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In Search of 'W'

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Abstract
This paper provides a survey and critique of how spatial links are taken into account in empirical analysis by applied economists/regional scientists. Spatial spillovers and spatial interrelationships between economic variables (e.g. unemployment, GDP, etc) are likely to be important, especially because of the role of local knowledge diffusion and how trade (inter-regional exports and imports) can potentially act to diffuse technology. Since most empirical economic studies ignore spatial autocorrelation they are thus potentially mis-specified. This has led to various approaches to taking account of spatial spillovers, including econometric models that dependent on specifying (correctly) the spatial weights matrix, W. The paper discusses the standard approaches (e.g., contiguity and distance measures) in constructing W, and the implications of using such approaches in terms of the potential mis-specification of W. We then look at more recent attempts to measure W in the literature, including: Bayesian (searching for 'best fit'); non-parametric techniques; the use of spatial correlation to estimate W; and other iteration techniques. The paper then considers alternative approaches for including spatial spillovers in econometric models such as: constructing (weighted) spillover variables which directly enter the model; allowing non-contiguous spatial variables to enter the model; and the use of spatial VAR models. Lastly, we discuss the likely form of spatial spillovers and therefore whether the standard approach to measuring W is likely to be sufficient.

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1. Introduction

In seeking to test for economic relationships between variables it is often hypothesised that there will be impacts external to the plant, firm, individual, or institution, which are related to the spatial location (e.g. region, city, local labour market, or neighbourhood) of that economic unit. For instance, in terms of the growth of firms, the development of new trade theory (e.g. Krugman, 1980; Krugman and Venables, 1990) and new economic geography models (e.g. Krugman, 1991; Krugman and Venables, 1995; Baldwin *et. al.*, 2003) has resulted in 'space' being recognised more widely as a crucial factor in determining economic development (with more of an emphasis in these models on trade flows and industrial location). Part of the reason why economic activities cluster is to realise agglomeration economies-of-scale (other factors include the importance of a large consumer market that minimises transportation and other trade barrier costs, and having good access to product markets). One sub-group of agglomeration economies is generally labelled localisation externalities and they are attributable to Marshall (1890), Arrow (1962), and Romer (1986) – that is, MAR-spillovers. Such spillovers minimise transport and transaction costs for goods, people, or ideas, and thus to benefit from them suggests that firms within a specific industry locate near other firms along the supply chain (be they customers or suppliers); locate near other firms that use similar labour; and/or locate near other firms that might share knowledge (Ellison, *et. al.*, 2007). MAR-spillovers are associated with industrial specialisation and are to a large extent an intra-industry phenomenon (where this covers firms belonging to a particular industry, or closely related industries). Clearly firms locate in close proximity to reduce the costs of purchasing from suppliers, or shipping to downstream customers. Co-location is also likely if there is a large, common pool of labour; and/or to obtain knowledge spillovers that occur when similar firms engage in, say, R&D to solve similar or related problems. The need for close physical proximity (and density) is mainly predicated on the notion that a significant part of knowledge that affects economic growth is tacit (and therefore difficult to codify), and such knowledge does not move readily from place to place as it is embedded in individuals and firms and the organisational systems of different places (Gertler, 2003).[1] That is, geographic boundaries are important since spillover affects are limited by distance.

As well as MAR-spillovers leading to specialisation and thus agglomerations, spillovers can also result from urbanisation externalities due to the size and heterogeneity (or diversity) of an (urban) agglomeration. These are labelled

[1] For evidence and more discussion on spillovers being spatially bounded, see Thorton and Flynne (2003); Bottazzi and Peri (2003); Niebuhr (2000); Henderson (2003); and Baldwin *et. al*. (2008). Recently, Peri (2005) used patent data for a panel of 113 European and North American regions over 22 years, finding that the externally accessible stock of R&D had a positive impact on firm innovation but that only about 20 percent of average knowledge is learned outside the region of origin and only 10 percent outside the country of origin. In contrast, Lehto (2007) used R&D data for Finnish firms and found that only when other firms' R&D is located in the same sub-region is there any positive spillover effect. On this evidence, R&D spillovers appear to be (very) localised. However, there are also studies that find stronger support for international knowledge spillovers, rather than localised spillovers. These emphasise transmission through international trade, FDI, international technology transfer, and other forms of internationalisation (e.g. Gong and Keller, 2003; Niosi and Zhegu, 2005; and a recent review by Harris and Li, 2006)

Jacobian spillovers (Jacobs, 1970, 1986), and they result when different industries benefit from economies of scope (rather than scale). A greater range of activities (e.g. R&D, business services, cultural and lifestyle amenities, and the overall quality of the public infrastructure – cf Florida, 2002; Glaeser *et. al.*, 2001) leads to inter-industry spillovers. (Larger) firms – and especially multinationals – tend to locate their head office management and R&D functions in urban agglomerations. Thus these agglomerations not only tend to generate more product innovations, but there is more likelihood of spin-offs and/or start-ups, which creates a thicker entrepreneurial culture.[2]

These MAR- and Jacobian-spillovers are based on different types of externalities, according to how they are mediated, i.e., pecuniary (also called vertical, welfare or rent) spillovers which are based on market transactions, and non-pecuniary (also called horizontal, knowledge and technological) spillovers which are based on non-market interactions usually involving the sharing of knowledge and expertise. A related literature, to the development of new trade theory and new economic geography models, emphasises the importance and role of knowledge assets in determining competitiveness, productivity, and ultimately output growth by drawing a useful distinction between knowledge that is already internal to the firm (through learning-by-doing that draws on existing knowledge and human capital, built-up through R&D and similar investments) and knowledge gained externally (some of which is through market transactions, such as spending on extramural R&D, and some of which is gained through spillovers). Processes of knowledge generation and acquisition *within* the firm are essentially organisational learning processes (Reuber and Fisher, 1997; Autio, *et. al.*, 2000) and although firms could develop and acquire much of the knowledge internally (through their own resources and routines), few (and especially SMEs) virtually possess all the inputs required for successful and sustainable (technological) development. Therefore, the fulfillment of firms' knowledge requirements necessitates the use of external sources to acquire and internalise knowledge (Rosenkopf and Nerkar 2001; Almeida *et. al.*, 2003), and it was argued above that proximity is likely to be important when accessing such spillovers.

Much of the discussion so far has been on how *firms* acquire and use knowledge, or what might be termed the 'learning firm'. In addition, regions show differential capabilities to absorb and translate available knowledge into (endogenous) economic growth. It is argued that the empirical evidence shows the "ability to adapt new technologies depends on the institutional infrastructure, education, geography, and resources devoted to R&D" (Maurseth and Verspagen, 1999, p.152). This therefore leads on to the importance of the regional innovation *system* in facilitating firms to acquire external knowledge; i.e. the concept of the 'learning region' (cf. Cooke and Morgan, 1998; Oughton *et. al..*, 2002; Cooke *et. al..*, 2003; Howells, 2002; Asheim and Gertler 2005).

How spatial spillovers are measured (and subsequently tested) is therefore of importance and needs to be taken into account in empirical analysis by applied economists/regional scientists; ignoring spatial autocorrelation leads potentially

[2] A third approach to agglomeration is the work of Porter (1998) which emphasises inter-firm local competition within his 'diamond' model.

to a mis-specified model. This has led to various approaches, including econometric models that dependent on specifying (correctly) the spatial weights matrix, W. Thus the next section discusses the standard approach (e.g., based on contiguity and distance measures) in constructing W, and the implications of using such approaches in terms of the potential mis-specification of W. Section 3 looks at more recent attempts to measure W in the literature, including: Bayesian (searching for 'best fit'); non-parametric techniques; the use of spatial correlation to estimate W; and other iteration techniques. In section 4 we consider alternative approaches for including spatial spillovers in econometric models such as: constructing (weighted) spillover variables which directly enter the model; allowing non-contiguous spatial variables to enter the model; and the use of spatial VAR models. In section 5 we discuss the likely form spatial spillovers take, and thus whether the standard approach to measuring W is appropriate. The last section comprises a summary and conclusions.

2. Spatial linkages and the standard approach to W

Given both theoretical and empirical evidence of the likely importance of spatial spillovers, the approach typically taken in the spatial econometrics literature is to model these via determining the type and extent of spatial dependence that exists between areas, in order to construct spatial weights to reflect such spatial interactions. Two types of spatial dependence are usually considered (although it is possible to allow for both) reflecting whether spillovers should be modelled by the inclusion of a (spatially weighted) variable directly into the model (the spatial lag model) or whether spatial dependence can be captured in the (spatially weighted) error term in the model (the spatial error model). These two standard models can be represented as:

$$y = \rho Wy + x\beta + u \tag{1}$$

$$y = x\beta + \lambda W\varepsilon + u \tag{2}$$

where y is the dependent variable; W is a spatial weight matrix; Wy is a vector of spatially lagged dependent observations;[3] x is a matrix of independent variables with associated parameters β; u is an independent error term [$u \sim N(0, \sigma^2)$]; ε is a spatially autogressive error term; and ρ, λ are parameters to be estimated that measure the strength of spatial autocorrelation in the model.

By requiring that spatial interaction be dealt with through inclusion of another lagged variable(s) in the model, the spatial lag model (1) presumes that omission of Wy will result in omitted variable bias when estimating the parameters of interest (β). In contrast, the spatial error model (2) treats spatial dependence as

[3] Note, a more generalized model is to also weight x, giving: $y = \rho Wy + x\beta + Wx\beta + u$ - the spatial Durbin model (see LeSage and Fischer, 2008, for a discussion).

a statistical nuisance, assuming that it occurs between variables that are not included in the model and which are therefore captured in ε. It is argued by some (c.f. Anselin, 2003) that the researcher must determine which model best fits the data (i.e. whether $\rho=0$ or $\lambda=0$)[4]; however, *a priori* the omission of variables from the model is undesirable because of the implications of misspecification (i.e. biased and inconsistent parameter estimates) and where data permits it is presumably more appropriate to treat spatial autocorrelation via either including additional relevant variables or by including (spatially) lagged values of the variables in the model to proxy for any missing variables. This point is often not discussed explicitly in the spatial econometrics literature[5] and it has implications, e.g. for how the spatial weight matrix W is constructed (see below).

Estimating either equation (1) or (2) requires the specification of W and model estimation using a maximum likelihood (ML) approach (indeed in the spatial lag model, the spatial lag term, Wy, is endogenous since there is a two-way relation between spatial "neighbours", and this requires simultaneity to be accounted for through IV or GMM estimation or the formulation of a full model ML model – see Anselin et. al., 2008, for details). It is well known in the literature that selection of an appropriate spatial weight matrix is crucial; Bhattacharjee and Jensen-Butler (2006) note that "… the choice of weights is frequently arbitrary, there is substantial uncertainty regarding the choice, and the results from studies vary considerably according to the choice of spatial weights". As LeSage and Fischer (2008) comment: "… competing specifications are usually non-nested alternatives so that conventional statistical procedures such as the likelihood ratio tests are inappropriate". Specifying W incorrectly could lead to wrong conclusions and while there are various approaches that have been adopted in creating W "… it may be that one of the … choices leads to good, parsimonious results but the pall of misspecification hanging over the chosen model may still remain" (Getis and Aldstadt, 2004).

Since essentially Wy (or analogously $W\varepsilon$) constructs a new variable consisting of the weighted average of neighbouring observations, the standard approach to specifying these weights is to either assume that spillovers only occur between contiguous regions ($w_{ij} = 1$ for i,j that share a common border, otherwise 0) or that the elements in W decay with distance ($w_{ij} \neq 0$ up to a pre-specified distance d, otherwise 0).[6] Such approaches are sometimes justified by arguing W is exogenous, being based on some theoretical model of how agents interact – such as tacit knowledge cannot be passed on except through face-to-face contacts, or labour market spillovers are truncated as mobility is highly limited by distance. The key role therefore of proximity or distance is thus used to justify constructing weights that are non-zero for nearest neighbourhood regions. However, 'distance' itself is not a straightforward concept; it is often measured

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[4] Where $\rho\neq0$ and $\lambda\neq0$, Anselin and Rey (1991) argue that whichever statistic is larger probably indicates which model is to be preferred.

[5] For an example where this does occur, see Andersson and Gråsjö (forthcoming) who state: "… a well-formed model should most likely not produce spatial autocorrelation at all. From this perspective spatial autocorrelation is not (pure) statistical nuisance but a sign … that a model lacks representation of an important economic phenomenon".

[6] Of course there are many forms of physical distance functions, from inverse distances raised to some power (often 2) to various forms of bandwidth approaches, as well as variations on *n* nearest neighbours, etc.

by the physical distance between (usually arbitrarily assigned) nodes, or inter-region journey/transportation times (such as fastest routes, or least cost distances by particular journey type). Distance can also refer to the 'economic' distance between regions, such as technological proximity and/or absorptive capacity differences – see for example, Parent and LeSage (2008) – or even distances based on the exchange of (intermediate or capital) goods between regions, given that technological diffusion often occurs among trading partners (see Vaya et. al. 2004, for a discussion and empirical example).[7]

The outcome of using contiguous or distance-related measures to weight the observations of other regions is to impose a structure of spatial interactions that is untested and potentially mis-specified. Thus even if the null hypothesis that ρ (or λ) equals zero is rejected, parameter estimates for ρ and the other parameters (β) in the model may be biased. Therefore in the next section we discuss the alternative approaches to constructing W that have more recently been proposed in the literature, before considering alternatives to estimating the models specified in equations (1) and (2).

3. Some alternative approaches to constructing W

It has become common practice to specify in advance a number of different versions of W, and then use 'goodness-of-fit' statistics to choose the model that best represent the data (e.g. minimising the Akaike information criteria). This is essentially the approach used by those who use Bayesian techniques to sort through a potentially large number of competing models (cf. LeSage and Fischer, 2008; Acs et. al., 2008). However, this will only find local maxima among the competing models, and not necessarily a correctly specified W (unless it is unknowingly included in the set of competing models considered).

One alternative is therefore to use the data in the model to estimate W, rather than impose any structure. One method that has recently been proposed is an extension of the approach used by Meen (1996), who used the residuals from a first-step regression to construct W. Bhattacharjee and Jensen-Butler (2006) suggest first estimating the model of interest (for them it was housing demand) for each region, without allowing for any spatial spillovers, and then use the residuals from such an approach to form the spatial auto-covariance matrix, $E(\varepsilon\varepsilon')$, which will include any spatial dependence between the error terms across each region. Then based on certain assumptions, they proposed a way to obtain ρW, which based on their approach must be symmetric and with ρ the same for each region. However, as discussed above, the first-stage model does not explicitly include any spatial spillovers (the latter are assumed to be due to omitted variables that are picked-up in the residual term of the regression model), and therefore it is mis-specified. Consequently, if spatial effects need to be explicitly modelled to begin with, the approach to estimate ρW fails. It is only applicable (based on the underlying assumptions of the spatial error approach) if it is assumed that whatever factors drive spatial autocorrelation (whether

[7] See Maggioni and Uberti (forthcoming) who consider these various 'distance' concepts when modeling knowledge networks across Europe.

distance or something more complicated), these have no direct effect on the dependent variable of interest but only shapes the pattern of spatial interactions.

Another way to empirically estimate W is to use non-parametric approaches to test for the order of spatial contiguity, such as the non-parametric test proposed by Lopez et. al. (2008), or grid-searches of spatial correlation based on, for example, the Ord and Getis (1995) local statistic (cf. Getis and Aldstadt, 2004; Aldstadt and Getis, 2006). These approaches let the data produce the most appropriate W for capturing linkages between neighbourhood regions. They are more applicable for identifying 'clusters' in the data around individual locations (i.e. nearby spatial units), rather than more general forms of spatial association based on broader definitions of 'distance'.

Lastly, there are a number of more 'ad hoc' approaches which construct W using a traditional approach (e.g. spatial contiguity or geographic distance) and then combine it with other concepts of distance to obtain a hybrid W. A recent example is Parent and LeSage (2008) who compute measures of both technological proximity (larger values being associated with regions granting patents in the same technological fields), and distance proximity (based on transportation times), and then weight these by a measure of the extent to which there are differences in economic intensity in each region.[8]The outcome is potentially an asymmetric pattern of potential spillovers, although Parent and LeSage (op. cit.) limit non-zero w_{ij} to contiguous regions only.

As with the standard approach to estimating W, the methods reviewed in this section also impose a structure of spatial interactions that is largely untested and thus potentially mis-specified. Although these empirically related approaches usually either involve searching for 'best fit' versions of W, or constructing a hybrid W that modifies the standard approach to allow for a wider concept of spatial linkages, they are based on prior assumptions of the form of spatial dependence that largely go untested. This is because W collapses all spatial interactions across regions into a single (weighted) variable, rather than directly testing which regions interact with each other (and the strength of such interactions). Thus in the next section we consider alternative approaches to constructing W (although in some instances there are close similarities through the way data are weighted in order to obtain measures of spatial spillovers).

4. Some alternative approaches to using W

Instead of constructing W in order to weight the influence of other regions on region *i*, an alternative approach is to directly enter variables, into the vector of determinants (i.e. the *x*-matrix) in the regression model, that proxy spillovers. Thus Paci and Usai (forthcoming) compute an N $\times$ N geographical distance matrix (based on distances between $i, j \in$ N); a dummy contiguity variable that takes on the value of 1 between regions sharing a common border; a dummy 'nation' variable assigned a value of 1 if regions *i*, *j* belong to the same nation;

[8] Differences in economic intensity are measured by the square-root of a region *i*'s GDP relative to the GDP of region *j*. Essentially this is a proxy for absorptive capacity, as regions with a large technology gap are assumed to be less-able to 'absorb' potential spillovers from another area.

and a dummy variable for each region itself to capture any fixed effects associated with being located in region *i*.[9] Combining these spatial variables in the regression model with others representing economic distance and technological effort, allowed for a direct test of spillover effects (and their source). The essential difference between this and the standard approach using W is that spillovers are not entered through the interaction between regions of the dependent or other (state) variables in the model, weighted by W, but rather through constructing 'stand-alone' proxies for spatial spillovers. The latter may involve some form of weighting (similar to the use of the W-matrix), but the resultant variables are not necessarily endogenous by construction, and the resultant model can be estimated using more flexible econometric methods.

Similarly, Aiello and Cardamone (2008) construct an R&D spillover variable to explain each firm *i*'s productivity in Italy. They weight the (external) R&D capital stock of all *j* firms ($i \neq j$) in their dataset by a variable that reflects firms' technological similarity *and* geographical proximity. The former is constructed to represent technological flows between firm *i* and *j*:

$$\begin{aligned} \hat{\omega}_{ij} &= \frac{X_i X_j'}{[(X_i X_i')(X_j X_j')]^{1/2}} \left[\frac{h_i}{\max(h_i, h_j)} \right] \\ \hat{\omega}_{ji} &= \frac{X_i X_j'}{[(X_i X_i')(X_j X_j')]^{1/2}} \left[\frac{h_j}{\max(h_i, h_j)} \right] \end{aligned} \qquad (3)$$

where X is a set of variables defining the technological space of firms; and *h* is a measure of human capital. Thus the first term after the equals sign in (3) is an uncentered correlation that measures the similarity between the technological space of firms *i* and *j*; and this is weighted by the second term representing each firm's relative human capital (which is intended to proxy for absorptive capacity and thus the ability of a firm to internalise external knowledge gained from another firm). Thus the weights between pairs of firms are asymmetric ($\hat{\omega}_{ij} \neq \hat{\omega}_{ji}$) unless they have the same quality of human capital. Geographic proximity is measured by:

$$g_{ij} = 1 - \frac{d_{ij}}{\max(d_{ij})} \qquad (4)$$

where d_{ij} is the distance between the provincial capitals in which the firms operate. Aiello and Cardamone (op. cit.) then form their spillover measure by combining the two sets of weights:

[9] Van Stel and Nieuwenhuijsen (2004) used a similar approach, estimating a model using NUTS3 data, but they also tested for the statistical significance of NUTS1 and NUTS2 dummies on the premise that interregional spillovers across NUTS3 areas (if present) can be captured by higher-level regional dummies. They recognised the limitations of their approach ("… distant regions may interact more than neighbours because they contain important cities and are well connected by communications networks" – van Stel and Nieuwenhuijsen, *op. cit.*, p. 400), but did not go further and include dummies in their model for regions located outside the higher-level region, although in principle this would seem an obvious extension of their approach.

$$Spill_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} \frac{\hat{\omega}_{ij} + g_{ij}}{2} K_j \qquad (5)$$

where K_j is the capital stock of the *j*th firm. They combine their technological and geographical weights to get one measure of R&D spillovers because of their particular modelling approach; however, in principle two measures of the external capital stock could be calculated and tested in the model, based separately on technological and geographical weights. Note, the variable captured in (5) is in this instance likely to be endogenous (at least in the long-run), if it is assumed that potentially spillovers encourage firms to co-locate.

Yet another (similar) approach is to create variables that proxy spillovers that measure 'accessibility' (and thus the potential for interaction). As pointed out by Andersson and Gråsjö (forthcoming), this is similar to the approach associated with gravity models. Essentially accessibility enters the model directly through one or more variables such as:

$$A_i^x = \sum_{j=1}^{n} x_j e^{-\gamma t_{ij}} \qquad (6)$$

where x_j is a variable likely to result in spillovers (such as R&D expenditure), weighted by a distance-decay function where t_{ij} is the (time) distance between location *i* and *j*, and γ is an *a-priori* imposed parameter. Note, different A_i^x (=$W_1 x_j$) can be specified in order to capture local, intra-regional or inter-regional spillovers by respectively confining the weight matrix (W) to either: $w_{ii} \neq 0$, $w_{ij} = 0$; $w_{ii} = 0$, $w_{ij} \neq 0$ if *i,j* are in the same region; and $w_{ii} = 0$, $w_{ik} \neq 0$ if *i,k* are in different regions. Note, as specified by Andersson and Gråsjö (*op. cit.*), spatial spillovers are assumed to be linked only to physical distance, and a particular distance-decay function has been imposed. But, it would be possible to use different weight matrices and different (perhaps combined) types of 'distance'.

A more general approach to measuring spillovers is to attempt to proxy MAR- and Jacobian spillovers directly. The former measure of agglomeration externalities is often proxied by some form of specialisation index (e.g., the share of industry output or employment to which a firm belongs co-located in the region – Harris and Li, 2009, use this approach – or some form of location quotient – as preferred by de Vor and de Groot, forthcoming); Jacobian measures of diversity can be proxied by simple counts of the number of industries present in a region (relative to the total number that could be present), as used by Harris and Li (op. cit.), or by similar proxies such as the Krugman specialisation index (cf. de Vor and de Groot*, op. cit.,* equation 3). Note, these type of spillover variables do not require the use of a specific form of weighting, but do presume spatial externalities are confined to the region in which the enterprise is located (e.g. a travel-to-work area). To the extent that spillovers are inter-regional, such measures are therefore mis-specified.

Finally, in this section we consider an alternative approach which is more in keeping with the standard spatial W-approach, but which does not *necessarily* specify the form of the weights in advance, but rather can directly test for spatial associations across regions. If observations over time are available (e.g. when using panel data), then spatial vector autoregressive (SpVAR) techniques can be used. The basic reduced-form model (e.g. when there is only a single-state variable, and temporal lags are limited to $t-1$) for N regions is:

$$Y_{nt} = \beta Y_{nt-1} + \rho \sum_{i \neq n}^{N} w_{ni} Y_{it} + \theta \sum_{i \neq n}^{N} w_{ni} Y_{it-1} + \varepsilon_{nt} \quad (7)$$

where ρ and θ represent the spatial lag and 'lagged spatial lag' coefficients (see Beenstock and Felsenstein, 2007, equation 18). In principle, and as long as N is small relative to T, it is possible to set the weights w_{ni} equal to 1 and estimate the model freely; but with N regions in the model free estimation involves (N-1) parameter estimates of ρ and θ for each of the regions, and this is likely to be too expensive in degrees of freedom, especially if the model is expanded to included more than one state variable and potential spatial association is extended to include these other variables as well. In such cases, a priori spatial weights (w) would need to be imposed, and (7) is equivalent to the standard spatial model set out in section 2.[10] Note, estimation of (7) requires the use of an instrumental variables approach (such as the dynamic GMM approach taken by Arellano and Bond, 1991, and Blundell and Bond, 1998), where lagged values of Y_{it-p} are used to instrument for the endogenous Y_{it}.

As this section shows, the alternatives to having to construct W in advance of estimation do provide some additional flexibility whereby a range of spillover proxies (reflecting different views – or theories – of how spatial externalities occur) can be constructed and directly tested for their significance; however, most approaches do involve some form of spatial weighting of the data, which as before means imposing a structure of spatial interactions that is largely untested and thus potentially mis-specified.

5. Spatial spillovers in practice

If special spillovers are mainly basic on the exchange of (tacit) knowledge, which is truncated by geographic distance, then the search for alternatives to constructing W (other than the use of some form of distance function) is not as important.

However, in the introduction we set out the types of externalities that can occur – those based on market (pecuniary) transactions, and those that are non-pecuniary spillovers which are based on non-market interactions usually involving the sharing of knowledge and expertise. The former usually depends

[10] If the model includes only cross-section data, then by definition $\beta = \theta = 0$. Otherwise (7) is a more general (panel data) model incorporating spatial and temporal effects.

Table 1: Percentage of UK enterprises selling to various geographic markets, 2002-04

Region	type	Local/ regional only	Local/ regional	National	Overseas
North East England	all[a]	46.6	86.7	48.4	19.6
	innovative[b]	37.4	87.6	60.1	28.8
North West England	all	42.5	84.8	53.5	22.0
	innovative	30.6	82.3	67.0	36.5
Yorks & the Humber	all	34.3	84.9	62.2	24.8
	innovative	22.3	84.0	75.7	41.9
East Midlands	all	36.7	85.0	59.0	26.1
	innovative	23.4	83.0	73.4	42.3
West Midlands	all	34.5	83.0	60.7	27.9
	innovative	20.7	80.9	75.5	48.8
Eastern England	all	37.0	82.8	57.4	29.2
	innovative	22.3	80.9	72.2	47.7
London	all	28.4	76.3	63.2	34.4
	innovative	20.0	77.6	72.7	47.6
South East England	all	36.7	83.3	57.8	28.3
	innovative	24.4	82.1	70.8	42.0
South West England	all	42.2	86.6	52.5	23.2
	innovative	31.1	82.8	64.5	38.9
Wales	all	46.8	87.3	48.2	20.4
	innovative	25.8	85.3	70.6	38.9
Scotland	all	43.5	88.6	51.0	23.8
	innovative	29.5	85.8	66.2	39.3
Northern Ireland	all	58.5	92.8	29.6	29.0
	innovative	47.6	90.2	40.0	38.3
UK	all	38.3	84.0	56.0	26.8
	innovative	25.9	82.4	69.4	42.3

[a] All market-based enterprises in region; [b] those enterprises introducing innovations and/or undertaking R&D and/or abandoning innovation activities. Source: weighted CIS4

on buyer-seller linkages and occurs because quality improvements in inputs and outputs are not fully appropriated and thus are not entirely reflected in the price of such goods and services. Thus, it is argued that a major transmission mechanism for welfare spillovers is trade – i.e. the exporting and importing of goods and services across geographical space. There is an extensive literature that discusses (international) technology diffusion (defined as the transfer and use of existing technology and techniques) via imports,[11] especially of capital or

[11] There is also a separate literature that looks specifically at exporting and technology diffusion, based on whether firms that export learn about foreign technology through their experience of exporting (i.e. through a 'learning-by-exporting' effect). See Greenaway and Kneller (2005, Table 1) and Greenaway and Kneller (2007, Table 3) for a summary of the evidence.

intermediate goods and services (cf. Dixit and Stiglitz, 1977; Ethier, 1982; Romer, 1990; Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1991; and Eaton and Kortum, 2001, 2002). Keller (2004) provides an extensive overview of this literature, noting that there is strong evidence that trade falls with geographic distance (e.g., Leamer and Levinsohn, 1995; and especially Hillberry and Hummels, 2005[12]) and thus we should expect that (international) technology diffusion is geographically localised if trade is the dominant diffusion channel. He also noted the arguments in the literature that diffusion will tend to be more geographically localised, the higher is the non-codified tacit knowledge in any technology, since such tacit knowledge can generally only be fully passed on through face-to-face interaction. As the costs of moving people typically increase with distance (von Hippel, 1994; Feldman and Lichtenberg, 1997) this suggests again that (international) technology diffusion should be geographically localised if trade is an important diffusion channel.

While this literature on technology diffusion through trade is dominated by cross-country studies, the arguments apply just as well to a sub-national setting. In fact most exports (and thus by implication imports) tend to be inter-regional, as shown in Table 1, which is based on data from the 4th Community Innovation Survey for the UK (see DIUS, 2008) and shows that more UK firms sell their goods and services to local/regional and national markets than internationally, although the more innovative a firm, the greater the likelihood that it (also) sells abroad. Given the importance of sales 'nationally' (i.e. within the UK but outside the region), together with the dominance in terms of size and performance of London and the South East region,[13] it seems highly likely that most regions trade with the 'South' which should mean that spatial spillovers (to the extent they are important) will often emanate from this region, even though for the peripheral regions of the UK the 'South' is geographically the furthest away.

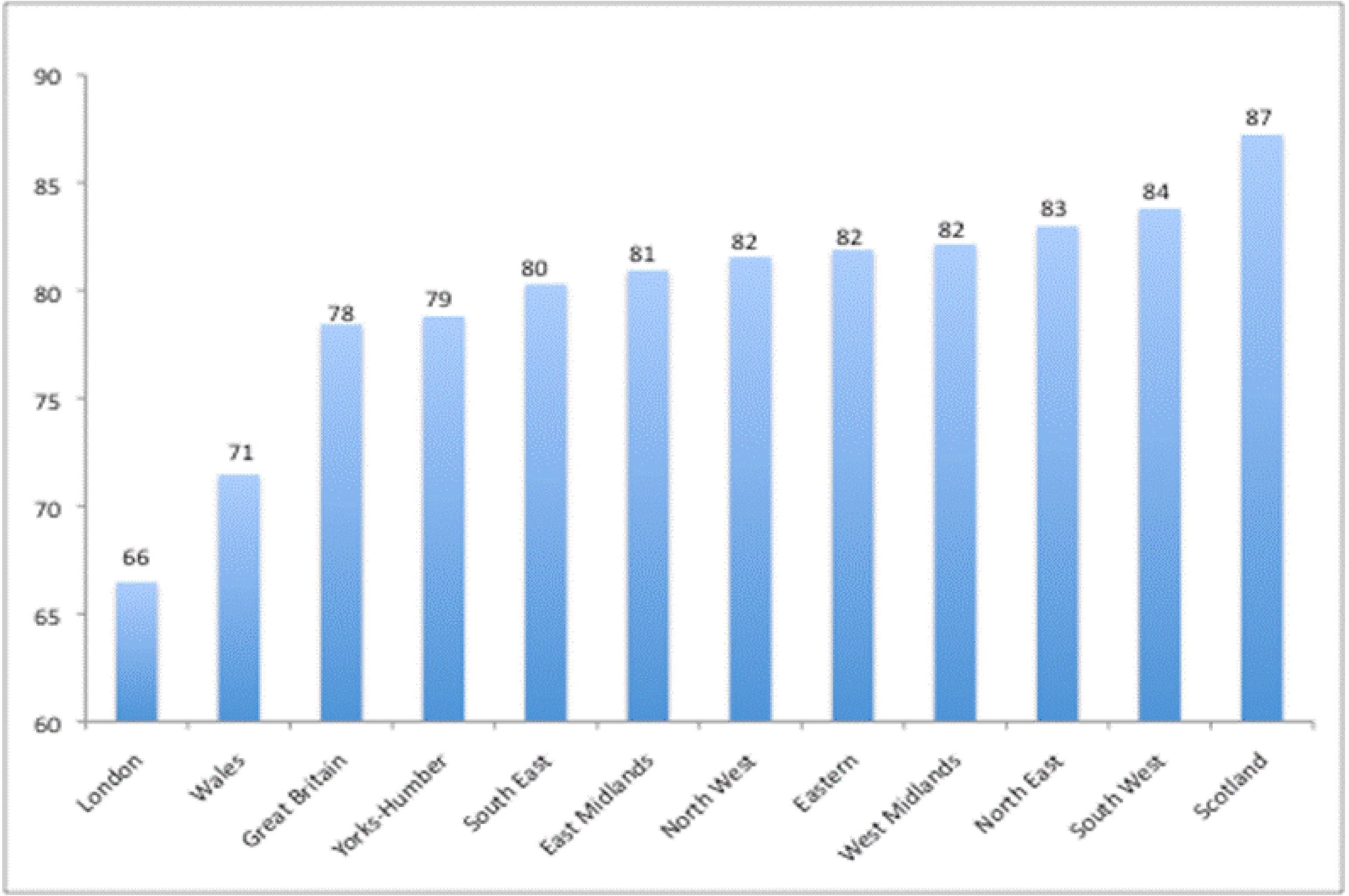
Table 1 also shows that while there are strong interregional connections likely to play an important role in technology diffusion, local and regional markets are also strongly linked through the demand-side. Thus, demand-side shocks that impact on one region are likely to be transmitted to other regions fairly rapidly through trade. In addition, most of the output produced in UK firms comes from enterprises that have plants located in more than one region (Figure 1); that is, production is by its very nature linked across space. Thus, regional output and employment (and consequently unemployment) tends to be strongly correlated over the economic cycle, and especially with the South East region (following e.g. Nocco, 2005; Gray, 2005; and for China see Groenewold, et. al. 2009). Similarly, spatial links across other types of economic variables (e.g., spatial housing markets) also occur whereby the South East can often have a stronger impact on the more peripheral regions than their neighbours.[14]

[12] Hillberry and Hummels (*op. cit.*) find using very detailed data for U.S. manufacturing that shipments had a median radius of just 4 miles.

[13] In 2007, London and the South East accounted for over 34% of UK gross-value-added.

[14] See Oikarinen (2006) for an example on the diffusion of housing price movements.

Figure 1: Percentage share of 2005 Market-sector Output in Great Britain produced in multi-regional enterprises



Source: ONS

As to non-pecuniary, non-market interactions, there is again an extensive literature that discusses the sources, and attempts to measure the importance, of knowledge spillovers.[15] The two main issues emphasized in the recent literature on spatial effects and knowledge spillovers are the role of knowledge accumulation and productivity growth in metropolitan areas (Morretti, 2004; Glaeser and Mare, 2001) and agglomeration effects on urban growth and the role of the cities in patterns of R&D activity (Carlino et al., 2007, Rosenthal and Strange, 2005, Glaeser and Saiz, 2003).

The effect of changes in the share of college educated employees on plant level productivity growth, in industries with different technological intensity and economic closeness, has been explored by Moretti (2004). He finds that industries with closer economic activities (defined by the intensity of cross-industry patent citations) benefit more from the increase in the share of college educated employees and the returns are higher for high tech industries.

The second strand of literature puts more weight on agglomeration effects in knowledge activities. The density of employment, for example, has been considered as one of the factors that plays an important role in the intensity of patents registered. Carlino et al. (2007) find that knowledge intensive activities do not occur in the densest metropolitan areas, but turn out to be highest in the medium sized cities with medium density of employment. These results suggest that the trade-off of locating R&D activities in the densest areas between returns to spatial effects of R&D activity and the other related costs, like for example rent and wages, is somewhere in the middle and that the spatial effect in locating R&D activity is not necessarily the dominant one.

As Table 2 shows there is also clearly scope for knowledge spillovers in the UK even if we limit ourselves to just those firms that actively engaged in cooperation when undertaking innovation-based activities. Nearly one-fifth of such firms were engaged in cooperation with other UK firms and institutions outside the region in which they were located, while 10% had direct links with overseas companies and bodies.[16] And again, we might expect that due to the sheer size of London and the South East region it seems highly likely that most regions cooperate on innovation with the 'South' which should mean that knowledge spillovers are likely to emanate from this part of the UK.

In summary, it seems very likely that in countries such as the UK there is a strong likelihood that in most every region there are important supply-side linkages with respect to knowledge and technology diffusion from the 'South' (the 'leading' region). The transmission of demand-side shocks from the 'South' are possibly even stronger, and therefore any model of spatial spillovers needs to recognise that contiguity and geographic distance measures of spatial links are likely only a poor approximation of the full range of spatial impacts that take place.

[15] See footnote 1.
[16] The list of cooperation partners comprises: supplier/customer/competitor companies; consultants, commercial labs, or private R&D institutes; universities or other higher education institutions; and Government or public research institutes.

Table 2: Percentage of UK enterprises[a] cooperating with other enterprises or institutions on innovation, 2002-04, located in UK or overseas

	UK-based (local, regional)	UK-based (national)	RoW-based
North East England	14.6	14.7	6.8
North West England	14.9	16.9	6.7
Yorks & the Humber	16.8	20.2	8.4
East Midlands	11.8	19.8	10.3
West Midlands	16.0	16.3	8.9
Eastern England	14.3	19.6	14.2
London	14.9	20.6	14.0
South East England	13.0	20.0	11.1
South West England	12.1	15.2	10.3
Wales	11.8	16.3	6.9
Scotland	18.7	18.8	11.4
Northern Ireland	12.9	9.1	7.0
UK	14.4	18.2	10.4

[a] Only those enterprises introducing innovations and/or undertaking R&D and/or abandoning innovation activities

Source: weighted CIS4

6. Summary and conclusions

The need to take into account potential spatial spillovers when considering economic relationships between variables is well-established, even though most economic models continue to ignore these linkages. However, the standard approach in the spatial econometrics literature to including such spillovers is to impose *a priori* a spatial weights matrix (W), which uses contiguous or distance-related measures to weight the observations of other regions so imposing a structure of spatial interactions that is untested and potentially mis-specified. The latter will also mean that the non-spatial parameter estimates are likely to be biased. This is especially true when using this approach with UK regional data (and likely most other countries), where there is a strong expectation that London and the South East are the source of many interregional spillovers.

Alternatives to specifying in advance W, based on a contiguity or distance-decay approach, include different forms and combinations of the standard weighting procedures, grid-searches for W, and/or combining geographic and other measures of 'distance' (including economic distance). As with the standard approach, hybrid forms of W are still based on prior assumptions of the form of spatial dependence that largely go untested. In essence, the major limitation of an approach based on using W is that it collapses all spatial interactions across regions into a single (weighted) variable, rather than directly testing which regions interact with each other (and the strength of such interactions).

This has led some researchers to construct proxies for spillovers that directly enter into the model being estimated. While this allows for direct tests of the significance of (a range of) such proxies, and also introduces more flexibility in terms of the econometric estimation of such models, often the stand-alone proxies themselves involve some form of weighting (similar to the use of the W-matrix), which as before means imposing a structure of spatial interactions that is largely untested and thus potentially mis-specified. An exception is the use of spatial VAR (SpVAR) models, which in theory can directly test for spatial associations across regions without having to use spatial weights. In practice, however, when the number of regions, N, is likely large, compared to the time-series length, T, of any panel data available, the number of 'free' parameters that would need to be estimated is likely to prove prohibitive and SpVAR models collapse down to the standard (panel) version of the spatial model.

The outcome therefore is a rather ad hoc and unsatisfactory approach usually being taken when including spatial effects in empirical models. Thus, while there have been significant advances in the spatial econometrics literature in the last 20 years, the key issue involved from the very start (the specification of the W-matrix and the form of spatial spillovers more generally) remains largely unsolved. Future advances in this area are likely to add significantly to the applied econometricians toolkit, and probably will ensure that spatial techniques become much more popular in economic modelling. Echoing the concerns of Fingleton (2003) with respect to the role of W, it seems appropriate to again ask: "… what is the theoretical and empirical basis of assumptions about the spatial reach of externalities, and how can this be enhanced? Can progress be made explicitly modelling knowledge spillovers between interacting firms or by modelling knowledge flows due to job switching in labour market areas?"

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