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Exploring the Spatial Pattern of Mental Health Expenditure

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Abstract

Background: Recent years have witnessed growing interest in cross-sectional variations in municipality mental health expenditure. However, empirical work to date has not examined the links between such variability and demand and supply factors, particularly in the spatial domain.
Aims of the Study: The aim is to examine whether a local authority's spending decisions in the mental health field respond to neighbouring expenditure decisions. We explore a number of reasons why there might be interdependence between local authorities' decisions, labelling them the demonstrative, market leader, contextual, directive, shared resource and inducement effects.
Methods: Exploratory techniques from spatial data analysis are used to test for the existence of spatial structure. Drawing hypotheses from these initial exploratory analyses, we then adopt a reduced form demand and supply model, extended to incorporate possible policy interaction. The analysis of expenditure and cost variations has traditionally been based on regression models under the classical assumption that the observations are independent. But omitting the recognition that observations are interdependent might lead to erroneous statistical conclusions. Hence, we use spatial econometric techniques that explicitly take into account the potential interdependence of data in order to study the sources of spending variation between municipalities.
Results: The exploratory data analyses reveal the presence of positive significant spatial correlation. Per capita mental health spending distributes in clusters, with the highest concentrations in metropolitan areas such as Greater London, Greater Manchester and Birmingham. The estimated spatial regression models indicate that spatial autocorrelation characterises local expenditure decisions, consistent with some degree of policy interdependence between neighbouring municipalities. Comparing the results from our spatial model with those from a classical ('non-spatial') model suggests that the differences in the regression coefficients could be explained by the evident spatial pattern of the phenomenon, since the omission of the lagged dependent variable induces bias in the OLS estimates.
Implications for Health Policies: These results help central and local decision makers understand the factors that influence local spending levels, including variations between municipalities in their achievement of expenditure-related and perhaps other performance targets. The actual patterns of spatial interaction may well be more complex than simple contiguity (the structure assumed here), but there seems little doubt that positive interdependence is an important feature of decision making.
Implications for Further Research: Statistical interrogation of a panel dataset would allow exploration of both time-series and cross-municipality variation in mental health expenditure. Subsequent analysis would also benefit from more disaggregated data (e.g. at a census ward level) and the accompanying use of spatial multilevel techniques.

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Introduction

Interest in the geography of mental health can be traced back at least as far as the 19th century, when Edward Jarvis[1] observed that the distance from a hospital was likely to explain much of the geographical variability in service utilization. He noted a relationship between hospitalisation and where someone lived: the nearer they were to the hospital the greater the chance of admission. He also observed that hospital utilization was higher for individuals closer to 'transportation' corridors, such as rivers, canals or roads leading directly to the hospitals. This led him to argue that small number of large regional hospitals at that time should be replaced by several smaller ones spread out so as to be more accessible to the population. Jarvis's ideas about distance decay factors fed into what would later become known as the first law of geography: things that are nearer are likely to be more closely correlated than things that are further apart.[2]

Thirty years after Jarvis, Tuke[3] observed wide geographical variation in the incidence of suicide across several countries. Tuke's seminal work, *Dictionary of Psychological Medicine*, signalled what would become an enduring interest in the geography of suicide. Spatial variation in mental illness would come to be analysed across many western countries against postulated or suspected factors such as geographical variation in socio-environmental attributes and individual characteristics (including, more recently, genetic markers). One of the earliest such

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investigations was the work by Faris and Dunham[4] in Chicago. By charting the place of residence of people admitted to hospital for psychiatric evaluation or treatment, they detected a concentration of psychoses in the more disadvantaged areas of the city. Indeed, their findings stimulated a number of other studies.[5] This gradient was subsequently replicated in Europe,[6,7] although not all studies have confirmed a significant association between the geographical distribution of mental health and environmental attributes.[8] These different conclusions have generated (in part) difficulties in understanding the relationship between where someone lives and their mental health.[9,10] There has been debate about so-called 'breeder' and 'drift' effects. The 'breeder' hypothesis is that specific environmental factors (such as poor living conditions) might induce or exacerbate mental health problems, whereas the 'drift' hypothesis is that people with psychiatric illnesses tend to move into disadvantaged areas.[11]

There have been other investigations of the links between geographical factors, mental illness and mental health care. Indeed, there has been quite noticeable recent growth in the literature on the geography of mental health.[6,12-16] Some of these studies have investigated spatial patterns of behaviour at levels of aggregation higher than the individual, for example at the level of census blocks or administrative authorities. Mental health economics appears to have been largely immune to these developments, with relatively few studies specifically looking at location or its effects. This is perhaps surprising given that marked cross-sectional variations have been found in a large number of indicators of economic relevance, and that the sources of those variations have also been examined.

This neglect can be illustrated by reference to the topic of this paper: patterns of expenditure. Many empirical studies have detected wide variations in the epidemiology of mental health problems across localities, which in turn – on the grounds of equity and efficiency – would be expected to induce variable levels of resource expenditure and service utilisation.[17] Recent years have witnessed growing interest in such variation. In the UK, for example, a few studies have focused on variation in utilisation patterns in small area analyses, including distance to health facilities as an explanatory variable alongside measures of clinical and social needs and the characteristics of health care supply.[18-22] (For an overview of some of the earlier international literature see.[23]) Much of this work has been focused on the distribution of resources in the mental health sector, and questions addressed have tended to be prescriptive rather than descriptive or analytical.[24] As a result, less attention has been paid to the actual fluctuations, at area level, of resource consumption or expenditure, or their causes. There is also a sizeable literature focusing on individual-level explanations of cost variations, particularly by reference to clinical characteristics (e.g. see Knapp[25]).

Our arguments in this paper are, first, that mental health spending will be influenced by factors other than 'need' and second, that those covariates are not randomly distributed across localities but are likely to display certain spatial patterns. The first argument is obviously not a new one, since the best studies of cost or expenditure variations have generally made adjustments for covariates when examining the equity of, for example, central grant allocations or related decisions. But the second argument – that there could be a non-random underlying spatial pattern – has been almost completely neglected.

We say 'almost completely' because – in the UK literature, for example – some previous authors have pointed to associations between spending and regional location or type of municipality. Bindman *et al.*[26] noticed the presence of a regional concentration in the ratio of expenditure to allocation in England, with a tendency for under-spending in four regions (Northern, Trent, West Midlands and North West) and overspending elsewhere. Their study indicated that there is often a substantial gap between the formula-based allocation and the actual level of health system expenditure on mental health, particularly in those areas with a high level of socio-economic deprivation. They suggest that some health authorities failed to spend resources in line with the underlying grant allocation formula because they might be reluctant to divert resources to psychiatry from non-psychiatry acute services. Similarly, high levels of expenditure on mental health in London have been attributed to levels of need greater than those accounted for by the need proxy used in the allocation formula.[27] Such grant allocation formulae in the UK are not binding; indeed not even necessarily recommendations. There is considerable local autonomy as to expenditure levels and components. These empirically observed divergences in local mental health policy suggest that variability in mental health expenditure might be partly explained by variables other than risk factors recognised by the literature.

In a different kind of study, Forsyth *et al.*[28] compared expenditure on learning disability health services across England with the 'burden' of services regionally, as estimated by numbers of people with learning disabilities. They observed wide geographical variability in the spend/burden ratio, with some health authorities spending considerably less on services in relation to the number of people with learning disabilities than do others.

There is also a small literature on more highly aggregated municipal expenditure patterns that has touched on the spatial dimension. Interesting work by Revelli[29,30] detected substantial spatial patterns in overall social care expenditure among English local authorities, including apparent 'mimicking behaviour' in local property tax setting (see below).

Expenditure Data

Mental health services in England are delivered in an increasingly mixed economy, with a diversity of funding routes and growing plurality of provision.[31] The great majority of funding for formally delivered services is tax-based, routed through two channels: the (centrally managed) National Health Service (NHS) and the 150 (locally elected) councils with social services responsibilities (more commonly if less precisely referred to as local authorities). NHS funds are allocated on a weighted capitation basis to primary care trusts (PCTs). (At the time of the Bindman *et al.*[26] study described above the allocated grant went to health authorities. These were replaced by PCTs following national reorganisation. Another reorganisation is now being mooted.) Local authorities are locally elected with a substantial proportion of their revenue coming from central government via a formula that endeavours to compensate for differences in need-generating factors (including demography, poverty, poor housing and a psycho-social morbidity measure) and exogenously determined input (especially labour) prices. Central funding allocations to local health systems and local authorities thus endeavour to pick up differences in the need for treatment and support, and also differences in the ability to deliver services.[21-23]

As long-stay hospitals have closed, the main locus of care has shifted to the community, and with it a growing role for non-health service agencies, and particularly for local authorities.

Health Service Expenditure

Both NHS and local authority expenditure on mental health have been increasing over recent years, in line with the concerted attempt by Tony Blair's government to improve access to and quality of health care. NHS expenditure on mental health care has hovered around 12% of total public sector health expenditure at least since the late 1980s, and is currently 13%. Notwithstanding the difficulties of making inter-country comparisons, this appears to be above the level in most western European and OECD countries.[33] As total NHS expenditure has increased so has the absolute amount going to mental health. In real terms, NHS mental health spending was 60% higher in 2000/01 than in 1990/91.

Local Authority Expenditure

Expenditure on mental health services from local authority social services budgets is roughly one-fifth the size of NHS mental health expenditure. There is substantial variation in this proportion: Aziz *et al.*[32] calculated that, at borough (local authority) level, social services spending on mental health in London actually ranged from 23% to as high as 79% of health service spending. These proportions are substantially higher than those reported by Evandrou and Falkingham[34] for earlier years: social services spending on mental health as a proportion of NHS spending on hospital and community mental health services was 3.1% in 1977, 4.7% in 1985, 4.0% in 1989 and 5.9% in 1994.

Within total social care spending the main growth areas have been proportionate increases in expenditure on accommodation (nursing home, residential care home and supported accommodation), as local authorities assumed responsibility for funding placements that previously would have been covered by social security support. However, mental health services account for only a modest proportion of total social care spending by authorities.

NHS and social care spending in London appear to be positively linked: there is no evidence (from albeit limited analyses to date) of substitution between the two expenditure streams.[32]

Hypotheses

The possible underlying causes of spatial patterns of behaviour are often discussed using a threefold categorisation suggested by Manski:[35] endogenous, exogenous and correlated effects. The endogenous effect hypothesises that the behaviour of an individual varies with the behaviour of his/her neighbours. The contextual (exogenous) effect argues that individual action varies with observed attributes of the reference group. The correlated effect argues that individuals in the same neighbourhood tend to behave similarly because they have similar characteristics or face similar institutional environments. These possible scenarios refer to what could be called within-neighbourhoods effects. Our interest is different. We are concerned with whether there are associations between or among neighbourhoods,[36] in particular whether there are spillover or other interactions among municipalities.[36]

Manski's threefold classification of potential spatial effects has been influential in the research literature. It is possible to suggest among-neighbourhood equivalents to, or corollaries of these effects, and certainly it is methodologically pertinent to be able to distinguish endogenous from exogenous effects. In our work to date we have found it helpful to posit the following reasons why there might be spatial interaction between local authorities in relation to expenditure. These are briefly described below; all can be reconciled with Manski's hypotheses. At the current, exploratory stage of our analysis these remain possibilities awaiting closer examination.

Contextual Effects

Neighbouring authorities share common general population characteristics or underlying socio-economic features. Environmental stressors such as long-term unemployment and poverty could be linked to *regional* rather than simply local trends, influencing prevalence and need across a wide area, and hence influencing expenditure.

Shared Resource Effects

Some mental health services are either organised at a level higher than the individual local authority, and/or serve a population that is not confined to a single administrative area. One obvious example is the large psychiatric hospital that accommodates people from a number of localities. The closure of such a hospital – and this has been one of the most prominent features of mental health policy in the UK for some years – will substantially increase the need for social care services. Spatial interaction will therefore arise from 'spillover effects' associated with such shared resource dependence. Another example would be the provision of high-secure and medium-secure units for people with forensic needs, often organised on a regional basis. Their funding may be a health service responsibility, but there will be social care expenditure impacts of *not* providing these services, and hence again a shared (spatial) resource effect.

Directive Effects

Social and health care services in England are monitored, inspected and audited by national government. Until recently the regionally organised Social Services Inspectorate had responsibility for some of these functions, and common guidance across a region may have influenced certain patterns of activity or expenditure. We suspect that such a 'directive effect' would have been quite modest in the English context.

Demonstrative Effects

One local authority's good (or bad) performance may encourage others to mimic (or avoid) the activities and expenditure patterns associated with (or *assumed* to be associated with) such performance. Growing use of publicly announced and widely reported performance indicators could encourage such mimicking behaviour. The introduction of the Social Service Performance Rating in England suggests that overt competition between municipalities – 'naming and shaming' – is thought to improve performance.

Market Leader Effects

Similar to the demonstration effect is the influence on others of a local authority that is seen to be a 'market leader' or exemplar. Some municipalities may develop good reputations for their championing of particular causes (such as better provision for people with mental health problems), again leading to mimicking by others.

Inducement Effects

A local authority may choose a particular course of action so as to persuade individual service users, families or indeed service providing bodies to migrate into or out of their area by ensuring that expenditure, activity or policy is more (or less) attractive than that offered in neighbouring authorities. There is a sizeable political science literature on this kind of interaction between municipalities. We are as yet unsure of its relevance in relation to mental health expenditure patterns.

Other sources of spatial interaction could undoubtedly be suggested, and some of the effects noted here could – with the right data – be tested empirically.

Method

Spatial Analyses

Spatial data analyses are techniques and models that explicitly use the spatial referencing associated with each data point within a system. Location in spatial data analysis has a similar role as does time in a time series analysis. There is a tendency for values of a variable that are close in time to be more similar then values separated by longer time intervals. Similarly, therefore, there might be expected to be a tendency for values for the same attribute measured at locations that are near to one other to be more similar than values separated by greater distance.

Spatial data analysis has developed in two directions, one data-driven and the other model-driven. In the data-driven approach, randomness is assumed and the spatial pattern as well as spatial interactions are derived from the data, without the constraints of a preconceived theoretical notion. This approach comprises a wide collection of techniques, originally developed for the analysis of the spread of a disease, such as spatial adaptive filtering, spatial point pattern analysis and indices of spatial association.[37]

The model-driven approach incorporates spatial structure in econometric specifications. The term 'spatial structure' indicates the presence of spatial dependence (also known as spatial interaction) or spatial heteroscedasticity (also known as heterogeneity across territory). Spatial dependence is a functional relationship between what happens at one point in space and what happens elsewhere. By considering an extended notion of space – which can include geographical, social, policy and economic space - the notion of spatial dependence can be employed to represent interdependencies and interactions among individuals. Spatial heterogeneity is the lack of stability over space of the behavioural relationship under study.[38]

The literature on spatial econometrics outlines two classes of specification for models with spatial dependence. Models belonging to the first class incorporate spatial correlation in the dependent variable, and are considered as the formal specification for the equilibrium outcome of spatial or social interaction processes, in which the value of the dependent variable for one agent is jointly determined with that of the neighbouring agents.[39] These models, known as spatial lag models, are particularly associated with the early work of Whittle[40] and Cliff and Ord.[41] Models belonging to the second class assume that spatial correlation affects the error term, and can be considered as a special case of a non-spherical error covariance matrix. These models are useful when the behaviour of an economic agent is influenced by characteristics of her/his neighbours that are unobservable to the analyst.

In both classes of model, the strength of potential interaction between units is explicitly introduced through the definition of a spatial weights matrix, usually signified as W. The construction of this matrix is based on non-sample information about the relative distance between the observations. Since in most economic applications there is no natural or uniquely superior measure of distance between units, the specification of the weights matrix can be difficult, sometimes controversial, in spatial econometrics.

The estimation of spatial models faces a number of methodological problems due to violations of the assumptions of traditional econometric approaches. Indeed, spatial dependence violates the Gauss-Markov assumption that exogenous variables are fixed in repeated sampling. Similarly, spatial heterogeneity does not conform to the Gauss-Markov assumption of a single linear relationship across a dataset. Thus, the spatial econometric literature has been focusing, for example, on alternative estimation methods such as instrumental variables and maximum likelihood approaches to address endogeneity of the dependent variable.

Tests for Spatial Patterns

A set of local and global statistics can be used to test whether authorities with similar expenditure levels are more spatially clustered than would be expected by chance. The statistics used in this paper are Moran's I, Geary's C and local Moran, which are the most widely used indicators with spatial data.

Moran's I statistic is a test of spatial autocorrelation between observations that are specified as neighbours by the weights matrix; it is very similar to a correlation index that compares statistical units, weighting each pair by a distance function. In a more formal fashion, for n locations for a variable x_i, Moran's I statistic is typically defined as:

$$I(d) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}},$$

where $S^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}$, x_i denotes the observed value at location i, $\bar{x}$ is the average of the x_i over the n locations, and w_{ij} indicates the generic element of the spatial weights matrix W, which captures the spatial relationship between observations. As noted earlier, the spatial relationship between observations is captured by the spatial weights matrix W. In a spatial weights matrix the rows and columns correspond to the observations, and the value in each cell represents whether the unit in the column header is a neighbour of the unit in the row. The term *neighbour* here is used to indicate that two units have some non-zero spatial relationship. In economic terms, the generic element of the matrix, w_{ij}, expresses the strength of potential interaction between unit i and unit j. The weights matrix is generally standardized so that the sum of the elements for each row is the unity.

Weights can be defined using the notion of contiguity between units, and assigning $w_{ij} = 1$ when i and j are neighbours, and $w_{ij} = 0$ when they are not. Alternatively, weights can have continuous values, such as a declining function of distance between points, based on measures of physical,[38,41] economic,[42] social[43] or policy distance. However, it is important to note that the elements of the weights matrix should be non-stochastic and exogenous to the model.[35]

In order to test for the existence of a spatial pattern the value for a computed I statistic is compared with its theoretical mean, which is approximately 0 (for large n). If the null hypothesis of absence of spatial correlation is rejected then there are two alternative interpretations. If the statistic is significantly larger than its expected value, it indicates *positive* spatial autocorrelation, meaning that municipalities with similar expenditure levels are more spatially clustered than could be caused by chance. A test statistic that is significantly lower than its expected value indicates *negative* spatial autocorrelation: municipalities with high and low expenditure levels are mixed together. Perfect negative spatial autocorrelation is characterized by a checkerboard pattern of high and low values. This I test can be carried out either by assuming a normal distribution (parametric approach) or by generating an empirical distribution through a resampling method (non-parametric approach).

Similar to Moran's I, Geary's C test statistic attempts to detect a global spatial pattern. However, in this case, interaction is not represented as the cross-product of the deviation from the mean, but as the square of the deviations in intensities of each observation location with one other. The Geary statistic is always positive and is asymptotically normal. The Geary statistic is 1 if there is no spatial autocorrelation, less than 1 if there is positive correlation, and greater than 1 if there is negative correlation. Geary's C statistic is expressed as:

$$C(d) = \frac{(n-1)\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - x_j)^2}{2n^2}$$

Where the observations x_i and x_j are in standardised form.

To detect *local* spatial patterns of expenditure, we can also calculate the Moran statistics at a local level. While global measures allow one to test for spatial patterning over the whole study area, it may be the case that there is significant autocorrelation in only a few small areas, e.g. a high concentration of a certain phenomenon in Inner London, which might get swamped in the context of the whole analysis. Local Moran tests seek for and measure any such local autocorrelation. The formula of the local Moran I statistic is

$$I_i = X_i \sum_{j,\, j\neq i}^{n} w_{ij} X_j$$

Note that the X_i and X_j correspond to x_i and x_j expressed as deviations from the mean.

These three tests are used in this paper in our preliminary descriptive analysis of data on mental health expenditure in English municipalities. Building on the findings we then go on to econometric exploration of the sources of variation.

Spatial Econometric Models

The analysis in this paper benefits from a model-driven approach. Spatial econometric techniques are used empirically to test the hypothesis that per capita mental health expenditure in one local authority 'spills over' to affect expenditure levels in neighbouring authorities. Following a model-driven approach, the variability of a phenomenon can be explained in terms of a set of explanatory variables and spatial effects.[38] Traditional econometric models can then be reinterpreted and adjusted to take into account the possible spatial effects in mental health expenditure.

Within the field of spatial econometrics, the distinction is often made between two types of regression model: the spatial lag and the spatial error models. The former is relevant when focusing on how expenditure in one area relates to expenditure in neighbouring areas, conditional on the other explanatory variables. Conversely, the spatial error model is relevant when the error terms from different areas display spatial correlation. Regression residuals are spatially correlated when they present a structure of correlation due to aggregated shocks that hit local authorities or to unobservable risk factors that are concentrated across territory (e.g. deprivation). Through econometric tests and a proper specification strategy it is often possible to discriminate between the spatial lag and the error model in order to choose the model which best describes the data generating process.[42]

The spatial lag and spatial error models are both incorporated in the following generalised model:

$$y = \rho W_1 y + X\beta + u$$
$$u = \lambda W_2 u + \varepsilon$$

Here y is an $n \times 1$ vector of the cross-sectional measure of expenditure and X represents an $n \times k$ matrix of explanatory variables, and ε is a $n \times 1$ vector of errors assumed to be independently and normally distributed, $\varepsilon \sim N(0, \sigma^2 I_n)$. W_1 and W_2 are known $n \times n$ spatial weight matrices, which contain distance (contiguity) relations. The spatial lag is obtained by setting W_2 equal to zero, so that the error term satisfies classical assumptions. Conversely, the spatial error model is derived by setting W_2 to a value different from zero so that autocorrelation of errors is allowed, and by fixing W_1 as equal to zero.

In this work we have adopted both data-driven and model-driven approaches, although we give more emphasis to the latter. The global and local spatial statistics were used to test for the existence of a spatial structure in the data. However, the data-driven approach is a preliminary, exploratory analysis that does not allow estimation of a demand-supply model. Therefore, once we had detected the presence of spatial correlation in the data, we incorporated it in an econometric specification adopting a model-driven approach.

Results

Data

We sought to investigate how expenditure varies across councils, controlling for socio-demographic risk factors that are proxy measures of mental health needs. The use of risk factors rather than direct measures of needs as explanatory variables is motivated by a number of reasons. First, information on the prevalence of serious mental illness at a council level is not available. Furthermore, prevalence is often measured as the number of people who are in contact with psychiatric services due to their mental health problems. However, this figure is as much a measure of service supply as of needs,[45] and its use as a determinant of expenditure would induce an endogeneity problem.

Our analysis has been undertaken at the local authority level, using data for the 150 local authorities in England, using data for 2001-02. The dataset is based on three different sources. First, we used data on personal social services expenditure published by the Department of Health for adults aged under 65 years with mental health problems. Second, we obtained data from the Office of National Statistics (ONS) on socio-demographic attributes. Finally, we gathered data from the New Earnings Survey on wage rates. Two local authorities, City of London and Isles of Scilly, were dropped from the dataset. These are common exclusions in this kind of work as the two authorities not only have very unusual population, economic and social characteristics, but also different administrative responses. Both are also tiny by comparison to the other 148 English authorities.

The empirical work has its roots in a demand-supply model, although here we estimate a reduced form equation with the following variables.

Dependent variable:

- Net per capita personal social services expenditure on mental health-specific services for people aged 18-65 years.

This measure includes nursing home placements, residential care home residents, direct payments (consumer-directed services), supported care, home care, day care, equipment and adaptations, meals, other non-residential costs, and other social care services to adults with mental health needs.

Regressors:

- Percentage of population aged 0-15.
- Percentage of population aged 65 and over.
- Percentage of males in the population.
- Percentage of single people in the population.
- Percentage of population of Asian ethnicity.
- Percentage of population of black Caribbean ethnicity.
- Percentage of population of black other ethnicity.
- Percentage of population with no educational qualifications.
- Percentage of households with a resident with a long-term illness.
- Median gross weekly wage.
- Density of population.

Demand-side factors were chosen with respect to what the literature suggests as variables linked to mental health needs. For example, several studies show that social position, in terms of gender and ethnicity, is correlated with use of mental health care.[11,44] Poorer mental health has also been linked to socio-demographic characteristics in the area, such as a high proportion of old people in the population, generally low education, and high percentage of non-married adults.[17,21,32] In particular, we considered the impact on per capita spending of a large number of variables, such as deprivation indices, age and gender structure, ethnicity, unemployment, number of homeless people and refuges, and crime rates.[45] However, we have endeavoured to be parsimonious in the choice and use of determinants, aiming

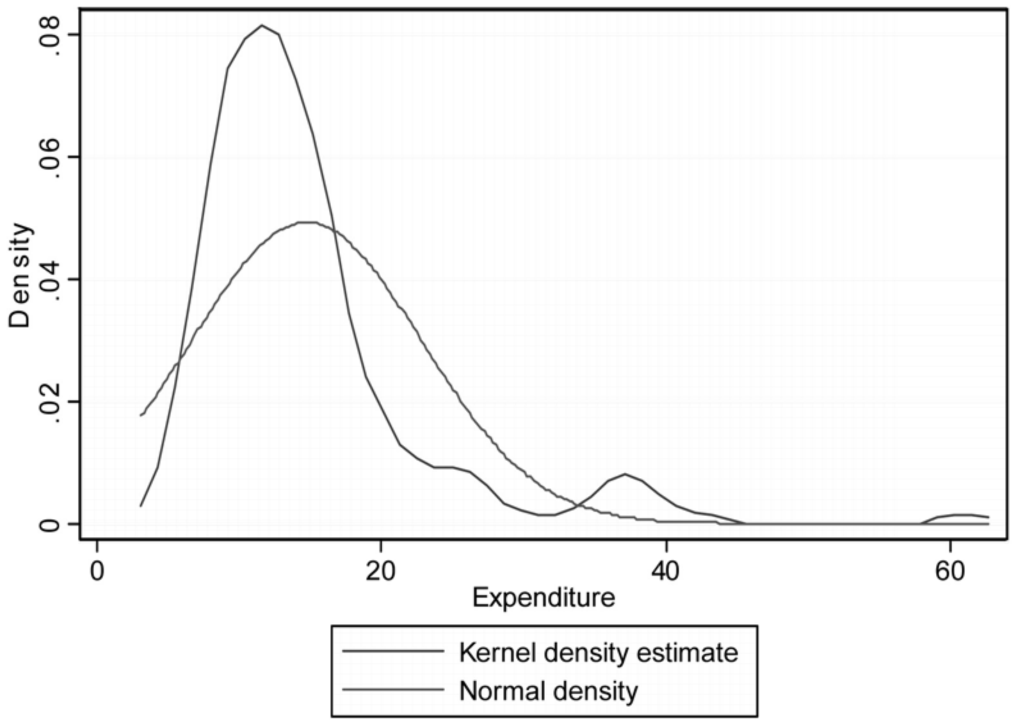

Figure 1. Kernel Density Estimate, by Municipalities, for Per Capita Net Expenditure.

to include a small set of variables that capture the essence of the phenomenon under study. This was also motivated by the problem of multicollinearity that affected our analysis. For instance, several deprivation indices were found to be correlated with many of the other potential explanatory variables. Thus we ended up with the demand-side variables listed above. Earnings and density of population were used to control for supply factors.

Table 1 gives some descriptive statistics on mental health expenditure expressed in per capita terms. A graphical visualization of the distribution is provided by the density distribution of per capita net expenditure (**Figure 1**), estimated through the kernel method. The curve is right-skewed indicating that many local authorities spend less than the average expenditure in England. The small number of local authorities characterised by a very high level of expenditure strongly influence the average, making the distribution asymmetric.

One consequence of positively skewed data when using a regression model is that residuals are frequently non-normal and heteroskedastic, leading to incorrect estimation of standard errors, and possibly to biased conclusions about the significance of the effects. The Wold test appeared to be highly significant, suggesting that the variable does not conform well to the normality hypothesis. To induce normality, we chose the logarithmic transformation of the dependent variable. To address the potential problem of heteroskedasticity when using multivariate analysis, we estimated the standard errors via the adjusted White variance matrix.[46,47]

The type and degree of concentration of per capita mental health expenditure was thoroughly investigated (see **Table 1**, **Table 2**, and **Figure 2**). **Table 1** shows results for some concentration indices, such as the Gini and the Theil statistics, which indicate a high concentration of per capita spending. **Figure 2** shows this visually. The higher level of per capita mental health expenditure, indicated in the map by the higher intensity of the colour, shows three important concentrations of spending: in Greater London, Birmingham and Greater Manchester. **Table 2** describes result for the Moran *I* and the Geary *C* statistics, estimated with both parametric and non-parametric approaches. Both indices are highly significant for per capita expenditure, and indicate strong positive spatial autocorrelation. This implies that geographically contiguous local authorities tend to spend similarly high amounts on mental health. These findings suggest substantial spatial correlation that ought to be incorporated in models that attempt to explain mental health spending at municipality level.

As we outlined earlier in the paper, there may be several reasons for this spatial correlation, such as unobservable risk factors, neighbouring municipalities sharing similar socio-demographic or underlying economic characteristics,[35] as well as interdependences in local decision making.[48,49] However, we feel that it would be premature given the stage of analysis that we have reached to hazard specific reasons for the underlying spatial pattern.

Table 3 shows the largest values (most positive values for *z*) for local Moran statistics by local authorities. The results show a very high concentration of expenditure in many local authorities in Greater London, such as Westminster, Kensington and Chelsea, Islington, and Camden. These first

Table 1. Descriptive Statistics for Per Capita Net Expenditure and Risk Factors*

Variables - proportion of the population with these characteristics	Mean	Median	Standard deviation	Skewness	Kurtosis	Wald test**	Gini	Theil
Male	0.487	0.487	0.0066	0.510	4.328	17.28 (0.00)	–	–
0-15	0.203	0.202	0.0174	–0.172	4.910	23.22 (0.00)	–	–
65 +	0.154	0.154	0.0286	0.138	3.281	0.96 (0.62)	–	–
Single	0.456	0.438	0.0624	1.173	3.799	37.86 (0.00)	–	–
Asian	0.107	0.049	0.1487	2.219	7.597	251.79 (0.00)	–	–
Black Caribbean	0.014	0.003	0.0247	2.636	9.812	457.52 (0.00)	–	–
Other black ethnicity	0.045	0.008	0.0850	2.835	10.948	587.83 (0.00)	–	–
No educational qualification	0.211	0.208	0.0453	0.068	2.605	1.08 (0.58)	–	–
Long-term illness	0.181	0.180	0.0327	0.208	2.329	3.85 (0.11)	–	–
Per capita net expenditure	14.66	12.88	8.09	2.46	11.31	575.98 (0.00)	0.26 (0.00)	0.13 (0.00)

* Number of observations = 148.
** Number in parentheses are *p*-values.

Table 2. Spatial Autocorrelation of Variables*

	Moran I (normal approx,)	Moran I (permutations)	Geary C (normal approx,)	Geary C (permutations)
Per capita net expenditure	0.62 (0.00)	0.62 (0.01)	0.39 (0.00)	0.39 (0.01)

* Number in parentheses are *p*-values.

exploratory findings indicate substantial heterogeneity of expenditure over space that, if not properly incorporated in the model, may lead to an incorrect conclusion of spatial correlation.

Table 3. Extreme Values for Local Moran

Municipalities	Z-value
Westminster	30.84
Kensington and Chelsea	15.72
Camden	15.58
Tower Hamlets	14.12
Southwark	12.44
Hackney	12.40
Lambeth	12.23
Islington	11.83
Brent	8.65
Hammersmith	6.99

Regression Results

As shown in the previous section, there is substantial variation in mental health spending across England. A classical regression model was run to determine the extent to which spending variations could be explained by variations in need for services. However, since part of the variation in spending could be explained by the interaction among municipalities, a spatial autoregressive model was specified and confronted with data. The results when specifying a spatial structure can then be compared with those from a classical ('non-spatial') model. All econometric analyses were conducted using SpaceStat.

Table 4 contains results of the estimation of the regression model by robust ordinary least squares (OLS), where the standard errors of the estimates are computed via the White covariance matrix estimator, to account for heteroskedasticity. Furthermore, the dependent variable was transformed on a

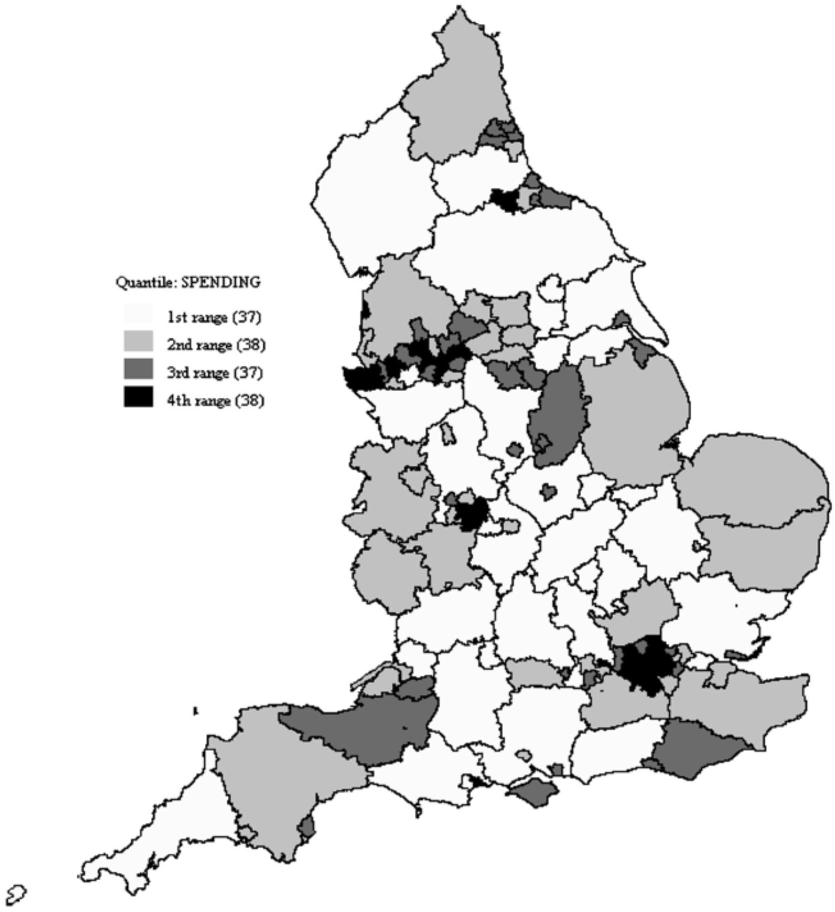

Figure 2. Quartile distribution of per-capita mental health expenditures by municipality.

Note: This work is based on data provided through EDINA UKBORDERS with the support of the ESRC and JISC and uses boundary material which is copyright of the Crone.

natural logarithm scale in order to induce normality. Seven coefficients out of eleven are highly significant and have the expected signs (with the exception of the percentage with no educational qualifications). An adjusted R^2 of 0.73 indicates a good fit, as do many other indicators, such as the maximium log-likelihood and the Akaike Information Criterion. As some of the tests to follow are based on the assumption of normality, we also calculated the Jarque-Bera (JB) test for normality of errors. Using the conventional 95 percent level of significance, the null hypothesis of normality is not rejected, however the p value is low (0.15) and suggests the use of estimation techniques that are robust to the normality assumption, such as an instrumental variable method.

This first multivariate regression model does not take into account the potential spatial structure of data. However, exploratory analyses in the previous section detected large and significant spatial correlation, which, if ignored, could lead to biased and inconsistent estimates. Thus, allowing for spatial dependence in the regression model should lead to more reliable inference.

Our specification strategy is primarily based on two robust Lagrange multiplier (LM) tests, the LM for spatially autoregressive errors and the LM for a spatial lag, according to the procedure suggested by Florax *et al.*[50]*

Since the p-value of the LM for a spatial lag is the lowest, this strategy leads us to conclude in favour of the *spatial lag model* (**Table 5**). The difference between the robust and non-robust statistics can be summarised as follows. The robust LM tests may actually have more power in pointing out the alternative then their classical counterpart. Further, the robust tests are designed to work well under a potential for local misspecification. Therefore, we end up with two variants. One is a test for spatial error autocorrelation in the

* The steps are: (i) Estimate the initial model using OLS; (ii) Test the hypothesis of no spatial dependence due to an omitted lag or spatially autoregressive errors, using robust Lagrange Multiplier tests; (iii) If none of these tests is significant, keep on with the OLS estimates from step i, otherwise proceed to; (iv) If both tests are significant, choose the estimates from the model with the lowest *p*-value of the two tests, otherwise proceed to step v; (v) If LM for spatial lag is significant while LM for the error is not, use the lag specification, otherwise proceed to step vi; (vi) If LM for the error is significant while LM for spatial lag is not, use the spatial error specification.[50]

Table 4. Robust Ordinary Least Squares Estimates for Logarithm of Per Capita Net Expenditure on Mental Health Services for Adults with Aged 18-65

Variable	Coefficient	Robust standard error	z-value	Prob.
Constant	5.5708	2.5968	2.1453	0.0319
% population male	–9.3929	4.6092	–2.0379	0.0416
% population aged 0-15	–0.3004	2.8479	–0.1055	0.9160
% population aged 65 +	–0.8303	1.9087	–0.4350	0.6635
% population single	1.3411	0.7277	1.8429	0.0654
% population Asian	0.4869	0.1697	2.8702	0.0041
% population Caribbean	0.7797	1.8510	0.4212	0.6736
% population other black ethnicity	0.0288	0.6020	0.0479	0.9618
% population with no educational qualification	–2.9264	1.0278	–2.8474	0.0044
% population with long–term illness	6.5218	1.5609	4.1784	0.0000
Mean weekly wage	0.0011	0.0005	2.1044	0.0353
Population density	0.0699	0.0174	4.0126	0.0001

$R^2 = 0.75$, adjusted $R^2 = 0.73$ LIK $= 14.41$ AIC $= -4.83$.
Jarque-Bera test for normality of error term (2df) $= 0.73$ ($p > 0.15$).

Table 5. Diagnostics for Spatial Dependence

Tests	MI/DF	Value	Prob.
Moran's I (error)	–0.01	0.35	0.73
Lagrange Multiplier (error)	1.00	0.04	0.84
Robust LM (error)	1.00	2.82	0.09
Lagrange Multiplier (lag)	1.00	1.64	0.20
Robust LM (lag)	1.00	4.42	0.04

Table 6. Maximum Likelihood Estimation of Spatial Lag Model for Logarithm of Per Capita Net Expenditure on Mental Health Services for Adults with Aged 18–65

Variable	Coefficient	Standard error	z-value	Prob.
Endogenous effect	0.1251	0.0870	1.4381	0.1504
Constant	4.0081	2.3750	1.6877	0.0915
% population male	–7.3308	3.8670	–1.8957	0.0580
% population aged 0–15	–0.0465	1.8795	–0.0247	0.9803
% population aged 65+	–0.0315	1.7215	–0.0183	0.9854
% population single	1.6438	0.9091	1.8081	0.0706
% population Asian	0.4458	0.1710	2.6074	0.0091
% population Caribbean	0.9931	2.4120	0.4117	0.6805
% population other black ethnicity	–0.1836	0.7727	–0.2376	0.8122
% population with no educational qualification	–2.5122	1.0776	–2.3313	0.0197
% population with long-term illness	5.9357	1.5410	3.8518	0.0001
Mean weekly wage	0.0011	0.0005	2.0407	0.0413
Population density	0.0632	0.0192	3.2906	0.0010

$R^2 = 0.75$; Sq. Correlation $= 0.75$: LIK $= 15.32$; AIC $= -4.65$.

possible presence of spatially lagged dependent variable, and the other a test for endogenous spatially lagged dependence in the possible presence of spatial error autocorrelation.[50]

The inclusion in the model of the spatially lagged dependent variable precludes the use of OLS and requires an estimation method that deals with the endogeneity of the spatial lag. In this paper we have considered two alternative approaches suggested in the literature, the maximum likelihood (ML) and instrumental variables (IV) methods.[38]

Table 6 shows results from the ML estimation of the

Table 7. Instrumental Variable (2SLS) Estimation of Spatial Lag Model for Logarithm of Per Capita Net Expenditure on Mental Health Services for Adults with Aged 18-65

Variable	Coefficient	Standard error	*z*-value	Prob.
Endogenous effect	0.2500	0.1275	1.9610	0.0499
Constant	2.4472	2.7421	0.8925	0.3721
% population male	–5.2710	4.3369	–1.2154	0.2242
% population aged 0–15	0.2072	1.9638	0.1055	0.9160
% population aged 65+	0.7664	1.9089	0.4015	0.6881
% population single	1.9461	0.9835	1.9787	0.0478
% population Asian	0.4048	0.1809	2.2372	0.0253
% population Caribbean	1.2063	2.5343	0.4760	0.6341
% population other black ethnicity	–0.3957	0.8252	–0.4795	0.6316
% population with no educational qualification	–2.0985	1.1785	–1.7807	0.0750
% population with long-term illness	5.3502	1.6702	3.2034	0.0014
Mean weekly wage	0.0010	0.0006	1.8013	0.0717
Population density	0.0565	0.0207	2.7230	0.0065

$R^2 = 0.76$; Sq. Correlation $= 0.75$.
Lagrange Multiplier Test on spatial error dependence $= 1.65$ ($p > 0.15$).

model including the spatially lagged dependent variable. The likelihood-based measures (LIK and AIC) can be used to compare the fit of the spatial lag with the ordinary regression model. It turns out that the fit improves when the spatial lag is added to the model, as indicated by an increase in the log-likelihood (from 14.41 for OLS to 15.32) and a decrease in AIC (respectively from -4.83 for OLS to -4.65). The improved fit was expected, since the spatial lag coefficient turned out to be significant.

Estimation of the model yields a positive value for the spatial effect (0.13) with a *p* value of 0.15, which is not far from significant, suggesting a potential local interaction as well as policy interdependence among municipalities. The existence of a positive, significant spatial effect will be explored below using an instrumental variable approach.

Compared to the OLS results, the estimated parameters of the regressors 'percentage of Asian', 'median weekly wage' and the 'population density' remain approximately the same, while the parameters for 'percentage male' (-7.33 vs. -9.39 for OLS), and 'percentage with long-term illness' (5.93 vs. 6.52 for OLS) have decreased relatively in absolute value. Furthermore, the estimated parameter of the variable 'percentage single' (1.64 vs. 1.34 for OLS) has increased relatively in absolute value. These alterations in the regression coefficients could be explained by a marked spatial pattern of expenditure. Indeed in this specific case, the omission of the lagged dependent variable induces bias in the OLS estimates.

Given the possible non-normality of the data, we also estimated the regression model using instrumental variables (IV). This estimation method is a robust alternative to the ML approach, since it does not require the assumption of normally distributed errors. Following the spatial econometrics literature, we selected as instruments the spatial lag of the regressors.[38] The estimation is carried out in two stages. First, the endogenous variable is regressed on the instruments and on the exogenous variables. Second, the predicted values from this regression are used as proxies for the endogenous variable in a standard regression.

Results from the IV estimation for the spatial lag model are shown in **Table 7**. In general, results are in line with those obtained via ML estimation. However, the model finds a stronger spatial effect in the dependent variable, with a coefficient of 0.25, significant at the 0.05 level. Therefore, after adjusting for each local authority's socio-environmental structure, our results show that adjacent local authorities tend to implement similar expenditure policies.

Compared to the OLS estimates, the variable 'percentage male' turns out to be not significant, three variables ('percentage of Asian', 'weekly wage' and 'population density') remain approximately the same, while parameter on the 'percentage with long term illness' (5.35 vs. 6.52 for OLS) has decreased relatively in absolute value. The 'percentage single' parameter (1.94 vs. 1.34 for OLS) has increased in absolute value.

Discussion

Explanatory Analyses

This exploratory paper gives voice to Giggs'[7] argument that a better understanding of the geography of mental health is possible (at least in part) thanks advances in the field of statistical and spatial analysis. In the spirit of this argument, our work has aimed in part to strengthen the link between mental health research and spatial data analysis, which – as we noted earlier - is still very rarely explored. Certainly it is a field almost entirely neglected by economists.

Our exploratory data analyses tested for the existence of a spatial structure and spatial interaction in mental health expenditure. To detect spatial autocorrelation and association, some global and local spatial statistics were used, including Moran's *I*, Geary's *C* and local Moran test statistics. The results of these tests showed the presence of positive significant spatial correlation. However, the high concentration of per capita mental health expenditure in the largest conurbations (Greater London, Birmingham and Greater Manchester – see **Figure 2**) indicates substantial heterogeneity over space.

Drawing hypotheses from these exploratory analyses we set up a model that allows both for the possibility of mimicking among neighbouring authorities, and for the presence of spatially autocorrelated shocks. Both processes could have driven the observed spatial dependence in the allocation of mental health spending by English local authorities. However, the spatial test results, according to the procedure suggested by Florax *et al.*,[50] suggest that the most likely source of spatial dependence is a substantive interaction process, by which local authorities tend to mimic the behaviour of their neighbours. Available data do not allow us to explore the underlying reasons for this similar expenditure behaviour, but they clearly warrant further exploration.

We compared the results from our spatial model with those from a classical ('non-spatial') model. The differences in the regression coefficients could be explained by the evident spatial pattern of the phenomenon, since the omission of the lagged dependent variable induces bias in the OLS estimates.

Limitations and Further Work

It is important to stress some limitations and to point to work needed in the future. Given that in our empirical study the statistical unit is the council, it is reasonable to expect a large degree of variability *within* such administrative areas. Subsequent analysis would benefit from more disaggregated data (e.g.: at a census ward level) and the accompanying use of multilevel techniques.

Further work is also needed to model heterogeneity in space, arising from expenditure choices in London. We noted the existence of significant spatial clusters, especially in Inner London and Outer London. Statistical interrogation of a panel dataset would give enough degrees of freedom to relax the hypothesis of constant parameter estimates across regions, allowing, for example, Greater London to be distinguished from the rest of the country. Relationships between per capita net expenditure and certain risk factors might change across the country.

Clearly, our results are sensitive to the problem of misspecification of the weights matrix. In the exploratory analyses reported here we employed a simple weight matrix, with neighbours defined simply as municipalities sharing a common border. However neighbours may also be defined by reference to travelling distance between authorities (the nearest, the two nearest, those within a travelling distance of less than 30 minutes, etc.) or based on distances measured in terms of, or weighted by population or population density.

Later analysis might include dummy variables to identify authority type (London borough, metropolitan district, unitary authority and county), and in this way to test for whether spatial correlation is in part due to the fact that neighbouring authorities are similar from an institutional or contextual point of view.

Lessons

What lessons do we draw from our findings in relation to spatial data analysis and econometrics? The relevance of our results from an economic perspective is to suggest that spatial effects should be incorporated, or at least tested for, in analyses of mental health spending patterns. Health economics and econometrics to date have underestimated the importance of two issues: spatial dependence between the observations and spatial heterogeneity when estimating regression models (in this case, models of spending). As we have tried to demonstrate, methods and techniques from spatial analysis offer valid and helpful tools in the interpretation of phenomena.

Our results also suggest that central government policies and funding allocation formulae might also need to consider the spatial interdependence of lower-tier administrative authorities, given the potential to influence levels of efficiency and distributive justice.

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