Geographic and Sectoral Characteristics of Academic Knowledge Externalities

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Abstract

This paper implements a novel approach to formalizing spatial externalities by employing spatial econometric methods that combine spatial dependence and spatial heterogeneity in the form of spatial regimes. The results confirm earlier findings that academic externalities are not uniform across sectors but also indicate important differences across sectors in terms of agglomeration effects.

Keywords: innovations, high technology R&D, spatial econometrics, knowledge production function

JEL Classification: O31, H41, O40

I. Introduction

The contribution of university research to the complex Arrow-Marshall-Romer externalities that characterize local innovation systems has received considerable attention in recent work on endogenous growth and the new economic geography (Romer, 1990, Grossman and Helpman, 1991, Krugman, 1991). These externalities, or "real effects of academic research" follow from the public good nature of the research produced by universities, and, ceteris paribus, result in a higher or more efficient innovative output on the part of the private sector. Crucial empirical aspects of these externalities are the extent to which they are uniform across sectors and their geographic scope.

In a recent paper (Anselin, Varga, Acs, 1997), we were able to shed some initial light on this issue for high technology innovations measured as an aggregate across five two-digit SIC industries. Our point of departure was Jaffe's (1989, p. 968) often cited finding that "there is only weak evidence that spillovers are facilitated by geographic coincidence of universities and research labs within the state." This runs counter to the pre-eminence of geographic clustering and the role of distance decay in the literature on agglomeration economies in urban and regional economics (Fujita and Thisse 1996). We found that the spillovers of university research on innovation extended over a range of 50 miles from the innovating MSA, but this was not the case for the private R&D.

In this paper we focus on two additional dimensions of this issue. First, as in Anselin, Varga and Acs (2000), we broaden the cross-sectional basis for empirical analysis by utilizing disaggregated data for four high technology sectors at the MSA level. However, distinct from that paper, we introduce a test for agglomeration effects in the form of "spatial regimes," which differentiates unconnected metropolitan areas from those that are part of a geographic network of innovation systems. This provides a different perspective on the spatial "range" of spillovers and introduces a formal mechanism to assess the difference between the spatial interaction in urban areas with and without "neighbors", an idea that recently is gaining increased attention in urban economics (Ioannides 2000). In the remainder of the paper, we first introduce the formal model underlying the knowledge production function and the specification of the geographic scope of spillovers. We next briefly describe the data set and outline some general methodological issues. Subsequently, we present the results of our disaggregated analysis at the MSA level. We close the paper with some concluding comments.

II. Knowledge Production and Geographic Scope of Externalities

The econometric specification for analyzing the geographic spillovers of university research on regional innovative capacity is derived from the knowledge production function (KPF) of Griliches (1979). In essence, this is a two-factor Cobb-Douglas production function where K is a proxy for knowledge, R is industry R&D and U is university research, with β and γ as associated parameters. In addition to R and U, a vector of "local" economic characteristics Z is often included as well, such that the operational specification becomes:

$$\log(K) = \alpha + \beta \log(R) + \gamma \log(U) + \delta \log(Z) + \varepsilon \qquad (1)$$

where ε is a vector of stochastic error terms. A positive and significant coefficient for γ indicates the presence of positive externalities from the university research on industrial innovative activity. By contrast, the lack of significance of γ would suggest that all innovative "knowledge" production is generated internally to the industrial sector. This does not preclude the presence of additional knowledge externalities of the Arrow-Marshall-Romer or Isard-Jacobs type, but these would be reflected by the coefficients of the local characteristics in Z. Typically, the latter would include measures such as the concentration of a given activity (a proxy for information exchange via "learning by doing") and the presence of business services in the local economy (reflecting the effect of locally accumulated knowledge regarding the financial, legal and marketing aspects of innovation).

Agglomeration economies encompass a range of effects due to spatial externalities, increasing returns and spatial competition that tend to provide benefits to economic activities carried out in geographic proximity. In the context of the role of university research, the most important aspect of agglomeration economies would be the existence of informational spillovers. However, the evidence at the aggregate level in Anselin, Varga and Acs (1997) suggests that the spillovers may well reach beyond the geographic definition of the MSA. To the extent that MSAs are within easy commuting distance from each other, they in effect become part of a larger system of networked and interacting agents. The additional benefits from being part of such a network should be reflected in higher values of the model parameters (more innovative output per unit of input) for those MSAs that are "connected" relative to MSAs that are "isolated". In other words, the geographic boundedness of the knowledge spillovers is directly linked to a distance decay effect. This implies zero interaction beyond a given critical distance threshold, but also suggests that when observational units (MSAs) are within such a distance threshold, there is no reason for the agglomeration economies to be limited to within-MSA effects.

Consider a set S of N geographical units (MSAs), partitioned into two non-overlapping subsets, I and J, $I \cap J = \emptyset$, and $I \cup J = S$; set I with connected units, J with isolated units. Each observational unit belongs to one and only one of the subsets:

$$i \in I \text{ iff } \exists\, h \in S \text{ s.t. } d_{ih} < \delta,$$

and

$$j \in J \text{ iff } \{\, k \mid k \in S \text{ and } d_{jk} < \delta \,\} = \emptyset$$

for a proper distance metric d_{ij} and with δ as a critical threshold distance.

The two subsets can be used to characterize "spatial regimes," or contiguous and non-overlapping subsets of the data that may correspond to different model parameters and/or functional forms, in a fixed-effects sense (Anselin 1990). In general:

$$y_i = \alpha_i + x_i\beta_i + \varepsilon_i,\ E[\varepsilon_i] = 0,\ Var[\varepsilon_i] = \sigma^2_i,\ \forall\ i \in I \tag{2}$$

$$y_j = \alpha_j + x_j\beta_j + \varepsilon_j,\ E[\varepsilon_j] = 0,\ Var[\varepsilon_j] = \sigma^2_j\ \ \forall\ j \in J \tag{3}$$

where the subscripts pertain to observations in each subset; the $\alpha_{i(j)}$ are the intercept, $\beta_{i(j)}$ a K by 1 vector of slope coefficients, $y_{i(j)}$observations on the dependent variable, $x_{i(j)}$ a 1 by K vector of observations on the explanatory variables, and $\varepsilon_{i(j)}$ stochastic error terms with mean zero and (fixed) variance $\sigma^2_{i(j)}$. The classification of observations into the two regimes allows for testable hypotheses on the constancy of model parameters α and β across regimes by means of test statistics for structural stability.

In the context of the KPF, the presence of structural instability stratified along spatial regimes pertaining to "connected" and "unconnected" MSAs provides an indication of agglomeration economies that transcend the MSA. In a sense, this design can be interpreted as a quasi-experiment, where the controls are the unconnected MSAs and the treatment is the more complex network structure that may be present due to the geographic closeness of the connected MSAs. Rejection of the null hypothesis of spatial homogeneity would suggest a significant difference in the production of knowledge between the two spatial settings. Failure to reject the null hypothesis would not allow such an interpretation and instead would suggest that the same mechanisms are working in both subsets, or, that any agglomeration economies would be contained within the MSA and are adequately captured by variables measured at that scale.

In the absence of spatial autocorrelation, a test for regional homogeneity of the regression coefficients between the two spatial regimes can be carried out by means of textbook test statistics for structural change, such as a Chow test. However, the presence of spatial autocorrelation requires a spatially adjusted test for structural stability (Anselin, 1990). In our application, this is carried out by stacking the data for the connected and unconnected observations and creating two sets of explanatory variables, $x_i = x \ \forall \ i \in I$ and $x_i = 0$ otherwise, and, similarly, $x_j = x \ \forall \ j \in J$ and $x_j = 0$ otherwise, with the subsets I and J defined as in (2)-(3). A test for regional homogeneity is then implemented as a test on the null hypothesis $\beta_i = \beta_j$, where the β coefficients are associated with x_i and x_j respectively. In the absence of spatial autocorrelation, this is equivalent to a Chow test. In the presence of spatial autocorrelation, the proper estimators incorporating either a spatial lag or spatial error term ensure that the standard errors of the estimated coefficients reflect the loss of information associated with (positive) spatial autocorrelation.

The specific implementation of this approach in our applications turns out to be straightforward, since the definition of the regimes precludes the presence of spatial autocorrelation in the unconnected set.[1] Consequently, potential misspecification in the form of a spatial lag or error model needs only to be considered for the "connected" subset. Specifically, we apply Lagrange Multiplier tests for spatial autocorrelation (Anselin and Bera, 1998) to test for this form of misspecification. If a spatial lag is the suggested alternative model, we apply maximum likelihood estimation when errors are normally distributed or spatial-two-stage-least-squares estimation, S2SLS otherwise (Anselin, 1988; Kelejian and Prucha, 1998). If a spatial error model is the suggested alternative, normality of error terms allows us to employ ML estimation (Ord, 1975) or, in case of non-normality, a Generalized Moments (GM) estimator

[1] This assumes that the "proper" definition of the spatial weights matrix is based on the same 50 mile distance cut-off as the definition of the spatial regimes. In practice, this assumption does not affect our conclusions. The overall results were not affected (in a qualitative sense) when other spatial weights were applied, such as a 75 mile distance cut-off and an inverse distance decay.

(Kelejian and Prucha 1999) is applied. In each of the alternative models, we also carry out specification tests for remaining autocorrelation, using LM tests (Anselin et al, 1996) or a generalization of Moran's I for S2SLS residuals (Anselin and Kelejian, 1997).[2]

A final issue is the potential presence of endogeneity in the KPF. In Jaffe (1989) this is assessed by extending the model with two additional specifications, one for private R&D and one for university research. In Anselin, Acs and Varga (1997), we followed a similar approach. For the sectorally disaggregated data considered here however, Durbin-Wu-Haussman tests for endogeneity did not allow for the rejection of the null hypothesis. Consequently, in the current empirical exercise, we could treat both variables as exogenous and limit the model to a single equation.

III. Data and Variable Definitions

The dependent variable in our empirical analysis is the count of innovations as reported in the U.S. Small Business Administration Innovation Database. The data set is a compilation of innovations that were introduced to the U.S. market in the year 1982, based on an extensive review of new product announcements in trade and technical journals (Edwards and Gordon, 1984). We considered innovations in four "high technology" sectors, broadly defined as Drugs and Chemicals (SIC 28), Industrial Machinery (SIC 35), Electronics (SIC 36) and Instruments (SIC 38). These four two-digit categories contain most of the 3 and 4 digit sectors that are typically categorized as high technology sectors. Except for Industrial Machinery, our sectoral

[2] No special considerations need to be taken into account, as long as the number of spatial regimes is fixed (which it is, by assumption) and the number of cross-sectional observations in the connected subset is allowed to increase to infinity in order to ensure the proper asymptotics. A more extensive discussion of technical issues is contained in Anselin and Bera (1998).

aggregation is the same as the one used in earlier studies by Jaffe (1989) and Acs, Audretsch and Feldman (1992).[3]

Our measure for industrial R&D activity is constructed from data on professional employment in high technology research laboratories in the Bowker directories [Jaques Cattell Press (1982)]. While imperfect, this allowed us to construct a private R&D variable at the U.S. county scale, which could be consistently aggregated up to states and MSAs (see Varga, 1998, for details).[4] Our data for university research expenditures follow the common approach in the literature and are compiled from the NSF Survey of Scientific and Engineering Expenditures at Universities and Colleges for the year 1982 (National Science Foundation, 1982).

In addition, we also included a number of variables compiled from County Business Pattern data for 1982 (Bureau of the Census, 1982) to capture agglomeration economies and size effects [the variables in Z in equation (1)]. Specifically, we included a location quotient for high technology employment, LQ; employment in business services (SIC 73), BUS; and the percent "large" firms (i.e., firms with employment exceeding 500), LARGE.

Our final data set only included those MSAs for which there were innovations in the high technology sector as well as both private industry R&D and university research expenditures. [5] The number of observations ranged from 48 for SIC 28, to 89 for SIC 35 (SIC 36 had 70 valid observations and SIC 38 had 63).[6] In addition, since the selection of MSAs was

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[3] Jaffe (1989) and Acs, Audretsch and Feldman (1992) use Mechanical Arts as the fourth sector, which is roughly similar but not identical to our Machinery (SIC 35).

[4] The use of laboratory employment as a proxy for expenditures assumes a constancy of the labor intensity and capital/labor ratio of R&D across the units of observation. To the extent that this is not the case, it will tend to yield heteroskedastic and/or spatially autocorrelated error terms, which will merit special attention in our analysis and will be addressed by means of a spatial econometric approach.

[5] Due to the presence of zeros, it was not possible to include the four sectors in a consistent system of unrelated regressions without losing too many observations (the matching set across all four sectors would only consist of 36 observations), so that any spillovers across sectors are assumed to be incorporated in the single equation error terms in an unspecified form.

[6] A full listing of the data is given in the Appendix of Anselin, Varga and Acs (2000).

different for each sector, the stratification into connected and unconnected spatial regimes differed as well. This was based on a distance threshold criterion of 50 miles.[7] For SIC 28, there were 18 unconnected MSAs, for SIC 35, 43, for SIC 36, 33, and for SIC 38, 29. In each case, this is slightly less than half of the total number of observations.

IV. Empirical Results

We estimated a KPF for a constrained OLS regression (constraining the coefficients to be equal in both spatial regimes) as well as, where appropriate, in an unconstrained feasible generalized least squares (FGLS) regression with different estimates for each regime.[8] For each regression, results of a test for regional homogeneity are reported, as well as the LM specification tests for spatial autocorrelation. If the null hypothesis of no spatial autocorrelation is rejected, results are presented with the estimation for the proper spatial alternative. All estimations and specification tests were carried out with the *SpaceStat* software (Anselin 1999).

Regional homogeneity is rejected for SIC 35 and SIC 38, but not for the other two sectors. Hence, for SIC 28 and SIC 36, there is no indication of a significant difference in the spillovers encompassed in the KPF between connected and unconnected MSAs.[9] As shown in Table 1, there is little evidence of any knowledge spillovers at all for drugs and chemicals (SIC 28), indicating only a significant and positive coefficient for industry R&D. This strongly contrasts with the earlier findings at the state level by Jaffe (1989) and Acs, Audretsch and Feldman (1992) where a significant coincidence effect was found for this sector.

The results are more interesting for the electronics sector (SIC 36), where there is a positive and significant effect of both industry and university research, as well as of the location

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[7] The analysis was also carried out for a distance cutoff of 75 miles, but did not yield substantively different conclusions.

[8] The FGLS regression estimated a separate error variance coefficient for each regime, thus allowing for groupwise heteroskedasticity across regimes.

quotient and business services (the firm size variable was not significant). There is a strong indication of positive spatial error autocorrelation, but its incorporation does not alter the lack of evidence of regional heterogeneity. Substantively, there is little change between the interpretation of the model with and without spatial autocorrelation, which is to be expected. The main effect of the spatial error autocorrelation is on the precision of the estimates, but in this case, this is not sufficient to alter any indication of significance.

For the machinery sector (SIC 35), the estimation results indicate the presence of both regional heterogeneity between the two spatial regimes, as well as a spatial lag model for the connected observations. This is the only sector for which our empirical results suggest the presence of knowledge externalities that transcend the geographic scale of the MSA in accordance with our conceptual framework. The spatial lag coefficient is significant and positive, as expected (0.231 for S2SLS). However, interestingly, neither R&D nor university research are significant contributors to innovations in this sector. Note that there is a very weak indication of some effect of R&D for the connected MSAs, but none at all for the unconnected metro areas. Both sectoral concentration and business services show a positive and significant effect, roughly similar in magnitude for the former, but almost twice as large in connected metro areas for the latter.[10] The failure of the KPF in this instance may be due to a number of factors, such as specification problems (the restrictive form of the Cobb-Douglas specification) or the lack of an explicit accounting of inter-sectoral innovation spillovers. More likely however, is the fact that the 2 digit SIC aggregation masks considerable underlying heterogeneity which would not affect the "catch-all" agglomeration variables (such as concentration or business services) but

[9] For SIC 28, the Chow test statistic was 11.86 and for SIC 36, 5.26, neither of which was significant at $p = 0.05$. Given this result, we do not report the estimates for regimes.

[10] A test for regional stability of the business services coefficient across spatial regimes reveals significant differences ($p < 0.01$).

may be to crude to allow R&D and/or university effects to be captured. This remains to be investigated by means of further disaggregated data.

Finally, for instruments (SIC 38), still a different pattern emerges. There is strong evidence of regional heterogeneity, but no indication of spatial autocorrelation. Industry R&D is significant in both regimes, but much more so in the unconnected MSAs. For university research, this pattern is more pronounced, with a positive and significant coefficient in the unconnected MSAs, but no significance in the connected ones.

V. Conclusions

The findings in this paper have broadened the empirical evidence for the existence of both sectoral and regional differences in the innovative process. This extension is three-fold. First, relative to the earlier results of Jaffe (1989) and Acs, Audretsch and Feldman (1992), we did not find uniform evidence of positive externalities for university research. Confirming the results in Anselin, Varga and Acs (2000) where no regimes were accounted for, we found such an effect only in the electronics sector (SIC 36), suggesting a much richer story than previously indicated and possibly indicating the uniqueness of electronics and the regional agglomerations in which they thrive. Secondly, the suggestion of a broader spatial range of the spillovers that we found for MSAs without taking into account the regimes (Anselin, Varga and Acs 1997, 2000) does not carry over to the sectoral disaggregated scale. Thirdly, for the machinery and instruments sectors, we found strong evidence of the existence of spatial regimes, implying that different mechanisms may be at work to generate externalities in connected as opposed to unconnected MSAs.

The empirical results raise a number of interesting issues. While the importance of carefully specifying spatial effects and the geographic scope of these effects was demonstrated, evidence supporting such effects is only the beginning. Moreover, a comparison of the regime approach taken here with a more standard spatial econometric modeling in Anselin, Varga and Acs (2000) suggests that the results are sensitive to the specification of the spatial design. A more thorough understanding of the nature and scope of spillovers involved will necessitate an extension of the cross-sectional framework to incorporate the time dimension as well.

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Table 1
Industrially Detailed Regression Results on Log(Innovations) for US Metropolitan Areas, 1982

Model	Chemicals (SIC28) OLS	Machinery (SIC35) Spatial Lag IV – GHET Spatial Regimes	Electronics (SIC36) Spatial Error ML	Instruments (SIC38) FGLS Spatial Regimes
Constant	-1.600 (0.431)	-2.930 (0.288) -1.419 (0.357)	-1.698 (0.297)	-2.092 (0.462) -0.988 (0.452)
W_Log(INN)		0.231 (0.089)		
Log(RD)	0.349 (0.131)	0.112 (0.063) 0.001 (0.048)	0.154 (0.057)	0.176 (0.081) 0.258 (0.113)
Log(URD)	-0.012 (0.061)	-0.051 (0.038) 0.060 (0.038)	0.097 (0.040)	0.079 (0.071) 0.162 (0.073)
Log(LQ)	0.242 (0.180)	0.583 (0.153) 0.640 (0.208)	0.524 (0.135)	0.467 (0.178) -0.091 (0.170)
Log(BUS)	0.226 (0.141)	0.838 (0.088) 0.420 (0.098)	0.413 (0.095)	0.530 (0.136) 0.109 (0.062)
Log(LARGE)	0.077 (0.125)	-0.060 (0.107) -0.278 (0.113)	-0.141 (0.083)	0.028 (0.101) 0.022 (0.092)
Sigma – 0		0.058		0.109 (0.026)
Sigma – 1		0.056		0.093 (0.024)
Lambda			0.339 (0.125)	
R^2 - adj	0.401	0.752	0.670	0.664
Log-Likelihood			-8.997	
Number of Observations	48	89	70	63
White	15.548			
Breusch-Pagan			5.326	
LM-Err (D50)	0.073			1.692
LM-Lag (D50)	0.972		0.076	1.467
Regional Homogeneity	11.86	27.060	5.26	22.026

Notes: estimated standard errors are in parentheses; critical value for the White statistic with respectively 20 degrees of freedom is 31.41 (p=0.05); critical value for the Breusch-Pagan test for heteroscedasticity is 5.99 (p=0.05); critical values for LM-Err and LM-Lag statistics are 3.84 (p=0.05) and 2.71 (p=0.10); critical value for the Chow-Wald statistic on regional homogeneity with 6 degrees of freedom is 16.81 (p=0.01); the spatial weights matrix is row-standardized: D50 is distance-based contiguity for 50 miles.