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Similarity of R&D activities, physical proximity, and R&D spillovers☆

George Deltas [a,*], Sotiris Karkalakos [b]

[a] Department of Economics, University of Illinois at Urbana-Champaign, 1407 West Gregory, Urbana, IL 61801, USA
[b] Department of Economics, University of Piraeus, Greece

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ABSTRACT

The diffusion of knowledge generates positive externalities if knowledge flows increase the productivity of R&D by the recipients of these flows. We investigate the extent to which these spillovers depend on the similarity of research activities by the originator and recipient of the knowledge, and at what rate the spillovers diminish with physical distance. We find, using regional patent and R&D expenditure data from the European Union, that similarity between R&D activities is not only statistically significant, but salient: regions with completely dissimilar R&D activities exhibit essentially no spillovers at all. An increase in the distance between the originating and recipient region by 500 km reduces spillovers by 55–70%.

1. Introduction

Industrial agglomerations exist in part because individuals learn from each other when they live and work in close proximity. Increasing amounts of evidence confirm this and document that the diffusion of ideas depends on physical proximity, technological specialization, the stage of economic development, labor mobility, and other factors. We focus on the relationship between the similarity in the research activities of any pair of regions and the extent of technological spillovers between them. This relationship sheds light on the nature of spillovers. If spillovers were due to the local availability of relevant know-how embodied in human capital, the spatial correlation between R&D successes would be stronger between regions with relatively similar R&D activities. This pattern of spatial correlation would be absent if the spillovers were driven by general rather than specific knowledge, or if the spatial correlation between R&D successes were spurious.

We also make a (minor) methodological contribution by employing a non-linear spatial econometric framework in which the spatial lag matrix is a function of a parameter that measures the rate at which the spatial effects dissipate. We assume an exponential rate of decay, and estimate the decay parameter jointly with all the other parameters of the model. This eliminates the need for specification searches by employing a set of possible spatial lag matrices and choosing among them on the basis of some measure of fit, as is often done in the literature. Using the exponential decay function also avoids the need to over-parameterize the model by specifying a large number of spatial lag matrices for different distances, and estimate parameters for each one of them. This exponential function allows us to parsimoniously estimate the geographic half-life of spillovers, i.e., the distance at which spillovers are reduced by 50%. This distance has a bearing on the possible nature of spillovers. We discuss our results and the implications we draw from them later in the paper.

We employ two variants of this approach. In the first variant, we obtain consistent estimates of all the parameters and obtain the standard errors via a standard bootstrap methodology, which ignores the spatial dependence of the error structure. This variant ensures that the confidence interval of the exponential decay parameter does not include zero, and avoids the systematic under-estimation of the standard errors, since they are not conditional on the choice of the spatial lag matrix. A drawback of this approach is that estimation is not efficient and standard errors may contain unknown biases, since any spatial correlation in the errors is not taken into account. The second variant takes the consistent estimate of the exponential decay parameter and constructs the corresponding spatial weight matrices. These matrices are in turn used in standard Maximum Likelihood estimation of the econometric model that allows for a spatial lag in the error term. Under this variant, which mimics the feasible-GLS approach to estimate econometric models with non-spherical disturbances, point estimates and standard errors fully reflect the spatial dependence in the disturbances, but are conditional on the weight matrix. Thus, standard errors are understated, as they would be

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* Corresponding author.
E-mail address: deltas@illinois.edu (G. Deltas).

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under the common estimation procedures in the spatial literature, which use fixed weight matrices. In contrast with the typical estimation approach in the spatial literature, in our approach the weight matrix is not fixed arbitrarily, but fixed at the values obtained by a consistent procedure.

Knowledge flows have been extensively analyzed in the literature following the Grilliches (1992) and Jaffe (1989) knowledge production function approach.[1] A complementary approach, by Jaffe et al. (1993), uses the distribution of patents across regions and measures the spatial autocorrelation of citations between any two regions. Related work includes Peri (2005), Hall et al. (2005), and others. Both approaches posit that patent counts are a reasonable measure of research output, a premise also supported by Trajtenberg (1990). Closer to our work are Bottazi and Peri (2003) and Peri (2005). The first of these two papers uses European regional data to investigate the effect of "technological proximity" on R&D spillovers, though this is done through a control variable and is not distance weighted (i.e., it is not part of the distance weight matrix). In that paper the authors pre-specify a set of distance weight matrices, rather than estimate the weights directly from the data using a non-linear model. The second paper, in which technology is a control, investigates the effects of technological proximity on citations, with citations being an input in the production of patents. Another contribution that is close to our work methodologically is Keller (2002), which estimates the effects of one country's R&D on productivity of that country and other countries. This paper estimates an exponential decline function for the spillover effects of R&D and, like the first of our two approaches, does not incorporate spatial dependence in the error structure.

2. Econometric model and data

Economists have drawn from the large pool of patent data and used them as a convenient measure of research output (Grilliches, 1990). A standard empirical specification measuring the extent of spatial spillovers in R&D estimates the relationship

$$\ln\left(P_j\right) = a + b\ln\left(R_j\right) + \sum_{i=1}^{I} w_{ij}\ln(R_i) + dZ_j + \varepsilon_j \tag{1}$$

where P_j is the number of patents in region j, w_{ij} is an element of spatial weight matrix that depends on the distance between regions i and j (with $w_{ij}=0$ when $i=j$), R_{ij} is R&D expenditure in region i, and Z_j is a set of regressors. The weights w_{ij} are typically equal to the inverse distance between two regions, or equal to 1 for regions that are closer than a pre-specified cut-off (or are the nearest neighbor) and 0 otherwise, and ε_j is a disturbance term that can potentially also exhibit spatial dependence, often of the spatial lag form $\varepsilon_j=\lambda\sum_{i\neq j}w_{ij}\varepsilon_i+e_j$ where e_j are iid normally distributed random variables.[2] The log transformation allows for the interpretation of the parameter estimates as elasticities and is often also justified by approximately lognormally distributed variables.

We augment the above framework in two ways. First, we allow R&D spillovers, and in particular the elements w_{ij}, to depend not only on the physical distance between two regions, but also on the similarity of their research activities. We define a similarity index, S_{ij}, of research activities in regions i and j over K different industries by

$$S_{ji} = 1-\left[\sum_k\left|\frac{P_{jk}}{P_j}-\frac{P_{ik}}{P_i}\right|\right]/K \tag{2}$$

where P_{jk} is the number of patents in region j and sector k and K is the total number of distinct sectors. This index ranges from 0 (if all the patents of region j are in sectors for which region i has no patents) to 1 (if the sectoral distribution of patents is the same for the two regions), is symmetric (i.e., $S_{ij}=S_{ji}$) and is independent of the aggregate number of patents in regions i and j. The index is not defined if one of the regions has no patents, but this does not occur in our sample.

Our second departure from the standard framework is that the elements of the spatial weight matrix, w_{ij}, are not constants but an estimable function of distance. In particular, we assume that $w_{ij}\propto e^{-\theta d_{ij}}$, where d_{ij} is the physical distance between regions i and j and θ is an unknown parameter. We also allow (in some specifications) the spatial weights to depend on whether regions i and j are in the same country. Thus, our general specification framework is given by

$$\ln\left(P_j\right) = a + b\ln\left(R_j\right) + \sum_{i=1}^{I} w_{ij}\left(\theta, c, d_{ij}, S_{ij}, B_{ij}\right)\ln(R_i) + dZ_j + \varepsilon_j \tag{3}$$

where B_{ij} takes the value of 1 if regions i and j are in the same country and c is a vector of parameters. We estimate many variants of Eq. (3), with the most comprehensive specification given by

$$\ln\left(P_j\right) = a + b\ln\left(R_j\right) + \sum_{i\neq j} e^{-\theta d_{ij}}\left(c_0 + c_1S_{ij} + c_2B_{ij}\right)\ln(R_i) + dZ_j + \varepsilon_j \tag{4}$$

which by expanding on the summation yields

$$\begin{aligned}\ln\left(P_j\right) &= a + b\ln\left(R_j\right) + c_0\sum_{i\neq j} e^{-\theta d_{ij}}\ln(R_i) + c_1\sum_{i\neq j} e^{-\theta d_{ij}}S_{ij}\ln(R_i)+ \\ &+c_2\sum_{i\neq j} e^{-\theta d_{ij}}B_{ij}\ln(R_i) + dZ_j + \varepsilon_j\end{aligned} \tag{5}$$

where Z_j is a set of variables that includes the distance of region j from the core of the European Union and also a vector of country dummies. Variants of Eq. (5) include more parsimonious specifications or specifications with alternative weights for the border effects.

Each variant of Eq. (5) has been estimated in two different ways. In the first approach, consistent estimates of the parameters are obtained using non-linear regression, with a bound on the parameter space that imposes a positive value for the exponential decay parameter θ (note that this parameter enters with a negative sign in the econometric model). A negative (or zero) value of the parameter would imply that activities have a bigger spillover effect the further away they are (or are independent of distance). Hence, this parameter is, or should be, positive for meaningful spatial effects. For the same reason, a test of whether θ is different than zero is not meaningful. Therefore, standard errors are obtained via bootstrap based on our estimation routine and, by construction, the confidence intervals do not include zero. Asymptotic standard errors, being symmetric in nature, could possibly use confidence intervals that cover zero. This would formally lead to the implication that one cannot reject the hypothesis that the exponential parameter is zero or of the wrong sign, a conclusion that would simply be an artifact of the way symmetric standard errors are computed. The bootstrap standard errors do not suffer from this weakness, but they are asymmetric as a result. However, this first approach does not take into consideration the possible spatial correlation of the disturbance term, resulting in bias in the standard errors of unknown sign.

The second approach involves the Maximum Likelihood estimation of the parameters and asymptotic standard errors in order to account for the possibility of spatial correlation in the error structure. However, the ML estimates are conditional on the consistent estimate of θ, as obtained under the first estimation approach. In other words, the weight matrix is fixed under the ML approach, but not fixed arbitrarily: it is fixed at a consistent estimate (this is reminiscent of what was known in the cross-section literature with non-spherical errors as "feasible GLS"). The use of an estimated θ for the calculation of

[1] Jaffe (1989) is the first to find a positive spatial relationship between the number of patents and R&D activities. In an analysis that does not use spatial lags, he finds that spillovers from academic research to the industry are limited to within technical areas, with essentially no spillovers across technical areas.

[2] Alternatives to this spatial lag specification of the error term are the spatial error components model, where $\varepsilon_j=\lambda\sum_{i\neq j}w_{ij}\xi_i+e_j$, and the spatial moving average model, where $\varepsilon_j=\lambda\sum_{i\neq j}w_{ij}e_i+e_j$.