ENTREPRENEURSHIP, GEOGRAPHIC SPILLOVERS AND UNIVERSITY RESEARCH: A SPAITAL ECONOMETRIC APPROACH

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Abstract

The paper investigates the issue of local geographic spillovers between university research and innovative activity by small high technology firms in the USA, using Small business Administration innovation data for 125 metropolitan regions (MSAs) and four different high technology sectors (drugs and chemicals, machinery, electronics and instruments). The analyses employ an explicit spatial econometric perspective to implement the classic Griliches-Jaffe knowledge production framework. This incorporates a multivariate approach allowing for factors such as the importance of large firms, of existing high technology industry, and of business services. However, in contrast to Jaffe's finding of only weak evidence of knowledge spillovers, the results of the spatial econometric analyses reveal a positive and significant relationship between university research and regional rates of innovation, both directly and indirectly through its impact on private sector R&D. Spillovers of university research on innovation extended over a range of 75 miles from the innovating MSA, and over a range of 50 miles with respect to private R&D. University spillovers appear to be particularly strong for innovations in the electronics and instruments sectors.

Note

This paper was presented by Professor Acs at the international conference on "Innovation and Performance of Small and Medium-Sized Enterprises" organised by the ESRC Centre for Business Research and Warwick University SME Centre on 17 March 1997, in Cambridge. Other papers from this conference will also be published in due course in the CBR Working Paper Series.

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ENTREPRENEURSHIP, GEOGRAPHIC SPILLOVERS AND UNIVERSITY RESEARCH: A SPATIAL ECONOMETRIC APPROACH

1. Introduction

The systematic relationship between output and productivity growth rates suggests that technological progress probably is not a random process, but rather one guided by market forces. Schmookler (1966) argued in great detail that it is the expected profitability of inventive activity, reflecting conditions in the relevant factor and product markets, that determine the pace and direction of industrial innovation. Schumpeter (1942) had expressed a similar view more than 20 years earlier when he wrote, "it is quite wrong...to say, as so many economists do, that capitalist enterprise was one, and technological progress a second, distinct factor in the observed development of output; they were essentially one and the same thing "(p.110). While there is some powerful econometric evidence that investment in education, capital equipment and R&D plays an important role in productivity growth, Baumol (1993) has argued that productivity growth rates are also influenced by entrepreneurship, investment in the innovation process, and technology transfer.

The accumulation of knowledge and its spillover into productive capacity through technological change is a central theme in the new theory of endogenous economic growth [e.g., Romer (1986, 1990, 1994), Grossman and Helpman (1991, 1994)]. An interesting aspect of this perspective has been the renewed attention to the geographic scope of the spillovers between knowledge creation and production, or, the extent of Marshallian spatial externalities [e.g., as exemplified in the new economic geography of David and Rosenbloom (1990), Krugman (1991), Glaeser et al. (1992), and others].

An important aspect of studies of technological innovation at the regional scale is the role of spatial interaction and spatial structure, as expressed in the form of organizational networks of entrepreneurs, regional innovation complexes and regional knowledge infrastructure [e.g., Stohr (1986), Von Hippel (1988), Storper and Walker (1989), DeBresson and Amesse (1992), Feldman (1994), Saxenian (1994)]. Universities play a central role in this process, not only as producers of basic research, but also by creating human capital in the form of higher skilled labor. Both of these aspects have received considerable attention in the literature, from a theoretical as well as from an empirical perspective. The importance of basic (university) research in the stimulation of technological innovation (and higher productivity) is derived from the public good nature of the research, and the resulting positive externalities to the private sector in the form of knowledge spillovers. The initial conceptualization of this process was provided by Arrow (1962) and Nelson (1959) and further refined by Griliches (1979), Nelson (1982), Von Hippel (1988), Cohen and Levinthal (1989), among others [for recent reviews, see, e.g., Dosi (1988), Acs and Audretsch (1990), Griliches (1990, 1992), Mansfield (1991), Florax (1992), Feldman (1994)].

In a recent paper (Anselin, Varga, Acs, forthcoming) we have been able to shed additional light on the issue of local geographical spillovers between university research and high technology innovations. 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." We approached this issue from an explicit spatial econometric perspective and implemented the classic Griliches-Jaffe knowledge production framework for high technology innovations in 43 U. S. states as well as in 125 Metropolitan Statistical Areas (MSAs). This yielded more precise insight into the range of spatial externalities between innovation and R&D in the MSA and university research both within the MSA and in surrounding counties.

In this paper we extend the empirical evidence in three important respects:

(1) We broaden the cross-sectional basis for empirical analysis by utilizing data for four high technology sectors at the MSA level. The number of observations vary by sector. This is the first time MSA-level data are used at the sectoral level, which avoids many problems associated with the inappropriate spatial scale of a state as the real unit of analysis. MSA-level results are obtained by using R&D laboratory employment as a proxy for R&D activity, based on a specially compiled data set.

(2) We focus on more precise measures of local geographic spillovers. At the MSA scale, we formalize the spatial extent of the geographic spillovers by means of so-called spatial lag variables that capture the research activities in concentric rings around the MSA as well as in the MSA itself.

(3) We explicitly consider the potential for spatial effects such as spatial autocorrelation that may invalidate the interpretation of econometric analyses based on contiguous cross-sectional data. In the existing literature, these effects are typically ignored or treated inappropriately (e.g., by the application of time series techniques). We implement a spatial econometric approach by both testing for the presence of spatial effects and, when needed, by implementing models that incorporate them explicitly [Anselin (1988, 1990), Anselin and Hudak (1992)].

In the remainder of the paper, we first introduce the formal model underlying the knowledge production function and briefly review the current empirical evidence on geographic knowledge spillovers of universities. We next elaborate on the data set, and outline the distinctive characteristics of a spatial econometric approach. Subsequently, we present the results of our disaggregated analysis at the MSA level. We conclude with a summary and evaluation of our findings.

2. The Knowledge Production Function

2.1 Model

The conceptual framework for analyzing the geographic spillovers of university research on regional innovative capacity is based on the knowledge production function of Griliches (1979) [see also Jaffe (1986, 1989)]. In essence, this is a two-factor Cobb-Douglas production function that relates an output measure for "knowledge" to two input measures: research and development performed by industry; and research performed by universities. Formally, this is expressed as:

$$\log(K) = \mathrm{b}_{K1} \log(R) + \mathrm{b}_{K2} \log(U) + \mathrm{e}_K \qquad (1)$$

where K is a proxy for knowledge (either patents or innovation counts), R is industry R&D and U is university research, with e_K as a stochastic error term. The analysis is typically carried out for aggregate cross-sectional units (e.g., states), possibly for several points in time and/or dis-aggregated by sector.

Following Jaffe (1989), the potential interaction between university and industry research is captured by extending the model with two additional equations that allow for simultaneity between these two variables:

$$\log(R) = b_{R1} \log(U) + b_{R2} Z_2 + e_R \quad (2)$$

and

$$\log(U) = b_{U1} \log(R) + b_{U2} Z_1 + e_U \quad (3)$$

where U and R are as before, Z_1 and Z_2 are sets of exogenous local characteristics, and e_R and e_U are stochastic error terms. Since our interest in university effects only, the third equation is not estimated.

2.2 Previous empirical evidence

The framework expressed in equations (1) to (3) has become the basis of several empirical investigations which we will briefly review. Almost all empirical investigations of geographic knowledge spillovers of universities in the U.S. have been aggregate in nature and based on the Griliches-Jaffe knowledge production function framework applied at the state level. Before we consider this more closely, it is important to note that there are also a few studies that take a micro approach, based on surveys or using the information included with individual patent records. For example, Mansfield (1995) finds strong support for the importance of geographic proximity between universities and industry R&D based on a survey of 66 firms and 200 academic researchers. Interestingly, in his results, there is some evidence of a trade-off between proximity and quality of the faculty. Jaffe, Trajtenberg and Henderson (1993) use a form of geographic control method to compare citation patterns of a large number of patents in terms of their localization and also find a "clear pattern of localization" at both the state and SMSA levels (p. 583). Similarly, Almeida and Kogut (1995) focus on patent citations and stress the importance of the mobility of scientists and engineers in explaining "spatial" patterns.

The strong evidence in micro studies of the importance of spatial interaction at the *local* level does not find uniform confirmation in the aggregate studies. As noted above, this may be somewhat due to the fact that the unit of analysis - the state - only partially captures this interaction. We argue in Anselin, Varga, and Acs (1996) that it is also due to the formal specification of local spatial interaction in the form of a geographic coincidence index. To obtain a more precise insight into the nature of the issue, we compare the research design and findings of four recent studies in Table 1.

These studies are all based on data for 29 U.S. states. Jaffe (1989) uses patent counts as the dependent variable [also replicated in Acs, Audretsch and Feldman (1992)], while Acs, Audretsch and Feldman (1992, 1994a) and Feldman and Florida (1994) use a more direct measure of innovative activity, based on a 1982 data set of innovation counts compiled by the U.S. Small Business Administration (see below for further details).

The empirical studies in the literature vary somewhat in terms of research design, but they all find a strong and positive relationship between innovate activity and both industry R&D and university research at the state level. However they differ in terms of the significance of a local geographic spillover effect. The results concerning the role of geographic proximity are clouded, however, by the lack of evidence that geographic proximity within the state matters as well. There is only weak evidence that spillovers are facilitated by geographic coincidence of universities and research labs within the state [Jaffe (1989)]. In the other studies, the evidence is non-existent, weak or mixed, only pertaining to a few individual sectors.

3. Data and Spatial Econometric Methodology

3.1 Data and variable definitions

We extend the current empirical evidence by using a more detailed data set and by applying the methodology of spatial econometrics. We consider each of these aspects in turn. The dependent variable for the geographic knowledge production function [K in (1)] in our empirical analysis is the count of innovations as reported in the U.S. Small Business Administration Innovation Database. This source was used extensively in earlier work by Acs, Audretsch and Feldman

(1992, 1994a, 1994b) and Feldman and Florida (1994). 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 publications [for details on the data set and a discussion of their limitations, see Edwards and Gordon (1984), Acs and Audretsch (1990, chapter 2) and Feldman (1994)].

In contrast to the earlier studies we use the innovation data at the county level, and aggregated the original data to the MSA level. Figure 1 shows the distribution of total innovations by county. Santa Clara, CA is the county where the greatest number of innovations were registered, followed by Los Angeles County, CA, Middlesex County, MA, Cook County, IL, Norfolk County, MA, Orange County, CA, and Bergen County, NJ. A particular striking feature shown in Figure 1 is that the bulk of innovative activity in the United States occurs on the coasts, and especially in Western California and in New England stretching into the Mid-Atlantic Region. In sharp contrast no innovative activity is registered in large parts of the Midwest. MSAs in the traditional manufacturing belt show strong pockets of innovative activity although the concentration is much less than on the coasts.

We consider innovations in four "high technology" sectors. We define these (broadly) as Drugs and Chemicals, SIC 28. Machinery, SIC 35, Electronics, SIC 36 and Instruments, SIC 38. These four two-digit categories contain most of the 3 and 4 digit high technology sectors [for a recent discussion, see, e.g., Herzog, Schlottman and Johnson (1986)]. At the two-digit SIC level, it is virtually impossible to designate sectors as "pure" high technology. To the extent that the sectoral mix in these sectors shows systematic variation over space in terms of its "pure" high tech content, our results in the relationship between innovation and research could be affected. However, we are confident that we will be able to detect such systematic variations by means of careful specification tests for spatial effects [Anselin (1988), Anselin and Bera (1997)].

Earlier studies of the aggregate knowledge production function were limited to data for 29 states. This was not due to the lack of data on innovations or patents (for which actual addresses are available), but to data limitations for the explanatory variables in the model, in particular for the variable on private R&D expenditures [*R* in (2) and (4)]. In Jaffe (1989), and also in Acs, Audretsch and Feldman (1992, 1994a, 1994b) and Feldman and Florida (1994), this was computed from information on total industry R&D by state, compiled by the U.S. Bureau of the Census on the basis of survey data from the National Science Foundation. However, this data was only consistently reported for 29 states [for details, see, e.g., Jaffe (1989, p. 968–969)]. Instead, we constructed a proxy for industrial R&D activity on the basis of data on professional employment in high technology research laboratories in the Bowker directories [Jaques Cattell Press (1982)]. While imperfect, this approach allowed us to construct a private R&D variable for 43 U.S. states and for 125 MSAs [see also Bania, Calkins and Dalenberg (1992, pp. 218–219), for a similar approach]. As it turns out, our proxy variable is remarkably similar to the R&D expenditure variable used in Jaffe (1989), yielding a correlation of 0.91 for the 29 states common to both studies. Clearly, the use of lab 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.

Our data for university research expenditures [*U* in (1) and (2)] 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. Figure 2 shows the distribution of university research expenditures by county. A strikingly similar pattern exists between the distribution of innovations and university research. A high concentration of university research exists on the coast of California and in New England.

In addition, this data set also provides the source for three exogenous variables used in the estimation of equation (1) at the MSA level: total educational expenditure EDUEX from the City and County Data Book; a dummy variable for the overall academic quality of high technology departments at universities, RANK; and a proxy for size, the total enrollment at universities, ENRL. Note that these variables will be used as instruments in the 2SLS estimation of equations (2). As shown in Table 2 we match the sectoral aggregation of the two-digit SIC industries to university departments using the same approach as in Feldman (1994, p. 58).

In addition we also included a number of variables compiled from County Business Pattern data for 1982: high technology employment, HTEMP; 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. An alternative proxy for firm size is a dummy variable for the presence of at least 10 headquarters of Fortune 500 companies in an MSA, FORTU, compiled from the May 2, 1982 listing in *Fortune Magazine.* FORTU is included to test for the importance of headquarters in the location of R&D companies. Following general practice in the literature the first three variables are included to capture agglomeration economies [see also Feldman and Florida (1994)], the last two to assess the effect of firm scale [see also Acs, Audretsch and Feldman (1994a)].

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 (see Appendix A for a listing of the MSAs, innovation counts and research data by high technology area). Admittedly, this excludes from consideration the joint determination of "location" and "magnitude" of high technology innovation and research. On the other hand, it avoids the problem of "zeros", and is motivated by a focus on the strength of interaction between the two forms of research and the generation of innovations where these are present. We leave the more complex issue for future research.

3.2 Spatial Econometric Methodology

When models are estimated for cross-sectional data on neighboring spatial units, the lack of independence across these units (or, the presence of spatial autocorrelation) can cause serious problems of model misspecification when ignored [Anselin (1988)]. The methodology of spatial econometrics consists of testing for the potential presence of these misspecifications and of using the proper estimators for models that incorporate the spatial dependence explicitly.[1]

The two forms of spatial autocorrelation that are most relevant in applied empirical work are so-called substantive dependence, or dependence in the form of a spatially lagged dependent variable, and nuisance dependence, or dependence in the regression error term. The former can be expressed as:

$$y = rWy + Xb + e \qquad (4)$$

where y is a vector of observations on a dependent variable, Wy is a spatially lagged dependent variable for spatial weights matrix W, r is a spatial autoregressive coefficient, X is a matrix with observations on the explanatory variables with coefficients b, and e is an error term. The weights matrix W is typically constructed from information on contiguity between two spatial units, but more general definitions are used as well, leading to a large range of potential specifications. The resulting spatial lag Wy can be considered as a (spatial) weighted average of the observations at "neighboring" locations. Ignoring a spatially lagged dependent variable yields inconsistent and biased estimates for the b coefficients in the model. The second form of spatial dependence is often expressed as a spatial autoregressive process for the error term in a regression model, or:

$$y = Xb + e \qquad (5)$$

with:

$$e = lWe + i \qquad (6)$$

where l is a spatial autoregressive coefficient and i is a standard spherical error term. Ignoring spatial dependence in the error term does not lead to biased least squares estimates, but the estimate of their variance will be biased, yielding misleading inference [for further discussion, see, among others, Anselin (1988, 1990), and Anselin and Hudak (1992)].

In this paper the procedure is to estimate b by regressing y on X, and then to test separately for r = 0 and l = 0 using LM tests. We will test each estimated model for potential spatial autocorrelation by means of Lagrange Multiplier (LM) or score tests. These are ideally suited to aid in the model specification search [for recent evidence, see Anselin et al. (1996)]. The LM test for spatial error dependence is:

$$LM_{ERR} = [N.e'We/e'e]^2 / tr[W'W + W^2] \qquad (7)$$

where e is a vector of ordinary least squares (OLS) residuals, tr is the matrix trace operator, and the other notation is as before. This statistic is asymptotically distributed as c^2 with 1 degree of freedom. The LM test for spatial lag dependence is:

$$LM_{LAG} = [N.e'Wy/e'e]^2 / \{N.(WXb)'MWXb/e'e + tr[W'W + W^2]\} \quad (8)$$

where $M = I - X(X'X)^{-1}X'$, b is the vector of OLS estimates, and WXb is a vector of spatially lagged predicted values. This statistic is also asymptotically c^2 with 1 degree of freedom [for implementation details and properties, see, Anselin and Hudak (1992), Anselin et al. (1996)].

If a form of spatial dependence is detected, the model with the proper alternative is estimated by means of maximum likelihood procedures or robust instrumental variables procedures. All estimations and spatial diagnostics in this paper were carried out by means of the SpaceStat software for spatial data analysis [Anselin (1992, 1995)].

4. Local Disaggregated Geographic Spillovers at the MSA Level

4.1 Spatially lagged variables

The use of R&D lab employment as a proxy for private R&D activity allows us to carry out an analysis of the geographic knowledge production function at the MSA level. We constructed a data base for 125 MSAs in the U.S. for which some innovative and research activity was present (see Appendix A for a listing). Given the indication of a wider range of spatial interaction than purely within-county between university and private R&D, we constructed two new variables that we refer to as *spatial lags* (see Anselin, Varga, and Acs, forthcoming). These variables are designed to capture the effect of respectively university research and private R&D in counties surrounding the MSA, within a given distance band from the geographic center of the MSA. Specifically, for any MSA *i*, the spatial lags $URDCOV50_i$ and $RDCOV50_i$ are the sums of respectively university research and private R&D in the MSA and those counties surrounding the MSA whose geographic centers are within 50 miles of the geographic center of the core MSA county. Similar measures were computed for a 75 mile range as well (URDCOV75, RDCOV75).

Note that since the analysis is carried out at the scale at which we assume that the spatial interaction takes place (MSA and possibly its surrounding counties), there is no need to create an artificial index of geographic coincidence, as is the case at the state level. In fact, by explicitly including both the research magnitude for the MSA as well as for surrounding counties, we are able to get a much more precise insight into the degree of "local" geographic spillovers.

4.2 Estimation issues

Our model consists of two equations, the knowledge production function for K (1), and an industry research equation, R (2). The knowledge production function contains both R and U as explanatory variables and will be extended with the two spatial lag variables, RDCOV50 (or RDCOV75) and URDCOV50 (or URDCOV75). Both R and U equations contain the other as explanatory variable, as well as the spatial lags. The form of this system of equations raises a number of issues with respect to estimation and identification.

First, while the system is recursive between K and R and U, the exogeneity of the latter two in the knowledge production function should not be taken on faith. In fact, misspecifications (e.g., errors in variables) could easily lead to endogeneity and must be checked. We address this by means of the Durbin-Wu-Hausman test for exogeneity [e.g., Davidson and MacKinnon (1993, pp. 237-242)]. We also take this approach to test the extent to which R and U are endogenous to each other in equation (2).

Secondly, even in a purely recursive system, ordinary least squares estimation of the knowledge production function would only be legitimate in the absence of inter-equation correlation, i.e., correlation between the error terms of the equations [e.g., Greene (1993) p. 600]. We check this by means of a Lagrange Multiplier test on the diagonality of the error covariance matrix for the least squares residuals [Breusch and Pagan (1980)].

In the absence of endogeneity and cross-equation correlation, we may proceed with an equation-by-equation estimation by means of OLS (or 2SLS in case of endogeneity without cross-equation correlation) and the commonly applied three stage least squares (3SLS) procedure is unnecessary.

Finally, the use of a cross-sectional sample potentially leads to spatial autocorrelation in the regression equations. We assess this by means of a Lagrange Multiplier test for spatial error dependence using three spatial weights based on distance: the same 50 and 75 mile cut-offs as used in the construction of the lag variables, and a squared inverse distance weights matrix. These tests are only valid when the explanatory variables in the regression are exogenous and should be interpreted with caution when this is not the case. They are used here to assess the extent to which remaining unspecified spatial spillover may be present, even after the inclusion of the spatial lags (provided that the latter are exogenous, which turns out to be the case in our study).

4.3 Empirical results

Table 3 presents the results of the estimation of OLS cross section regressions for the four high technology sectors at the MSA level in 1982. All variables are in logarithms. We estimate a standard Jaffe knowledge production function with spatial lags for university and industrial R&D, and local economic characteristics as explanatory variables as well.

Most regressions yield significant and positive coefficients for both private R&D and university research (at $p<0.05$), confirming the consensus result in the literature (only the most significant of respectively RD, RDCOV50, RDCOV75, URD, URDCOV50 and URDCOV75 are reported). However, there are variations across industries. Industrial R&D was significant for all four sectors; however, lagged industrial R&D was insignificant, indicating that industrial R&D spills over only within the MSA. University research was positive and significant for only electronics and instruments.

All three local economic variables are highly significant (with $p<0.01$) and have the expected sign. Concentration of business activity (measured by LQ) has a significant effect on innovation in the Instruments and Electronics industries. Innovative activity depends on the presence of business services (BUS) in all sectors but the Chemical industry and is negative for the presence of large firms (LARGE). However, in three out of four cases (Chemicals, Electronics and Instruments) the coefficient was insignificant. Note that the negative sign for the presence of large companies confirms earlier evidence in Acs, Audretsch and Feldman (1994, 338) that smaller firms tend to be more innovative in only the Machinery industry. In other words, *ceteris paribus*, MSAs dominated by the presence of large firms tend to show less innovative activity.

A fourth variable is added to correct for potential unmeasured "quality" effects that may cause inter-equation correlation. Following Jaffe (1989), a fourth variable rank (RANK) is added to equations 2 and 4 to correct for potential unmeasured "quality" effects that may cause inter-equation correlations. There is evidence of heteroskedasticity in only one sector (Instruments), but there is strong evidence of misspecification in the form of a spatial lag (at $p<0.01$) in Machinery and of spatial error (at $p<0.05$) in Electronics.

We further tested the exogeneity of each of the four variables RD, URD, URDCOV50, and URDCOV75, using the Durbin-Wu-Hausman test for a two stage least squares estimation with Log(EMP), Log(ENRL), LOG(EDEXP), and FORTUNE as instruments. We failed to reject the null hypothesis for each (none achieved a p value less than 0.12). In other words, there was no evidence against exogeneity of these variables. By and large these results are consistent with aggregate results at the MSA level found in Anselin, Varga and Acs (1996).

Table 4 presents revised regression results for all four sectors corrected for spatial dependence and heteroskedasticity. Regression (1) shows OLS regression results for the Chemical sector. While industrial R&D spills over only within the MSA, the positive coefficient for lagged university research (URDCOV50) is insignificant. Local spillovers from university research were not significant. Equation (2) shows the regression results of a spatial lag model for Machinery. While the spatial lag has been eliminated the coefficient for industrial R&D and university research remain positive although insignificant. These results are broadly consistent with Jaffe (1989) and Acs, Audretsch and Feldman (1992) that there are no local spillovers in the Mechanical Arts sector.

The spatial error model in equation (3) shows regression results for the electronics industry. With the exception of Log(Large) all signs are as expected and significant at least at the (at $p < 0.05$) level. The coefficient for industrial R&D and lagged university research

(URDCOV75) are both about the same magnitude. This is consistent with Acs, Audretsch and Feldman (1994) and inconsistent with Jaffe (1989) who found the elasticity of industrial research to be about twice as large as university research. While we find strong research spillovers in electronics from both within the MSA and from up to 75 miles around the MSA, Jaffe (1989) and Acs Audretsch and Feldman (1992) found no such spillovers. This is due to significant spatial error autocorrelation at the state level.

The results in Table 4 can thus be reliably interpreted to indicate the strong influence of university research in the Electronics and Instruments industries in an MSA, not only of university research in the MSA itself, but in the surrounding counties. By contrast, the effect of private R&D seems to be contained within the MSA itself. Of course, private and university R&D are not independent, and we turn to their interaction/simultaneity in Table 5.

Following Jaffe (1989), we estimate one additional model that explicitly incorporates the potential simultaneity between the private R&D equation (2) in which, in addition to university research, the spatial lag for university research is included, as well as the log of the high technology employment (HTEMP), the FORTUNE dummy and the RANK measure as exogenous variables (the latter to control for potential quality effects). Strong significance of the Durbin-Wu-Hausman test for Chemicals ($p=0.01$), and its marginal significance for Instruments ($p=0.16$) suggest that 2SLS is the appropriate estimation method for these two equations. University enrollment (ENRL) and education expenditures (EDEX) were used as instruments in the specifications reported in columns 1 and 4 of Table 5.

Focusing on the results in Table 5 we find a strong positive and significant effect of university research on private R&D ($p < 0.05$) within the MSA for Chemicals and Instruments, and of spillovers from up to 50 miles for Electronics and Instruments.

5. Conclusions

In this paper, we have been able to shed additional light on the issue of *local* geographic spillovers between university research and high technology innovations. 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." We approached this issue from an explicit spatial econometric perspective and implement the classic Griliches-Jaffe knowledge production framework for high technology innovations in 125 MSAs for four technical areas. The latter became possible by using a specially compiled set of data on R&D laboratory employment. This yielded more precise insight into the range of spatial externalities between innovation and R&D in the MSA and university research both within the MSA and in surrounding counties.

Overall, we confirmed the positive and significant relationship between university research and innovative activity, both directly, as well as indirectly through its impact on private sector R&D. We found that the spillovers of university research on innovation extended over a range of 75 miles from the innovating MSA, and over a range of 50 miles with respect to private R&D.

Our findings are important in that they highlight the relevance of a precise consideration of the spatial range of interaction in the analysis of spatial externalities. However, some cautionary remarks are in order as well. Our analysis is limited by the use of a single cross-section. Unfortunately, there is currently no update of the 1982 U.S. SBA innovation data base for later points in time, precluding a more extensive analysis of the space-time dynamics. Also, we have elected to focus on studying the relations between research and innovations in those locations for which both were observed. This leaves aside the issue of why certain locations have research and innovative activity and others do not, especially when one of the two is present, but the other is not. We leave this aspect of the study for a separate paper.

Notes

1. A more extensive treatment of spatial regression models can be found in, among others, Paelinck and Klaassen (1979), Cliff and Ord (1981), Ripley (1981), Upton and Fingleton (1985), Anselin (1988), Haining (1990) and Cressie (1993). For a recent overview from an econometric perspective, see Anselin and Florax (1995) and Anselin and Bera (1997).

FIGURES AND TABLES

FIGURE 1:

INNOVATIONS

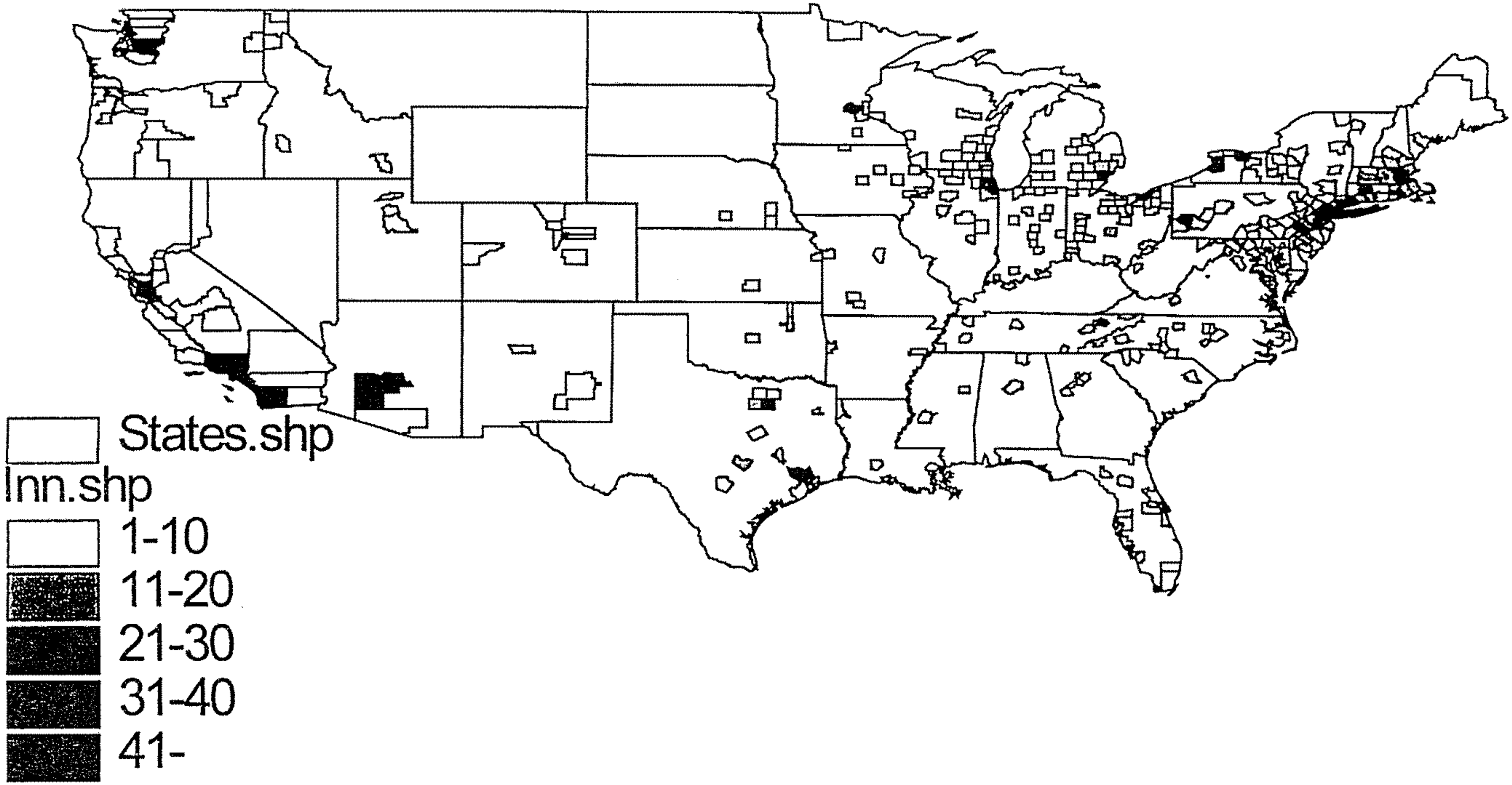

FIGURE 2:

UNIVERSITY RESEARCH

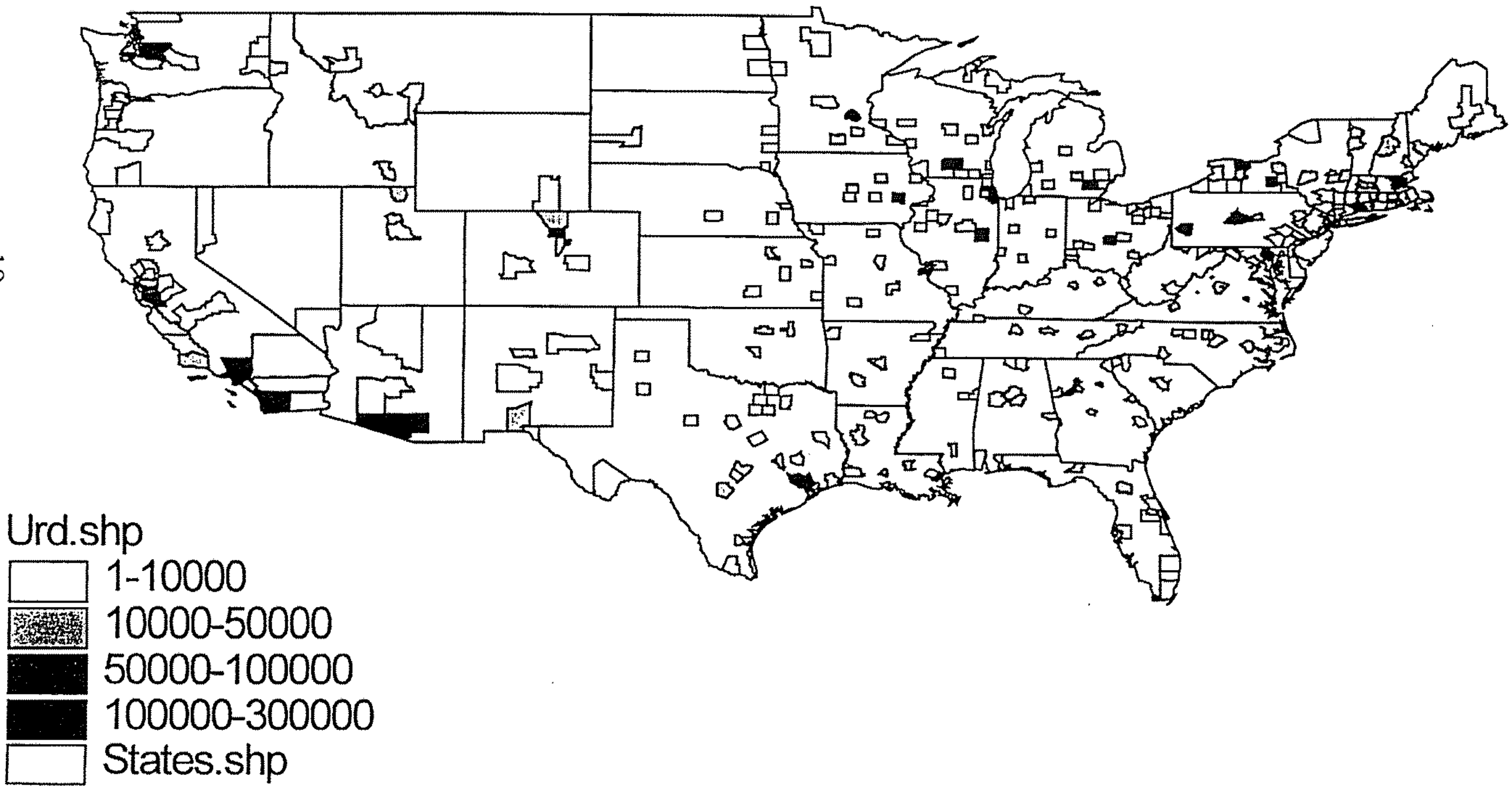

Table 1. Research Design Characteristics in Recent Studies

Characteristic	Jaffe	AAF-92	AAF-94	FF
space	29 U.S. states	29 U.S. states	29 U.S. states	29 U.S. states
time	8 years (72–77, 79, 81)	1982	1982	1982
sectors	pooled + 4	pooled + 2	pooled	pooled
coincidence index	log U x log C (C centered)	log U x log C (C centered)	log U x log C (C uncentered)	C (share of state manufacturing shipments by largest MSA)
auxiliary variables	population	population	• population	related industry presence industry sales • business services population
estimation	OLS/3SLS	OLS	tobit	3SLS
zeros	log(y) = -1	dropped	included	log (10(y+1))
spatial diagnostics	none	none	none	Durbin-Watson

TABLE 2. Linking Industries to University Departments*

Industry	**University Department**
SIC28: Chemicals	Medicine, Biology, Chemistry and Chemical Engineering
SIC35: Industrial Machinery	Electrical Engineering, Astronomy, Physics, Computer Science, Mechanical Engineering and other engineering and physical sciences
SIC36: Electronics	Electrical Engineering, Astronomy, Mathematics and Computer Science
SIC37: Transportation Equipments	Mechanical Engineering, Physics, Aeronautical Engineering, Computer Science
SIC38: Instruments	Medicine, Biology, Electrical Engineering, Astronomy, Physics, Computer Science, Mechanical Engineering and other engineering and physical sciences

***Source**: Feldman (1994)

Table 3. Industry Detailed Regression Results for Log(Innovations) at the MSA-Level (1982) - OLS Results

Model	Log(INN28)	Log(INN35)	Log(INN36)	LOG(INN38)
CONSTANT	-1.796 (0.438)	-2.041 (0.275)	-2.620 (0.437)	-1.850 (0.600)
Log(RD)	0.322 (0.126)	0.081 (0.047)	0.133 (0.064)	0.190 (0.071)
Log(URD)		-0.013 (0.035)		
Log(URDCOV50)	0.0361 (0.028)			
Log(URDCOV75)			0.165 (0.063)	0.256 (0.112)
Log(LQ)	0.275 (0.157)	0.591 (0.156)	0.400 (0.153)	0.157 (0.134)
Log(BUS)	0.191 (0.126)	0.632 (0.080)	0.545 (0.097)	0.212 (0.065)
Log(LARGE)	0.077 (0.114)	-0.254 (0.097)	-0.087 (0.097)	0.008 (0.080)
RANK		0.337 (0.104)		0.237 (0.125)
R^2-adj	0.423	0.673	0.654	0.538
N	48	89	70	63
White	16.193	28.130	21.150	41.388
LM-Err	0.583 (IDIS2)	2.338 (IDIS2)	5.908 (D50)	0.425 (IDIS2)
LM-Lag	1.553 (IDIS2)	10.459 (D50)	2.620 (IDIS2)	1.105 (D50)

Notes: Estimated standard errors are in parentheses; critical values for the White statistic with respectively 5, 20 and 35 degrees of freedom are 11.07, 31.41 and 49.52 ($p = 0.05$); critical values for LM-Lag and LM-Err statistics are 3.84 ($p = 0.05$) and 2.71 ($p = 0.10$); spatial weights matrices are row-standardized: D50 is a distance-based contiguity for 50 miles; D75 is a distance-based contiguity for 75 miles; IDIS2 is inverse distance squared; only the highest values for a spatial diagnostic are reported.

Table 4. Industry Detailed Regression Results for Log(Innovations) at the MSA-Level (1982)

Model	Log(INN28) OLS	Log(INN35) IV Spatial Lag	Log(INN36) ML Spatial Error	LOG(INN38) OLS Robust
CONSTANT	-1.796 (0.438)	-2.12 (0.261)	-2.55 (0.414)	-1.850 (1.883)
Log(RD)	0.322 (0.126)	0.029 (0.048)	0.132 (0.058)	0.190 (0.095)
Log(URD)		0.002 (0.034)		
Log(URDCOV50)	0.0361 (0.028)			
Log(URDCOV75)			0.164 (0.065)	0.256 (0.122)
Log(LQ)	0.275 (0.157)	0.612 (0.147)	0.420 (0.136)	0.157 (0.132)
Log(BUS)	0.191 (0.126)	0.649 (0.075)	0.534 (0.087)	0.212 (0.410)
Log(LARGE)	0.077 (0.114)	-0.239 (0.091)	-0.086 (0.085)	0.008 (0.097)
RANK		0.255 (0.102)		0.237 (0.181)
W_Log(INN)		0.199 (0.073) (D50)		
λ			0.303 (0.13) (D50)	
R^2-adj	0.423	0.720	0.670	0.538
N	48	89	70	63
White	16.193			
LR-Err			5.190 (D50)	
LM-Err	0.583 (IDIS2)			
LM-Lag	1.553 (IDIS2)		2.197 (IDIS2)	

Notes: Estimated standard errors are in parentheses; critical values for the White statistic with respectively 5, 20 and 35 degrees of freedom are 11.07, 31.41 and 49.52 (p = 0.05); critical values for LM-Lag and LM-Err statistics are 3.84 (p = 0.05) and 2.71 (p = 0.10); critical value for LR-Err statistic with one degree of freedom is 3.84 (p=0.05); spatial weights matrices are row-standardized: D50 is a distance-based contiguity for 50 miles; IDIS2 is inverse distance squared; only the highest values for a spatial diagnostic are reported.

Table 5. Industry Detailed Regression Results for Log(Private Research) at the MSA-Level (1982)

Model	Log(RD28) 2SLS	Log(RD35) OLS	Log(RD36) OLS	Log(RD38) 2SLS
Constant	1.197 (0.506)	-1.930 (0.621)	-1.677 (0.682)	-0.173 (0.891)
Log(URD)	0.240 (0.068)			0.283 (0.151)
Log(URDCOV50)		0.440 (0.091)	0.280 (0.105)	
Log (EMP)	0.233 (0.129)	0.617 (0.152)	0.732 (0.156)	0.310 (0.172)
FORTU	0.387 (0.161)	0.520 (0.254)	0.358 (0.210)	0.372 (0.254)
RANK		-0.128 (0.227)		-0.059 (0.267)
R^2-adj	0.637	0.491	0.453	0.394
N	48	89	70	63
White		8.674	7.597	
LM-Err		0.960 (D75)	0.735 (D75)	
LM-Lag		0.731 (IDIS2)	0.664 (IDIS2)	

Notes: Estimated standard errors are in parentheses; critical values for the White statistic with respectively 5, 20 and 35 degrees of freedom are 11.07, 31.41 and 49.52 ($p = 0.05$); critical values for LM-Lag and LM-Err statistics are 3.84 ($p = 0.05$) and 2.71 ($p = 0.10$); spatial weights matrices are row-standardized: D50 is a distance-based contiguity for 50 miles; D75 is a distance-based contiguity for 75 miles; IDIS2 is inverse distance squared; only the highest values for a spatial diagnostic are reported. Log (URD) is considered endogenous in the Chemicals and Instruments research equations. Instruments in 2SLS estimations are Log(ENRL) and Log(EDEX).

APPENDIX A
Innovation, Private R&D and University Research for 125 MSAs (1982)

MSA	INN28	INN35	INN36	INN38	RD28	RD35	RD36	RD38	URD28	URD35	URD36	URD38
Akron	2	4		1	1001	1507	1500	1500	1824	2355	937	3584
Albany-Schenectady-Troy		1			1288	1158	557		18242	14460	6181	28226
Albuquerque			1		40	113	141	41	15865	9964	2294	25380
Allentown-Bethlehem-Easton	2	3		2	930	730	678		2953	5926	1164	6237
Anaheim-Santa Ana-Garden	2	48	24	31	1688	863	729	86	22917	8061	6457	29037
Ann Arbor	1	2	2	2	825	516	105	300	62110	20856	11618	79533
Asheville				1	10							
Atlanta	2	9	6	9	339	181	125	21	26688	41457	27318	59344
Austin	1	4	4	3	876	757	176	149	17225	25604	22496	35458
Baltimore	1	7	1	3	1317	615	332	723	82816	5406	3665	85040
Bay City		1										
Bellingham				1	27		51		91	164	0	241
Benton Harbor		1			279	49		39	16	3	3	16
Binghamton N.Y.-Pa.		1	1		107		45		2471	326	517	2030
Birmingham		1			643				35019	50	93	35042
Bloomington-Normal		1		1	15		1		351	2	5	201
Boise City		1	1		17							
Boston	19	88	60	114	6414	6907	5497	7860	183096	127736	88683	284713
Bridgeport	6	31	15	12	2243	745	770	223	1	13	13	14
Bryan-College Station		2			17	20			15328	22521	3849	31021
Buffalo	3	8	3	10	2218	584	40	962	22008	3248	2551	22256
Burlington		3					25	16	13422	463	462	13308
Canton	1	3			510	737	188	106				
Cedar Rapids		1		2		155	160	5				
Champaign-Urbana-Rantoul		1		1					18703	34881	18935	46273
Charleston				1	840		6	8				
Charlotte-Gastonia		4	1	1	122	55	14	25	135	446	123	526
Chicago	17	70	25	50	11971	4559	4654	1655	118050	25607	20312	131808
Cincinnati Ohio-Ky.-Ind.	1	8	2	2	794	192	405	6	24977	1305	1093	24607
Cleveland	4	20	14	15	3726	1493	1475	359	30182	12467	3753	39378
Colorado Springs		4	1	1	46	511	187		36	11	5	20
Columbia		1			62	11	62		19655	3546	686	22790
Columbus	6	1	3	10	1058	1405	684	470	34465	16575	7280	47629
Cumberland Md.-W. Va.		2			217							
Dallas-Fort	4	42	24	5	589	740	257	420	41018	5592	5270	44541
Davenport-Rock Island-Moline		3		2	9	4271	136	128	2	1	1	2
Dayton		2	2	7	933	1269	230	89	5671	12883	5901	16933
Daytona BEACH				1		97	81		0	31	31	31
Denver-Boulder		16	5	5	1967	1808	837	62	42540	22081	16825	57588
Detroit	1	17	4	10	4280	2943	2300	730	17714	3713	1642	17955
Dubuque		1							5	1	1	6
El Paso			3	4	4		1156		620	214	168	697
Elkhart			1				71					
Erie		2	1	2	209	89	170	16				
Evansville Ind.-Ky.	1	1	1		170		144	343				
Flint			1		52	1028	52					
Florence		1										
Fort Collins			2	4	83				15640	5733	3583	18894
Fort Lauderdale-Hollywood		5	3	1	100	1	181	3	90	9	9	99
Fort Myers-Cape Coral		2		1			4					
Fort Smith Ark.-Okla.			2			12	44					
Fresno					48				234	42	42	201
Gainesville		1			154	4			30857	12848	4260	40637
Galveston-Texas				2	6		93	93	11882	0	0	11882
Glens FALLS		1			153							
Grand Rapids	1	3			207	12	149		14	7	2	20
Greensboro-Winston-Salem		1		4	976	34		9	9028	129	128	9093
Greenville-Spartanburg	1	3	2	3	466	18	10	12	3948	4736	1201	7821
Hamilton-Middletown		1	2	1	25	26			614	80	69	349
Harrisburg		1	3		75	33	85					
Hartford	3	10	4	9	519	211	1249	113	44948	7012	4306	47316
Houston	11	2	3	13	1865	1182	113	31	109045	9351	9835	113496
Huntsville		2		1	14	8	411	500	278	1565	1148	1729
Indianapolis	2	4	4	2	347	337	355	21				

Innovation, Private R&D and University Research for 125 MSAs (1982) (Continued)

MSA	INN28	INN35	INN36	INN38	RD28	RD35	RD36	RD38	URD28	URD35	URD36	URD38
Jackson				2								
Jackson		1	2									
Janesville-Beloit			2		48	143	36	16	23	26	26	45
Jersey City	1	4	4	2	561	146	68	85	240	4100	422	4100
Johnson City-Kingsport-Bristol	2				725				704	2	32	702
Kalamazoo-Portage	4				943		2	7	101	23	34	87
Kansas CITY	2	6	2	2	1112	142	188	39	758	195	198	735
Kenosha			1						118	0	0	3
Knoxville			1		113	243	243		24261	5694	3323	21756
La Crosse		2	2	1					237	24	31	233
Lafayette-West Lafayette		1			96	15	13	23	22604	20596	8900	37674
Lancaster		2		2	636	58			47	22	22	38
Lansing-East		1			30		13	7	22773	12772	3592	32822
Lima		2		1	20							
Lincoln				2	121			27	8358	4726	2107	9786
Long Branch-Asbury Park	3	3	2	1	308	181	159	40				
Longview-Marshall		1			149		39					
Lorain-Elyria			1	1	184	9	20		52	23	23	59
Los Angeles-Long Beach	5	71	39	42	5385	3374	5504	2250	134246	60621	49860	176223
Louisville		4	2		364	18	50		4550	442	263	4603
Madison		2		2	516	147	133	126	78529	25652	16721	97845
Manchester		15		4	216		109	6				
Mansfield		2				9	6					
Melbourne-Titusville-Cocoa		4	6	1		66	32		651	128	21	779
Memphis Tenn.-Ark.-Miss.		1		2	122				376	406	208	733
Miami	2	1		1	122	34	18	37	31408	1228	332	32456
Milwaukee	1	12	6	12	1124	668	706	334	16357	2359	1214	17709
Minneapolis-St.	4	39	13	24	6406	811	5333	107	87247	13534	7793	94204
Nashville-Davidson		1		4	44	54	65		19036	1522	1180	19743
Nassau-Suffolk	2	34	32	51	662	777	1378	560	19970	11203	9125	28344
New Bedford		1	2	3	21		65	9	225	335	344	428
New Brunswick-Perth Amboy-	9	4	6	11	2023	187	229	104	11940	7149	6224	17232
New Haven-West Haven		4	5	10	1396	150	121	51	72372	11044	9231	79432
New London-Norwich		1			867	719	89	33	43	106	85	133
New Orleans		1			139	181			13086	1120	651	13691
New York N.Y.-N.J.	33	79	44	65	7132	3879	1913	1573	252798	26625	22618	267859
Essex county	42	36	19	46	8119	17553	18171	658	16956	536	455	16720
Newburgh-Middletown		2		1	50		8	266	81	125	89	125
Newport News-Hampton		1		1	306				368	1308	1308	1395
Norfolk-Virginia Beach				1	60	71		5	1207	1531	905	2554
Northeast		1	1		11	10			7	63	63	70
Oklahoma City				1	204	40	40		13657	5256	5228	15694
Orlando		3	2		64	439	396	347	423	4194	521	4432
Owensboro			2									
Oxnard-Simi Valley-Ventura	1	12	8		67	20	62					
Parkersburg-Marietta	1	1		1	250							
Paterson-Clifton-Passaic	6	13	1	5	2953	87	92	8	213	1	13	213
Peoria			1			27			18	128	94	146
Philadelphia Pa.-N.J.	20	57	10	51	8340	6204	7323	5215	114921	18107	13044	127315
Phoenix		5	15	9	586	1683	825	812	4375	3332	1875	4469
Pittsburgh	2	14	9	13	3709	1732	50	279	39564	27028	20959	60246
Pittsfield	1				14				167	164	187	285
Portland			1		257	28	6		463	0	0	64
Portland Oreg.-Wash.		10	6	6	230	6	55		18711	2023	1344	19596
Portsmouth-Dover-Rochester		3	2		12	57	45		1528	3885	3106	5139
Providence-Warwick	3	6	5	1	407	45	94		10799	9216	6315	17795
Provo-Orem		3				278	3		2869	543	317	1178
Racine		2		3	528	732	102	59				
Raleigh-Durham	4		4		1947	43	301	119	85966	13256	9676	92696
Reading	1				176	24	207		3	120	120	121
Reno		1			11	4	4	8	2682	544	147	2748
Riverside-San Bernardino		3	3	6	67	24	7	10	7100	1650	2391	8390
Rochester		7	9	16	4160	333	267	2060	43474	17095	7341	57081
Rockford		6	2	1	34	36	22					
Sacramento		5	2		193	14	33	56	29398	3084	1810	30559
Saginaw		1		1	45	299						

Innovation, Private R&D and University Research for 125 MSAs (1982) (Continued)

MSA	INN28	INN35	INN36	INN38	RD28	RD35	RD36	RD38	URD28	URD35	URD36	URD38
St. LUIS	3	6		4	2560	336	91		61313	7597	6525	67615
Salem		1			44				0	20	20	20
Salinas-Seaside-Monterey			1	4					509	2409	2074	2421
Salt LAKE		6	2	2	600	279	778	58	29553	10805	4552	36642
San Antonio		3			1666	19			19521	18	17	19497
San Diego	1	16	18	20	1085	3303	825	289	60590	18534	15698	74753
San Francisco-Oakland	1	41	19	14	4152	1335	2362	391	123392	28501	16722	145459
San Jose	3	173	151	47	2615	3134	5646	200	65686	55560	31134	111400
Santa Barbara-Santa Maria		1	3	5	584	1197	1330	546	3868	5620	4885	7249
Santa Cruz		2					30		2723	4236	4445	6331
Santa Rosa		4	2		67	2	72	16				
Sarasota		2					20					
Seattle-Everett		15	13	4	357	201	426	287	73050	10254	8589	80057
Sheboygan			1		4							
Shreveport			1	1	84	81						
South Bend		2	1	2	163	124	3		6505	4113	1529	5766
Spokane		3			9		2		226	4	4	230
Springfield		3			22	109			0	18	19	18
Springfield-Chicopee-Holyoke	1		1	1	426	7	12	4	21698	7435	6058	23461
Stockton		1		1	10				645	3	3	646
Syracuse		5	1	3	918	223	97	68	25385	6205	3534	25559
Tacoma		2			269	35			20	56	56	69
Tampa-St.		3	4	4	634	7	284	27	3738	999	628	4256
Toledo Ohio-Mich.		2	2	2	540	244	236	55	6053	647	417	6248
Trenton	1	11	6	11	1685	1101	625	78	8774	9243	10660	13967
Tucson		4	4	1	93	5	118	15	30022	23149	15511	51188
Tulsa		4	3	5	85	4			99	1200	271	1200
Utica-Rome		2		1	29	57		12				
Vineland-Millville-Bridgeton				3	40		6	82				
Visalia-Tulare-Porterville												
Waco		1		2	34	3			348	15	15	62
WASHINGTON DC	1	9	6	5	1529	2883	2651	622	29386	5124	5444	32511
Waterloo-Cedar Falls		1			14				5	0	0	5
Wichita		3	1		232	11	11	75	74	392	281	412
Williamsport		1			23	5						
Wilmington Del.-N.J.-Md.	4	2	2	3	6338	211	305	126	3990	2643	1277	3547
Worcester	3	10	3	1	607	194	247	164	1764	2809	500	3302
York		3	3		50	415						
Youngstown-Warren		1			50	4	115	18	65	0	1	18

Sources: compiled from U.S. SBA Innovation Data Base; compiled from R.R. Bowker Company Directories; compiled from NSF Survey of Scientific and Engineering Expenditures at Universities and Colleges

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