to retain the same set of districts for both analyses to secure comparability, despite the information discarded in this way (see Section 2 for a discussion of the possible impact of missing data on estimation results).

Testing Eq. (1) for spatial mis-specification may be undertaken using a modified

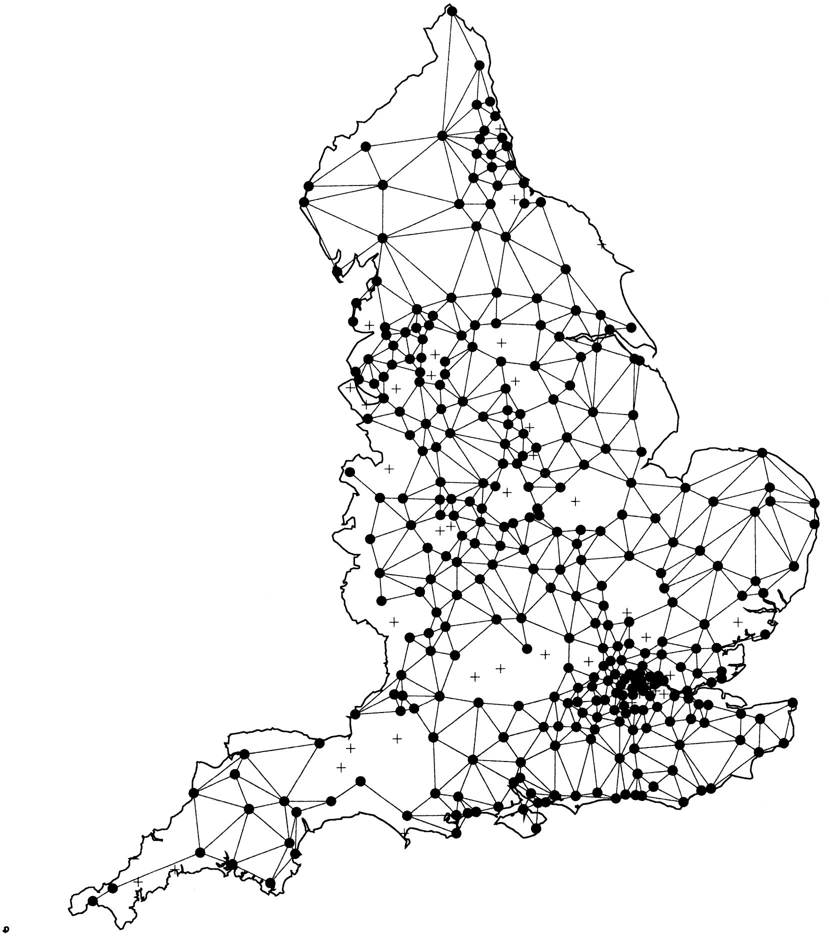

Fig. 1. Lattice of English districts used for the construction of the weights matrix **W** where districts are located at their administrative centres; ●, included observations; +, missing observations.

version of Moran's *I*, but this does not discriminate between lag and error processes. Many of the simpler Lagrange Multiplier tests presented in the literature have also shown themselves to be affected by non-zero values of nuisance parameters: the LM test for a missing spatial lag also responds to the presence of spatial dependence in the disturbance, and vice-versa. New modified LM tests, presented by Anselin et al. (1996) and tested by Anselin and Florax (1995) are more robust, have good finite-sample properties, and are more suitable for the identification of the source of the spatial dependence.

Ord (1975) gives the Maximum Likelihood methods for estimating models (4) and (5); no satisfactory alternatives have been found subsequently, chiefly because of the important role of the Jacobian expressing the spatial transformation of either the dependent variable in Eq. (4), or the disturbance in Eq. (5). Estimates reported below are calculated using SpaceStat 1.80 (Anselin, 1995), which finds the spatial parameter estimate by a line search on the concentrated log-likelihood function, and computes estimates of $\boldsymbol{\beta}$, σ^2, and the asymptotic standard errors analytically, rather than relying on numerical approximation of the information matrix (Anselin and Hudak, 1992).

Table 2 gives our estimation results for 324 English districts. The results reported in columns (1) and (3) of Table 2 are OLS estimates calculated using Eq. (1) above. The coefficient estimate for the wage variable becomes significant, and a similar, but much weaker, tendency is shown for the density variable. The metropolitan district dummies do not play an important role, while the number of properties is clearly the most important scaling explanatory variable – costs are highest in districts with most properties. Finally, costs are significantly lower in districts with a higher proportion of domestic properties.

Applying the modified LM spatial dependence tests to the results reported in

Table 2
Models of log net real expenditure by English districts on garbage collection: OLS and ML spatial error estimates[a]

		Pre-CCT		Post-CCT	
		(1) OLS	(2) ML error	(3) OLS	(4) ML error
Constant		−4.535***	−4.992***	−5.947***	−6.556***
		(1.233)	(1.467)	(1.111)	(1.272)
Log properties		0.953***	1.002***	0.914***	0.954***
		(0.039)	(0.037)	(0.038)	(0.036)
Houses %		−1.611***	−1.689***	−1.354***	−1.306***
		(0.332)	(0.315)	(0.316)	(0.307)
Log density		0.012	−0.001	−0.021	−0.027*
		(0.012)	(0.012)	(0.012)	(0.012)
London district		0.146*	0.099	0.084	0.044
		(0.067)	(0.079)	(0.064)	(0.072)
Other met. district		0.101	−0.024	0.129*	−0.046
		(0.063)	(0.066)	(0.060)	(0.062)
Log wage rate		0.466*	0.489	0.782***	0.818***
		(0.229)	(0.273)	(0.206)	(0.237)
λ		–	0.363***	–	0.285***
			(0.069)		(0.073)
LM_λ	Estimate	9.081**		8.074**	
	Prob-value	0.0026		0.0045	
LM_ρ	Estimate	1.870		0.003	
	Prob-value	0.1715		0.9551	

[a] * (**) [***] indicate statistical significance at the 5% (1%) [0.1%] level. Standard errors in parentheses.

columns (1) and (3) of Table 2, we find firstly that dependence is present in both models, and that the tests indicate that the spatial error specification should be preferred to the spatial lag form. This result is disappointing, because we had expected that spatial dependence would be attenuated by the introduction of CCT. We estimated spatial error models (Eq. (5)) above for the pre-CCT and post-CCT cases; the results are shown in columns (2) and (4) of Table 2. The ML estimate of the value of λ declines, but spatial dependence is still significant after CCT. Estimates of other coefficient values and standard errors change little; the standard errors of the constant term, the London dummy, and the wage variable increase somewhat, indicating that they were underestimated in the OLS estimates.

5. The impact of politics

The model estimated in the previous section might be thought of as one in which principals behave alike irrespective of politics. Behaviour is here understood as not just setting the terms of contracts, but also the patterns of neighbourhood or yardstick comparison that it would be normal for a given political majority to undertake. However, this assumption is questionable given the significant political controversy surrounding CCT. The data set was divided into three political regimes, using the criterion of the party with the majority of members on the district council in the year in which competitive tendering was implemented, 87 districts having a Labour majority, 118 – a Conservative majority, and the remainder, 119, no overall control (NOC, including Liberal Democrat majorities, of which there were only five).

The spatial distribution of political control is shown in Fig. 2, from which clustering is evident. Joint-count statistics, testing hypotheses about the randomness or otherwise of say Labour–Labour contiguities between districts (see Cliff and Ord, 1973, pp. 4–5), are used to determine whether the binary classifications of Labour majority, Conservative majority, or NOC are assigned to nodes on the lattice at random. The hypothesis of random assignment was rejected for all three political dummies for first order spatial lags, the results of the tests being standard normal deviates with values of 4.56 for the Labour control dummy variable, 6.19 for the Conservative control dummy variable, and 2.82 for the NOC/Liberal Democrat dummy variable.

In order to test our previous assumption that principal behaviour was neutral with regard to politics, we carried out Chow tests on the models presented in Table 2. For the pre-CCT model, the Chow test result was 3.066, with a prob-value of 0.0002; for the post-CCT model, the result was 3.585, prob-value 0.00002. Applying the Chow–Wald test proposed by Anselin (1990), distributed as χ^2 with $2k$ d.f.) for the ML spatial error models, the results were: pre-CCT 40.962, prob-value 0.0002, post-CCT 52.674, prob-value 0.000002. The encompassing

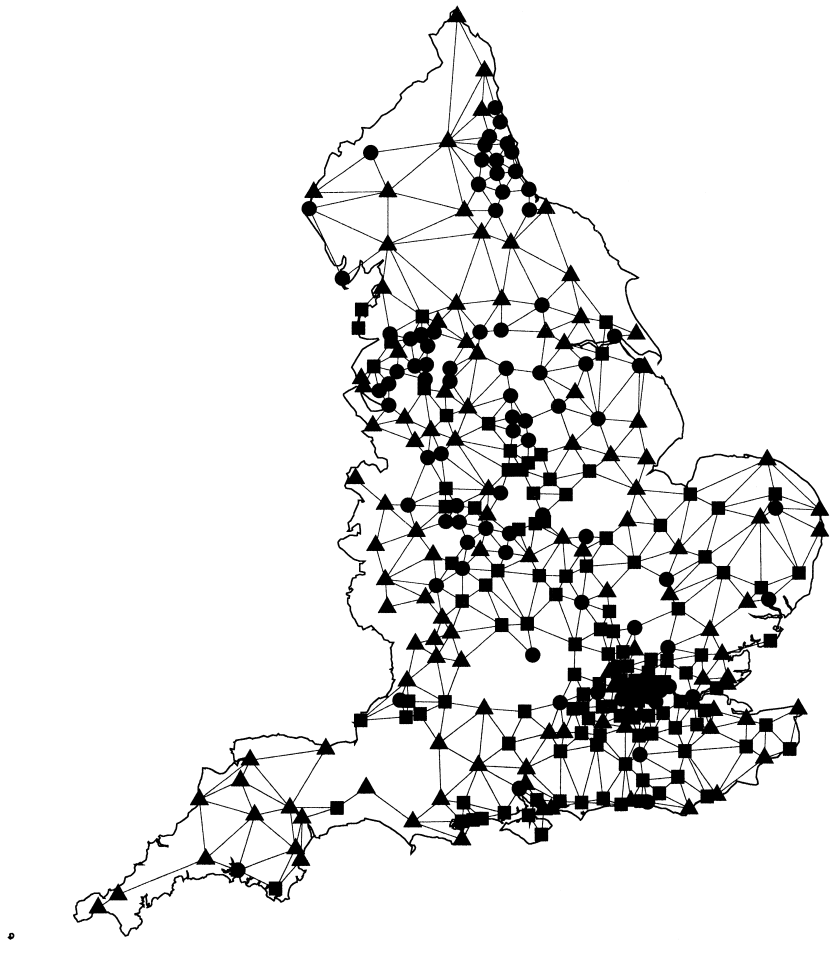

Fig. 2. Majority political control in 324 English districts; filled circles – Labour; filled squares – Conservative; filled triangles – no overall control and Liberal Democrat.

models, with separate sets of explanatory variables for each political regime, improved the fit of the pre-CCT and post-CCT models. In the pre-CCT case, the error variance of the OLS estimates fell from 0.0597 to 0.0547, the Akaike information criterion (AIC) from 13.03 to -1.89, and adjusted R^2 rose from 0.835 to 0.847; in the post-CCT case, σ^2 fell from 0.0541 to 0.0485, AIC from -18.88 to -40.55, and R^2 rose from 0.825 to 0.843. Many of the individual coefficients were, however, insignificant, and they did not vary significantly between regime either, differences occurring only where the coefficient estimates were themselves not significant. In practice we preferred a model including only dummy variables for political control rather than the encompassing model.[4]

The OLS results from estimating pre-CCT and post-CCT models with majority political control dummies are given in columns (1) and (3) of Table 3. The introduction of the dummies, of which only the estimated Labour coefficient is

Table 3
Models of log net real expenditure by English districts on garbage collection including majority political control dummies: OLS and ML spatial lag estimates[a]

		Pre-CCT		Post-CCT	
		(1) OLS	(2) ML lag	(3) OLS	(4) ML lag
Constant		−4.377***	−4.962***	−5.952***	−6.235***
		(1.212)	(1.177)	(1.072)	(1.053)
Log properties		0.954***	0.971***	0.925***	0.936***
		(0.038)	(0.037)	(0.036)	(0.035)
Houses %		−1.720***	−1.727***	−1.397***	−1.376***
		(0.321)	(0.310)	(0.302)	(0.296)
Log density		−0.016	−0.022	−0.047***	−0.050***
		(0.013)	(0.012)	(0.012)	(0.012)
London district		0.177**	0.075	0.108	0.054
		(0.064)	(0.068)	(0.061)	(0.064)
Other met. district		0.048	−0.046	0.051	−0.005
		(0.062)	(0.064)	(0.059)	(0.061)
Log wage rate		0.480*	0.379	0.798***	0.711***
		(0.223)	(0.217)	(0.197)	(0.196)
Labour dummy		0.209***	0.199***	0.190***	0.184***
		(0.038)	(0.037)	(0.036)	(0.035)
Conservative dummy		0.056	0.040	−0.005	−0.015
		(0.032)	(0.031)	(0.030)	(0.030)
ρ		–	0.149***	–	0.097*
			(0.042)		(0.044)
LM_λ	Estimate	2.235		1.853	
	Prob-value	0.1349		0.1734	
LM_ρ	Estimate	4.770*		1.035	
	Prob-value	0.0290		0.3091	

[a] * (**) [***] indicate statistical significance at the 5% (1%) [0.1%] level. Standard errors in parentheses.

[4] Compared to the encompassing models the error variance and R^2 are virtually identical. However, with the dummy variable model the AIC values fell substantially, to −13.05 in the pre-CCT case, and −50.48 in the post-CCT case, since the dummy models have only $k+2$ coefficients, while the encompassing models have $3k$. In the dummy variable model NOC is chosen as the baseline group.

significant, only modifies other coefficient estimates slightly in the pre-CCT model, with values on the London dummy and the wage rate rising a little. In the post-CCT OLS estimates in column (3), density is now significant, but other coefficient estimates are very similar to those in Table 2. Testing for spatial mis-specification of these OLS models, we find that the results of the modified LM tests on the pre-CCT OLS model estimates indicate clearly that there is a lag dependence, but now no error dependence. The tests on the post-CCT estimates no longer show any significant spatial dependence. It appears that the omission of politics from our earlier model, politics that are highly spatially autocorrelated albeit as dummy variables, was being picked up in the residuals sufficiently strongly to mask both the pre-CCT spatial lag dependence, and the marked attenuation of spatial dependence in the model post-CCT.

6. Concluding remarks

In this paper we have shown how the use of statistical techniques for the modelling of spatial dependence can enhance our understanding of economic processes, and that searching for spatial dependence is a fruitful way of improving model specification. We have shown that there existed a strong and significant spatial dependence in the distribution of garbage collection costs in England before the introduction of CCT which has been significantly eroded following CCT. This change in relationships is clear once differences in political control are accounted for, although we cannot completely dismiss the possibility that unstability in patterns of spatial dependence has affected our results. In our earlier work (Bivand and Szymanski, 1997), we have presented a theoretical explanation as to how spatial dependence might exist in world of local monopoly franchises not subject to competition, and how competition under standardised rules might eliminate this spatial dependence.

The results presented here permit us to demonstrate that the main predictions of our model are substantiated. Including politics sharpens the picture by making it clear that the spatial lag specification is to be preferred for the pre-CCT setting, and that the influence of spatial dependence is strongly reduced after the introduction of CCT. Taking spatial dependence into account also helps highlight the other two outcomes of introducing CCT, namely the increase in significance of two variables reflecting operating efficiency: real wages with a positive sign, and log density with a negative sign.

An important direction for future research is to analyse in more detail the effect of political influence by partitioning the weights matrix, for instance into Labour–Labour, or Conservative–Conservative.[5] Finally, moving from the exploration of

[5] See e.g. Besley and Case (1995), whose work on US political districts zeroes out the influence of states with 'lame-duck' governors by assumption; Case et al. (1993) compare pairs of alternative weights matrices using an ad-hoc scheme.

possible local non-stationarity to its estimation, the technique of Geographically Weighted Regression has been put forward to map spatial variations in estimated regression coefficients empirically (see Brunsdon et al., 1996; Fotheringham et al., 1996).

Given the renewed interest in geography in economics, it is fortuitous that tools, such as the modified LM statistics, are now available, and can be estimated at little extra cost using standard econometric software; the extra cost is associated with entering data on the relative positions of the observations in space, which is necessarily more involved than in the time-series case. Our experience suggests that other modelling studies using geographical data would benefit from the application of these methods; at the very least, such studies now ought to carry out tests of the assumption that that spatial dependence is not present.

From an economic perspective, our research has shown not simply that spatial dependence exists between economic units, but how this spatial dependence might be generated by the behaviour of economic agents. This contrasts with much of the existing literature, which is either driven by statistics in the absence of a behavioural model or consists of an elegant but statistically untestable theoretical model. We believe that the real challenge in this field of research is to develop testable models of individual behaviour that can account for spatial dependence.

References

Anselin, L., 1988. Spatial Econometrics: Methods and Models, Kluwer, Dordrecht.

Anselin, L., 1990. Spatial dependence and spatial structural instability in applied regression analysis. Journal of Regional Science 30, 185–207.

Anselin, L., 1995. SpaceStat version 1.80 User's Guide, Regional Research Institute, West Virginia University, Morgantown, WV.

Anselin, L., Bera, A.K., Florax, R., Yoon, M.J., 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, Springer, Berlin, pp. 21–74.

Anselin, L., Hudak, S., 1992. Spatial econometrics in practice: a review of software options. Regional Science and Urban Economics 22, 509–536.

Aten, B., 1996. Evidence of spatial autocorrelation in international prices. Review of Income and Wealth 42, 149–163.

Aten, B., 1997. Does space matter? International comparison of the prices of tradables and nontradables. International Regional Science Review 20, 35–52.

Audit Commission, 1993. Realising the Benefits of Competition. London: HMSO.

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

Bivand, R.S., 1984. Regression modelling 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.

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

Brunsdon, C., Fotheringham, A.S., Charlton, M., 1996. Geographically weighted regression: a method for exploring spatial nonstationarity. Geographical Analysis 28, 281–298.

Burridge, P., 1981. Testing for a Common Factor in a spatial autoregressive model. Environment and Planning A 13, 795–800.

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

Case, A.C., Rosen, H.S., Hines, J.R., 1993. Budget spillovers and fiscal policy interdependence: evidence from the states. Journal of Public Economics 52, 285–307.

Cliff, A.D., Ord, J.K., 1973. Spatial Autocorrelation, Pion, London.

Cliff, A.D., Ord, J.K., 1981. Spatial Processes – Models and Applications, Pion, London.

Cressie, N.A.C., 1993. Statistics For Spatial Data, Wiley, New York.

Cubbin, J., Domberger, S., Meadowcroft, S., 1987. Competitive Tendering and Refuse Collection: identifying the source of efficiency gains. Fiscal Studies 8 (3), 49–58.

Demsetz, H., 1968. Why Regulate Utilities? Journal of Law and Economics 11, 55–65.

Domberger, S., Meadowcroft, S., Thompson, D., 1986. Competitive Tendering and Efficiency: the case of refuse collection. Fiscal Studies 7 (4), 69–89.

Dubin, R.A., 1988. Estimation of regression coefficients in the presence of spatially autocorrelated error terms. Review of Economics and Statistics 70, 466–474.

Escott, K., Whitfield, D., 1995. The Gender Impact of Compulsory Competitive Tendering in Local Government. Equal Opportunities Commission.

Fotheringham, A.S., Wong, D.W.S., 1991. The modifiable areal unit problem in multivariate statistical analysis. Environment and Planning A 23, 1025–1044.

Fotheringham, A.S., Charlton, M., Brunsdon, C., 1996. The geography of parameter space: an investigation of spatial non-stationarity. International Journal of Geographical Information Systems 10, 605–627.

Griffith, D.A., 1995. Some guidelines for specifying the geographic weights matrix contained in spatial statistical models. In: Arlinghaus, S.L., Griffith, D.A. (Eds.), Practical Handbook of Spatial Statistics, CRC Press, Boca Raton, pp. 65–82.

Haining, R.P., 1990. Spatial Data Analysis in the Social and Environmental Sciences, Cambridge University Press, Cambridge.

Hendry, D.F., Mizon, G.E., 1978. Serial correlation as a convenient simplification, not a nuisance: a comment on a study of the demand for money by the Bank of England. Economic Journal 88, 549–563.

Hepple, L.W., 1976. A Maximum Likelihood model for econometric estimation with spatial series. In: Masser, I. (Ed.), Theory and Practice in Regional Science, Pion, London, pp. 90–104.

Laffont, J.-J., Tirole, J., 1987. Auctioning incentive contracts. Journal of Political Economy 95, 921–937.

Laffont, J.-J., Tirole, J., 1993. A Theory of Incentives in Procurement and Regulation, MIT Press, Cambridge.

Okabe, A., Boots, B., Sugihara, K., 1992. Spatial Tesselations: Concepts and Applications of Voronoi Diagrams, Wiley, New York.

Ord, J.K., 1975. Estimation methods for models of spatial interaction. Journal of the American Statistical Association 70, 120–126.

Painter, J., 1991. Compulsory competitive tendering in local government: the first round. Public Administration 69, 191–210.

Pinkse, J., Slade, M., 1998. Contracting in Space: an application of spatial statistics to discrete-choice models. Journal of Econometrics 85, 125–154.

Shaw, K., Fenwick, J., Foreman, A., 1994. Compulsory competitive tendering for local government services: the experiences of local authorities in the North of England 1988–1992. Public Administration 72, 201–217.

Stewart, J., 1992. The Changing Organisation and Management of Local Authorities. In: Stewart, J., Stoker, G. (Eds.), The Future of Local Government. Macmillan, London.

Szymanski, S., 1996. The impact of compulsory competitive tendering on refuse collection services. Fiscal Studies 17 (3), 1–19.

Upton, G.J.G., Fingleton, B., 1985. Spatial Data Analysis By Example: Point Pattern and Quantitative Data, Wiley, London.

Vagstad, S., 1994. Promoting Fair Competition in Public Procurement. Norwegian Research Center in Organisation and Management working paper no. 9428, Bergen.

Walsh, K., 1991. Competitive Tendering for Local Authority Services: Initial Experiences, HMSO, London.

Walsh, K., 1995. Public Services and Market Mechanisms, Macmillan, London.

Walsh, K., Davies, H., 1993. Competition and Service: The Impact of the Local Government Act 1988, HMSO, London.