LOCAL ACADEMIC KNOWLEDGE SPILLOVERS AND THE CONCENTRATION OF ECONOMIC ACTIVITY

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ABSTRACT

Agglomeration effects on the intensity of local knowledge spillovers from universities to high technology innovations are examined within the modified Griliches-Jaffe knowledge production function framework. Estimations are carried out at the level of US metropolitan areas. Concentration of high technology employment turns out to be the most important factor promoting local academic knowledge spillovers. It is found that a "critical mass" of agglomeration needs to be reached in order to expect substantial local economic effects of academic research spending. (*JEL* O31, H41, O40)

Local Academic Knowledge Spillovers and the Concentration of Economic Activity

The phenomenon of economic growth supported by academic institutions in such prominent high technology concentrations as Silicon Valley and Route 128 in the US, and Cambridge in the UK[1] has focused research on the extent to which spatial proximity of research universities can generate positive externalities for regional production. It seems certainly plausible, that geographic proximity of an academic institution to a knowledge intensive industry can be the source of positive knowledge externalities. Among other means, personal networks of academic and industrial researchers, university spin-off firms and fresh graduates may be important channels for disseminating the latest knowledge from academia to the local high technology industry.

The first formal indication of positive university research impacts on firm performance was published in Richard Nelson (1986). Since this effort, evidence of knowledge transfers from universities has been growing in the relevant literature. Applying the knowledge production function framework of Zvi Griliches (1979, 1986), Adam Jaffe (1989) found strong and very significant university research effects on corporate patenting activity at the level of US states. State level knowledge spillovers between university research and product innovations were evidenced in Zoltan Acs et al. (1991, 1994), Maryann Feldman (1994a) and David Audretsch and Feldman (1996). Studying the paths of patent citations, Jaffe et al. (1993) observed that citations to university patents are localized around the patent issuing academic institutions. Based on a survey of industrial researchers, Edwin Mansfield (1991, 1995) indicated that for applied industrial research, geographic proximity plays a vital role in transmitting new technological knowledge from universities. Luc Anselin et al. (1997a, 1997b) found a highly significant association between university research and high technology innovations at the metropolitan area level. In addition, they provided evidence that local university knowledge spillovers follow a strong distance decay pattern.

Increasing understanding of the nature of local academic knowledge spillovers provides an important empirical support for both the theory of endogenous economic growth (e.g., Paul Romer, 1986, 1990 and Robert Lucas, 1988) and regional economic policy makers. However, it is very likely that geographic proximity might not be a sufficient condition of meaningful university technology transfers. Several observations support this hypothesis. For example, Acs, Lanny Herron and Harry Sapienza (1992) and Feldman (1994b) point to case of Johns Hopkins University and Baltimore. Despite that Johns Hopkins is the largest recipient of federal research funds, no significant high technology concentration has emerged in the Baltimore area. Feldman (1994b) suggests that the absence of a "critical mass" of high technology enterprises, the lack of producer services, venture capital and entrepreneurial culture may explain this apparent dissonance in local spillover effect. Similarly, based on data in the early 1980s, while roughly equal in terms of research activity, Cornell University ($110 million in 1982) and Stanford University ($130 million in 1982) were situated in completely different regional innovative complexes: only 2 innovations were recorded for the production sector in Ithaca, versus 374 in the San Jose region.

Increasing returns resulted from spatial concentration of economic activities were observed by Alfred Marshall (1920) and re-introduced into economics by Paul Krugman (1991a 1991b). The cases of Johns Hopkins and Cornell suggest that agglomeration might also have a crucial role in the process of academic knowledge spillovers. It could be possible that, as a consequence of agglomeration economies, the same university R&D expenditure results in a higher level of

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[1] For detailed descriptions see Nancy Dorfman, 1983, Anna Saxenian, 1983, 1985, 1994, Everett Rogers and Judith Larsen, 1984, and Segal Wicksteed, 1985.

innovative activity in large metropolitan areas than in smaller cities. An agglomeration effect on academic knowledge spillovers was suspected in Neil Bania et al. (1993) and Audretsch and Paula Stephan (1996), but no formal evidence of it has yet been provided in the literature.

This paper presents the first attempt to model and demonstrate the effect of agglomeration on academic knowledge spillovers. Applying a unique data set of innovation counts and private research laboratory employment, an MSA level analysis is carried out within the modified Griliches-Jaffe knowledge production framework. Section I presents the empirical model. Section II introduces the data and discusses some important estimation issues. Section III reports the regression results. Section IV suggests a measure for the "critical mass" effect and illustrates this for the applied data. Concluding remarks follow.

I. The Empirical Model

The various mechanisms of local university knowledge transfers have been widely discussed in the literature (e.g., National Science Board, 1983, Dorfman, 1983, Lynn Johnson, 1984, Rogers and Larsen, 1984, Wicksteed, 1985, Douglas Parker and David Zilberman, 1993, Saxenian, 1994). In order to model the effect of agglomeration on local university knowledge spillovers, knowledge transfer mechanisms are classified into three categories: information transmission via the local *personal networks* of university and industry professionals (local labor market of graduates, faculty consulting, university seminars, conferences, student internships, local professional associations, continuing education of employees), technology transfers through *formal* business relations (university spin-off companies, technology licensing), and spillovers promoted by university *physical facilities* (libraries, science laboratories, computer facilities).

It is presupposed that the amount of technological information transmitted to the local high technology industry from the available pool of knowledge at academic institutions is controlled to a large extent by agglomeration. *Concentration of high technology production* is assumed to intensify information flows through the personal networks of university and industry professionals (for example, it increases local demand for faculty consulting services and raises the probability that graduates get jobs in the proximity of universities). Professional assistance from local *business services* (e.g., financial, legal, marketing services) enlarges knowledge spillovers by facilitating faculty spin-offs and technology licensing from academic institutions. In general, relative to large companies, small firms are less endowed with research facilities. It is a major reason why small businesses rely more on university knowledge transfers (Albert Link and John Rees, 1990, Acs et al., 1994). Consequently, it is expected that *small firm concentration* enhances local university technology spillovers.

Based on the above considerations, an empirical model of the effect of agglomeration on local academic knowledge spillovers can be formulated by relating university technology transfers to the concentration of high technology production, business services, and small firms. A major obstacle of testing this model empirically is the lack of a comprehensive measure of academic knowledge spillovers. Technology transfers from academic institutions might be captured by university patent citations (as was done in Jaffe et al., 1993), by the number of graduates finding jobs in the area, or by counts of local faculty spin-off firms, but these variables cover local academic knowledge spillovers only partially.

To empirically account for the effect of concentration of economic activities on university knowledge transfers, an implicit measure of knowledge spillovers is proposed. The Griliches-Jaffe knowledge production function (Zwi Griliches, 1979, Jaffe, 1989) offers this implicit measure. The knowledge production function has the form of:

(1) $\log (K) = \alpha_0 + \alpha_1 \log (RD) + \alpha_2 \log (URD) + \varepsilon,$

where K measures new knowledge produced by high technology companies, RD is industrial research and development, URD is university research in the respective fields of engineering and hard sciences and ε is a stochastic error term. According to equation (1), production of economically useful new knowledge depends on two local inputs: the high technology industry's own R&D efforts and local university research. As emphasized by Jaffe [Jaffe, 1989, p. 957], a positive and significant coefficient of the university research variable signals university technology transfer effects on industrial knowledge production. As such, the magnitude of α_2 measures local academic knowledge spillovers: the higher the value of this coefficient, the more intensive the effect of university knowledge transfers on local innovation activities. This measure has a particular feature: it is not tied to any specific manner of technology transfers. It summarizes knowledge spillovers of any form in a single value.

To test for the effect of agglomeration on academic knowledge spillovers measured by the size of the university research coefficient, equation (1) will be estimated within a hierarchical regression context. Hierarchical regression models (Anthony Bryk and Stephen Raudenbush, 1992) are designed for empirical situations when data follow a hierarchical structure, that is, the relationship between an independent and the dependent variable of a regression is influenced by other variables at a higher order[2]. In the present case, data exhibit a two-level structure: the relationship between university research and high technology innovations takes place at the company level, while this relationship is expected to be influenced by certain agglomeration features of the geographical area where the firms are located. The following equation models the dependence of academic knowledge transfers on the concentration of economic activities.

(2) $\alpha_2 = \beta_0 + \beta_1 \log(PROD) + \beta_2 \log(BUS) + \beta_3 \log(LARGE) + \mu.$

In equation (2), the magnitude of university knowledge spillovers, measured by α_2, is expected to be positively influenced by the concentration of high technology production (PROD) and business services (BUS). Technology transfers from academic institutions are supposed to be negatively affected by the relative importance of large firms (LARGE) in the geographical area.

Knowledge spillovers from industrial research laboratories measured by α_1 in equation (1) are also assumed to depend on agglomeration. It is widely recognized in the innovation literature, that local networks of related firms are major sources of new technological information (Giovanni Dosi, 1988, Eric von Hippel, 1988, Edwin Mansfield and Elizabeth Mansfield, 1993). By enlarging the pool of available technical knowledge, concentration of production intensify knowledge flows through the local network of firms (Feldman, 1994a). It has been well documented that locally available business services promote technological spillovers via supporting spin-off firm formation (Dorfman, 1983, Rogers and Larsen, 1984, Saxenian, 1994). Acs et al. (1994) found that knowledge spillovers are more significant sources of innovation for large companies than for small firms. Thus, agglomeration effects on technology spillovers among firms are modeled as follows

(3) $\alpha_1 = \gamma_0 + \gamma_1 \log(PROD) + \gamma_2 \log(BUS) + \gamma_3 \log(LARGE) + \eta,$

[2] Hierarchical regression models exhibit a close conceptual familiarity with other variable coefficient specifications in the econometric literature, such as random coefficient models (Hildreth and Houck, 1968) and spatial expansion models (Emilio Casetti, 1997).

with the same notation as above. It is assumed that concentration of production and business services and the relative importance of large firms influence local inter-firm technology transfers positively.

A substitution of equations (2) and (3) into the Griliches-Jaffe knowledge production function provides the estimable form of the hierarchical system:

$$\text{(4)} \quad \log(K) = \alpha_0 + \gamma_0 \log(RD) + \gamma_1 \log(PROD)*\log(RD) + \gamma_2 \log(BUS)*\log(RD) + \gamma_3 \log(LARGE)*\log(RD) + \beta_0 \log(URD) + \beta_1 \log(PROD)*\log(URD) + \beta_2 \log(BUS)*\log(URD) + \beta_3 \log(LARGE)*\log(URD) + [\eta \log(RD) + \mu \log(URD) + \varepsilon].$$

Equation (4) will be used for estimation. It models the production of economically useful new technological knowledge as being dependent on industrial and university R&D interacted with local agglomeration factors: concentration of production, business services and large companies.

II. Data and Estimation Issues

Estimation of equation (4) will be based on the same unique data set of 125 US metropolitan areas as is in Anselin et al. (1997a, 1997b). New technological knowledge (K) is measured by counts of product innovations introduced on the US market in 1982 (Keith Edwards and Theodore Gordon, 1984). Innovation counts come from the United States Small Business Administration (SBA) innovation citation database. This data set is a result of an extensive survey of the new product sections of trade and technical journals. To date this is the best available measure of US innovative activity[3]. Private research activities (RD) are proxied by

[3] For a detailed description of the data set and its advantages over the traditionally used patent data see Acs and Audretsch, 1990 and Feldman, 1994a.

professional R&D employment. The source of this data is the 17^{th} edition of Industrial Research Laboratories of the United States (Jaques Cattell Press, 1982). Following the common approach, university research expenditures stand for research activity at academic institutions (URD). The data are collected from the NSF Survey of Scientific and Engineering Expenditures at Universities and Colleges (National Science Foundation, 1982). Data measuring the concentration of high technology production (PROD), business services (BUS) and the relative presence of large firms (LARGE) come from County Business Patterns (Bureau of the Census, 1983). Concentration of high technology activities is measured by the share of MSA high technology employment in the national total. Similarly, share of business services employment (SIC 73) represents the concentration of business services. The percentage of high technology firms with employment exceeding 500 accounts for the relative importance of large companies in the MSA high technology economy. The "high technology sector" is an aggregate of data on five two-digit SIC industries: SIC 28 and SIC35-38. For a detailed description of the data see Anselin et al. (1997a).

The fact that both firm- and MSA-level information are aggregated at the metropolitan area level makes the estimation of equation (4) simpler than it is the case with usual hierarchical models where not only the relationships of variables, but also the levels of data aggregation exhibit a certain hierarchy (Bryk and Raudenbush, 1992). However, three potential estimation problems of the equation need closer attention: the problems of heteroskedasticity, multicollinearity, and spatial dependence. The fact that the error term of equation (4) depends on observation-specific private and university research values may cause heteroskedasticity in the estimated model. Repeated occurrence of the same variables in subsequent terms of the knowledge production function could be the source of serious multicollinearity. In the following analysis, the Breusch-Pagan (BP) heteroskedasticity test (Breusch and Pagan, 1979) and the multicollinearity condition number (David Belsley et al., 1980) will be applied to test for misspecifications in the forms of heteroskedasticity and multicollinearity.

Potential statistical problems associated with dependence among observations in cross-sectional data are extensively treated in spatial econometrics literature (e.g., Anselin, 1988, Anselin and Raymond Florax, 1995, Anselin and Anil Bera, 1998). Two forms of spatial dependence may exist in a linear regression context: spatial lag dependence and spatial error autocorrelation. A presence of any kind of spatial dependence can invalidate regression results. In the case of spatial error autocorrelation, OLS parameter estimates are inefficient whereas in the presence of spatial lag dependence, parameters become not only biased but also inconsistent (Anselin, 1988).

The general expression for the spatial lag model is

(5) $y = \rho Wy + x\beta + \varepsilon$,

where y is an N by 1 vector of dependent observations, W is a row standardized spatial weight matrix[4], Wy is an N by 1 vector of lagged dependent observations, ρ is a spatial autoregressive parameter, x is an N by K matrix of exogenous explanatory variables, β is a K by 1 vector of respective coefficients, and ε is an N by 1 vector of independent disturbance terms.

[4] Relative positioning of observations is modeled in spatial weights matrices. The dimension of a spatial weights matrix W is given by the number of observations of the regression. A matrix element $w_{i,j}$ reflects the spatial relation between observations i and j. Depending on the expected structure of spatial dependence, a matrix element $w_{i,j}$ can represent either contiguity relations between observations or it can model the role of distance in dependence. If two observations are contiguous (i.e., they share a common border or are located within a given distance band), the value of $w_{i,j}$ is larger than zero, and zero otherwise. The larger-than zero value is 1 in case of a simple contiguity matrix and it is a number between zero and one if the elements are row-standardized, that is, every element is divided by the respective row sum. If spatial dependence is expected to be determined by distance relations, a matrix element is based on the distance of observations i and j (i.e., their inverse distance or the square of the inverse distance).

Autocorrelation among regression error terms represents an alternative form of spatial dependence. Spatial error autocorrelation is modeled as follows

(6) $y = X\beta + \varepsilon$

with

(7) $\varepsilon = \lambda W\varepsilon + \xi$

where λ is the coefficient of spatially lagged autoregressive errors $W\varepsilon$ and ζ is an N by 1 vector of independent disturbance terms. The other notation is as before.

Three spatial weights matrices will be applied in the following empirical study. D50 and D75 are distance-based contiguities for 50 and 75 miles, respectively while the third one, IDIS2, is an inverse distance squared weights matrix [5]. The presence of spatial dependence will be tested by Lagrange Multiplier test statistics (Burridge, 1980, Anselin and Florax, 1995). Empirical regressions will be carried out in SpaceStat, an econometric software designed for the analysis of spatial data (Anselin, 1992).

III. Estimation Results

Given that knowledge spillovers are non-observable phenomena, the effects of agglomeration on academic knowledge transfers are studied indirectly, within a hierarchical linear regression context. Estimation results for regressions on 125 MSAs in 1982 are reported in Table 1. The first column lists parameter estimates along with the appropriate test statistics for the original Griliches-Jaffe knowledge production function (Jaffe, 1989). Both private and university R&D

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[5] Two MSAs are considered contiguous in D50 if their center counties are located within a 50-mile distance range. The same reasoning applies for D75. These matrices are intended to reflect potential spatial dependencies within commuting distances around an MSA. IDIS2 captures spatial effects that might come from the whole geographic area of the regression.

variables enter the equation with highly significant and positive coefficients. Spatial lag dependence among observations located within a fifty-mile distance range is detected by the LM-Lag statistic.

The second column presents the empirical results for equation (4), a hierarchical version of the knowledge production function. The added interaction variables increased regression fit considerably from an adjusted R-square of 0.60 in the Griliches-Jaffe knowledge production function to 0.78 in the full model. Among possible local agglomeration factors, concentration of high technology production seems to have the largest effect on university knowledge spillovers, while business services turns out to be the most influential variable governing private technology transfers. Clearly, high multicollinearity (with condition number exceeding 133) makes it impossible to reasonably evaluate the relative importance of different agglomeration factors in the processes of local knowledge spillovers. Although heteroskedasticity is not an issue of the full model, lag dependence within a 75-mile distance band is still a potential problem.

The final model in column three of Table 1 exhibits the best properties in terms of regression fit and multicollinearity. These results reinforce the findings suggested by the full model. The positive and highly significant ($p<0.01$) parameters indicate that concentration of high technology employment is the major agglomeration factor explaining academic knowledge spillovers while technology transfers among private companies are dominantly promoted by local business service concentrations. According to the LM-Lag test statistics in column three, lag dependence is the strongest among observations located within a 75 mile distance range from each other. As indicated by the Kiefer-Salmon normality test [6], the distribution of error terms is non-

[6] Nicholas Kiefer and Mark Salmon, 1983. The value of the test is 8.621 (p = 0.01).

normal. Consequently, instrumental variables estimation of the spatial lag model is the appropriate regression technique[7].

The last column lists spatial lag estimation results for the final model. Following the commonly used approach in spatial econometrics, spatial lags of the explanatory variables are used as instruments for the lagged dependent variable (Harry Kelejian and Dennis Robinson, 1993). Compared to the OLS results in the third column, the spatial lag model exhibits a better overall regression fit. However, neither the size of the estimated parameters nor their significance have changed meaningfully[8].

The highly significant spatially lagged dependent variable (p=0.01) indicates that the geographic area of agglomeration effects exceeds MSA boundaries. The fact that innovative activity in an MSA is positively related to the average level of innovative activity in MSAs located within a 75 mile distance band suggests that, in addition to spillover effects originated in the same location, technology transfers from neighboring metropolitan areas are also of substantial effects on new knowledge creation[9]. Given that spillovers depend on certain agglomeration characteristics,

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[7] The spatially lagged dependent variable on the right hand side of the spatial lag model is endogenous: it determines and, at the same time, is determined by the dependent variable. The model can be estimated either by maximum likelihood or by instrumental variables techniques (Anselin, 1988). In the present case, non-normality of error terms implies the choice of the IV estimation.

[8] In order to have the missing spatial statistics computed for the final model, a separate ML-Spatial Lag regression was run (not reported in Table 1). Both the parameter values and their standard errors in the ML regression were very close to the respective values in the IV estimation. No remaining spatial effects were found: the value of the B-P test was 1.064 and the highest value of the LM-error statistics was 1.213 (for IDIS2). The LR-lag statistics indicated that lag dependence within a 75-mile range is very significant: the value of the statistics was 5.347.

[9] A strong evidence was found in Anselin et al. (1997a) that universities located in adjacent MSAs are the major sources of these inter-metropolitan knowledge transfers.

presence of these factors in closely located MSAs reinforces innovative potential in the whole cluster of metropolitan areas.

IV. The "Critical Mass" of Agglomeration

The final regression in Table 1 provides formal evidence that the most influential agglomeration factor affecting the intensity of local academic knowledge spillovers is concentration of high technology production in the metropolitan area (measured by employment concentration). The higher the concentration of employment in an MSA, the more intensive the communication of knowledge through the network of local university and industry professionals. As a consequence, this result suggests that a pure proximity of an academic institution is not a sufficient condition for considerable knowledge transfers to the high technology industry. Without having a certain level of agglomeration in a metropolitan area, the available pool of technological knowledge at academic institutions exerts only a limited impact on the local economy. However, the size of local economic activities that is sufficiently enough to yield substantial academic knowledge spillovers still remains an important issue for the analysis.

In order to address the "critical mass" of economic activity problem, the sample of MSAs is categorized into four different "tiers." The categorization is based on the intensity of local academic knowledge spillovers, which is measured by the coefficient of the university research variable of the Griliches-Jaffe knowledge production function. Based on the final model in the last column of Table 1, innovation elasticities with respect to university research spending for location j are calculated as follows:

(8) Elasticity [Innovation, University Research] = $\partial \log (K) / \partial \log (URD) = (I - \rho W)^{-1} i \alpha_2$,

where

(9) $\alpha_2 = -0.041 + 0.058 * \log(PROD_j)$.

$(I - \rho W)^{-1}$ in equation (8) is an N by N matrix, and i is an N by 1 identity vector[10]. The term $(I - \rho W)^{-1}$ in equation (8) is called spatial multiplier. It represents the interdependence of new knowledge production in adjacent metropolitan areas: the effect of university research on innovation is determined not only by the concentration of economic activities in the metropolitan area, but also by research spillovers from private and academic research institutions situated in closely located MSAs[11].

Based on local university knowledge spillover predictions, MSAs are classified into four tiers. The values of innovation elasticities of first tier MSAs are more than one standard deviation above the mean elasticity value. (The mean is 0.046, while standard deviation is 0.040). Elasticities of second tier cities are above the mean within a one standard deviation range, while university research coefficients of MSAs in the third tier are below the mean within a same one standard deviation range. Elasticities of the last tier of cities are more than one standard deviation less than the mean value of innovation elasticities.

Table 2 presents average values of innovations and certain indicators of agglomeration by the respective innovation elasticity ranges.

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[10] The spatial lag model in equation (5) can be re-written as $y = (I - \rho W)^{-1} x\beta$. Partial derivatives in equation (8) are based on this "reduced form" of the spatial lag model.

[11] The last column in the Appendix table lists the spatial multiplier values for each MSA in the sample. It is 1.167 for metropolitan areas located within a 75 mile distance range from other MSAs and its value is 1 for unconnected observations. Additionally, the table provides the respective predicted innovation elasticity values for every MSA.

Table 2. Innovations and the Values of Certain Indicators of Agglomeration by Innovation Elasticity Categories

TIERS	ELUR	ELRD	INNHT	PREDIN	EMPHT	BUS	LARGE	POPUL
I.	0.104	0.416	110	105	162,000	4,300	2.6	3,000
II.	0.061	0.297	14	14	37,000	1,000	3.5	1,000
III.	0.029	0.203	4	4	12,000	300	4.6	400
IV.	-0.022	0.150	2	2	3,000	150	2.7	200

Notes: ELUR stands for elasticity of innovation with respect to university research; ELRD is elasticity of innovation with respect to industry research; INNHT is observed innovations; PREDINN is predicted innovations; HTEMP is high technology employment; BUS is employment in business services; LARGE is percentage of large firms in the MSA; POPUL is population in thousands of people.

The first column of the table lists average elasticities of innovation with respect to university research. Although 1 percent change in university research results in a 0.1 percent change in innovations in a typical first tier MSA, this value is practically zero in the fourth tier. (Given that the average number of innovations in this tier of cities is only two, the value of the average elasticity, -0.022 is interpreted as an indicator of a missing university effect on local innovations.) Innovation elasticities with respect to industry research exhibit a similar strong decreasing pattern. The third and fourth columns indicate that, not only high technology employment, but also presence of business services are positively associated with local academic spillovers. Unlike the effects of employment in high technology and in business services, the tendency of the impact of small firm dominance is not clear from the table. To have an indication of the size of cities belonging to university spillover categories, average MSA populations are listed in the table. While mean population is three millions in the first tier, it is two hundred thousands in the fourth one.

Given that university spillovers are non-observable, any information that helps evaluate the precision of the university effects listed in Table 2 is highly valuable. Based on the final model in the last column of Table 1, innovation predictions were calculated for each MSA. As shown in the fourth and fifth columns of Table 2, the average value of predicted innovations in the first tier is very close to the average value of observed innovations (the observed value is 110 while the model predicts 105 innovations on average), and the two values are exactly the same for the rest of the tiers. It suggests that, despite the fact that individual city predictions are not always precise (as demonstrated in the Appendix), the *general tendency* between agglomeration and university spillovers is well represented by average innovation elasticities with respect to university research[12].

Figure 1 demonstrates how dramatically differs the "productivity" of the same amount of university research spending among geographic areas with different levels of agglomeration. The X axis represents university research expenditures, while the Y axis depicts expected innovations for university research spending sizes and for different MSA tiers. The four curves stand for different innovation outcomes associated with the same amounts of university research expenditure. Sample university research spending ranges between \$ 0.5 million and \$ 324.5 million. Expected innovations for each tier were calculated based on the final model in the last column of Table 1. For

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[12] A comparison of estimated marginal university research cost of innovations and observed average university expenditures required for one innovation suggests the same conclusion. Based on the final regression in Table 1, marginal university research cost of innovations can be calculated for each city in the sample. It has the formula of MCU = {[1/ELUR]*[URD/INN]}, where URD stands for university research expenditures and the rest of the notation is as before. For the first tier of cities this value is \$ 8 million. Primary data on university research expenditures associated with local innovations are rare. However, Parker and Zilberman (1993) give some hints about the real costs. They report *average* university costs of one transferred technology. For Harvard, it is \$4.5 million, for MIT it is \$7.3 million, and for Stanford it is \$5.3 million. (The original dollar values have been converted to 1982 dollars.) Although the value of MCU and the ones in Parker and Zilberman (1993) are conceptually different [average costs in Parker and Zilberman (1993) and marginal costs in the present calculation], the fact that both of them are qualitatively in the same range suggests that ELUR is an acceptable measure of academic knowledge spillovers.

each tier, average values of private research and the two research coefficients were held constant while university research spending was the only variable element in the calculation[13].

It is clearly manifested in the figure that innovation productivity heavily depends on agglomeration. While a $0.5 million university research spending is expected to yield 63 innovations in an average top MSA, this value is 11 in the second tier, and 5 and 2 in the third and fourth tiers, respectively. The effect of increasing university research expenditures is even more striking. The curve of an average first tier MSA increases sharply from 63 expected innovations associated with a $ 0.5 million expenditure on university research to 115 with $ 324.5 million of university research spending. In the second tier, the growth path is relatively modest: it ranges from 11 to 16. Academic impact on local innovations is basically non-existent in the third and fourth tiers. For these tiers, the return on the $ 324 million additional university research spending is zero: the number of expected innovations is the same for both the highest and the lowest possible university research expenditure levels (i.e., five for the third and two for the fourth tier).

The examination of Figure 1 suggests that first tier MSAs utilize university research expenditures with the highest productivity. It is indicated that increased university research funding makes basically no difference for the rest of the cities. Therefore, the "critical mass" of the local high technology infrastructure can be characterized as follows. Substantial real effects of academic research can be expected in metropolitan areas that exhibit local characteristics that are not significantly different from those of an average first tier city in Table 2.

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[13] Because the four tiers represent four "typical" MSAs of each category the use of location-specific information is not appropriate. The lack of this information does not make it possible to correctly account for the endogenous spatial lag effect on innovations via the inclusion of the

V. Summary and conclusions

This paper provided formal evidence of the positive effects of agglomeration on local academic knowledge spillovers. Regression analysis was carried out within a hierarchical version of the Griliches-Jaffe knowledge production function framework. After controlling for agglomeration impacts on technology transfers among high technology companies, concentration of high technology employment turns out to be the most important agglomeration factor promoting knowledge spillovers from universities. In addition, the pattern of predicted innovation elasticities with respect to university research suggests a positive association between business services employment and local academic knowledge spillovers as well.

It was demonstrated that the same amount of university research spending can be associated with dramatically different levels of innovation outputs depending on the concentration of economic activities in the metropolitan area. Additionally, it was found that a “critical mass” of agglomeration in the metropolitan area is needed in order to expect substantial local economic effects of academic research spending

These findings have an important consequence for regional economic development policies. The efforts of several US states to advance local universities in order to develop their high technology economic base have been widely recognized in the relevant literature [e.g., Roger Vaugham and Robert Pollard (1986), Jurgen Schmandt and Robert Wilson (1987), Fosler (1988), David Osborne (1994)]. The empirical results presented above suggest that strengthening universities in order to advance local economies can be a good option in relatively well-

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spatial multiplier in the calculations. Instead, average values of the lagged variable were used for each city category to calculate expected innovations.

developed areas. However, there is strong evidence that MSAs that are far below the "critical mass" cannot expect meaningful academic impacts on their economies when considered in isolation. Instead, this suggests that a more comprehensive approach is needed, including a complex regional economic development plan that targets not only local academic institutions, but also high technology employment, business services, and small firms.

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Table 1. Regression Results for Log (Innovations) at the MSA level (N=125)

Model	The knowledge production function	The full model	The final model	The final model
Estimation	OLS	OLS	OLS	IV-Spatial lag
Constant	-1.045	-0.045	-0.047	-0.106
	(0.146)	(0.150)	(0.157)	(0.155)
W_Log(INN)				0.143
				(0.056)
Log(RD)	0.540	-0.243	0.025	0.003
	(0.054)	(0.122)	(0.076)	(0.075)
Log(PROD)*Log(RD)		-0.154		
		(0.142)		
Log(BUS)*Log(RD)		0.490	0.160	0.160
		(0.136)	(0.034)	(0.033)
Log(LARGE)*Log(RD)		0.090		
		(0.100)		
Log (URD)	0.112	0.186	-0.044	-0.041
	(0.036)	(0.078)	(0.038)	(0.038)
Log(PROD)*Log(URD)		0.231	0.058	0.058
		(0.102)	(0.023)	(0.022)
Log(BUS)*Log(URD)		-0.310		
		(0.102)		
Log(LARGE)*Log(URD)		-0.113		
		(0.069)		
R^2-adj	0.599	0.782	0.761	0.781
Multicollinearity Condition Number	9	133	22	22
Breusch-Pagan test for heteroskedasticity	0.631	1.026	0.176	
LM-Err				
D50	1.465	0.016	0.080	0.366
D75	2.688	0.035	0.290	0.475
IDIS2	1.691	0.078	0.061	1.174
LM-Lag				
D50	5.620	2.688	5.275	
D75	2.968	3.061	5.440	
IDIS2	2.039	1.207	2.976	

Notes: Estimated standard errors are in parentheses; critical values for the Breusch-Pagan test statistic with respectively 1 and 2 degrees of freedom are 3.84 and 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); spatial weights matrices are row-standardized: D50 is distance-based contiguity for 50 miles; D75 is distance-based contiguity for 75 miles; and IDIS2 is inverse distance squared; instruments in the IV-Spatial Lag estimation are W_Log(RD), W_Log(URD), W_[Log(RD)*Log(BUS)] and W_[Log(URD)*Log(PROD)], where W stands for the weights matrix D75.

Appendix. Innovation Elasticities, Innovation Predictions, High Technology Employment, Business Services Employment, and the Spatial Multiplier by Sample MSAs

MSA	ELUR	ELRD	PREDIN	INNHT	EMPHT	BUS	SM
Los Angeles-Long Beach	0.137	0.511	453	161	420135	9992	1.167
Chicago	0.127	0.497	215	164	297846	8409	1.167
San Jose	0.12	0.386	70	374	231658	2122	1.167
Boston	0.117	0.445	155	282	212427	4383	1.167
Detroit	0.114	0.42	78	51	189510	3234	1.167
Dallas-Fort Worth	0.109	0.444	40	77	159434	4363	1.167
Philadelphia Pa.-N.J.	0.107	0.447	136	139	148473	4509	1.167
Anaheim-Santa Ana-Garden Grove	0.105	0.416	68	108	141751	3073	1.167
Houston	0.103	0.446	47	29	133792	4470	1.167
New York N.Y.-N.J.	0.1	0.539	249	222	117784	14049	1.167
Essex county	0.097	0.4	86	143	106873	2520	1.167
Seattle-Everett	0.096	0.384	20	34	104500	2066	1.167
Nassau-Suffolk	0.095	0.425	46	120	99824	3433	1.167
Rochester	0.094	0.285	23	32	98630	609	1.167
Milwaukee	0.093	0.352	24	34	93575	1390	1.167
Cleveland	0.092	0.377	35	54	91496	1895	1.167
Hartford	0.091	0.325	21	27	87894	1008	1.167
San Diego	0.089	0.385	47	59	80491	2095	1.167
Cincinnati Ohio-Ky.-Ind.	0.085	0.339	16	13	71698	1195	1.167
Bridgeport	0.084	0.366	17	67	68511	1664	1.167
Phoenix	0.083	0.383	29	29	67194	2057	1.167
Minneapolis-St. Paul	0.082	0.345	43	80	103957	2623	1
Baltimore	0.081	0.376	29	12	63338	1876	1.167
San Francisco-Oakland	0.081	0.453	75	75	63088	4881	1.167
St. Louis	0.08	0.328	27	13	95205	2045	1
Pittsburgh	0.078	0.36	26	39	55901	1535	1.167
Buffalo	0.077	0.305	21	24	54021	779	1.167
Denver-Boulder	0.077	0.402	32	26	54204	2578	1.167
Portland Oreg.-Wash.	0.071	0.349	8	22	44692	1340	1.167
Dayton	0.07	0.288	13	11	42195	632	1.167
Atlanta	0.067	0.353	16	26	55929	2925	1
New Brunswick-Perth Amboy-Sayreville	0.063	0.287	14	30	33718	626	1.167
New Haven-West Haven	0.063	0.297	13	19	34026	707	1.167
Wichita	0.062	0.217	6	5	45715	414	1
Binghamton N.Y.-Pa.	0.061	0.167	3	2	31927	142	1.167
Kansas City	0.061	0.306	11	12	45374	1497	1
Tampa-St.	0.061	0.361	12	12	31713	1562	1.167
Syracuse	0.06	0.254	7	9	30558	419	1.167
Columbus	0.059	0.326	18	20	29015	1020	1.167
Lansing-East	0.059	0.233	5	4	29592	322	1.167
Salt Lake City	0.059	0.318	11	10	29264	916	1.167
Worcester	0.059	0.248	7	17	29682	389	1.167
Toledo Ohio-Mich.	0.058	0.268	9	6	28715	498	1.167
Grand Rapids	0.057	0.266	4	4	27357	482	1.167

Greenville-Spartanburg	0.057	0.25	6	10	27413	399	1.167
Johnson City-Kingsport-Bristol Tenn.-Va.	0.057	0.185	4	2	27782	179	1.167
Louisville	0.057	0.251	6	7	38659	673	1
Charlotte-Gastonia	0.056	0.301	6	6	26230	745	1.167
Allentown-Bethlehem-Easton Pa.-N.J.	0.055	0.242	7	7	25513	360	1.167
New London-Norwich	0.055	0.165	4	1	26104	139	1.167
Providence-Warwick-Pawtucket	0.055	0.295	8	15	25692	689	1.167
Ann Arbor	0.054	0.216	7	7	24899	260	1.167
Davenport-Rock Island-Moline Iowa-Ill.	0.053	0.215	4	5	24250	257	1.167
Greensboro-Winston-Salem-High Point	0.053	0.295	9	5	24238	690	1.167
Nashville-Davidson	0.053	0.312	5	5	23963	858	1.167
Paterson-Clifton-Passaic	0.053	0.255	9	25	23787	425	1.167
Washington DC	0.053	0.429	48	21	23862	3597	1.167
Youngstown-Warren	0.053	0.212	3	1	23887	249	1.167
Fort Lauderdale-Hollywood	0.052	0.355	7	9	23366	1457	1.167
Austin	0.051	0.3	9	12	22614	737	1.167
Orlando	0.051	0.316	7	5	22511	894	1.167
Raleigh-Durham	0.051	0.292	12	8	22662	665	1.167
Tulsa	0.051	0.263	4	12	30295	801	1
Miami	0.05	0.391	9	4	22021	2265	1.167
Wilmington Del.-N.J.-Md.	0.05	0.257	11	11	21723	434	1.167
Akron	0.049	0.262	9	7	21129	461	1.167
Peoria	0.049	0.206	2	1	21117	232	1.167
Albany-Schenectady-Troy	0.048	0.266	9	1	19974	482	1.167
Melbourne-Titusville-Cocoa	0.048	0.215	3	11	19955	258	1.167
Riverside-San Bernardino-Ontario	0.048	0.325	9	13	20481	1004	1.167
Oklahoma City	0.047	0.281	5	1	25397	1031	1
New Orleans	0.044	0.292	6	1	22335	1210	1
Tucson	0.044	0.27	7	9	17670	510	1.167
Huntsville	0.043	0.206	4	3	17217	232	1.167
Portsmouth-Dover-Rochester	0.043	0.214	4	5	16863	255	1.167
Reading	0.043	0.183	3	1	17230	173	1.167
South Bend	0.043	0.208	3	5	17102	236	1.167
Springfield-Chicopee-Holyoke	0.042	0.237	5	3	16291	340	1.167
Jersey City	0.041	0.243	6	11	15775	366	1.167
San Antonio	0.04	0.316	11	3	15404	898	1.167
Lancaster	0.039	0.188	4	4	15127	186	1.167
Memphis Tenn.-Ark.-Miss.	0.039	0.262	4	3	18839	787	1
New Bedford	0.037	0.195	3	6	14164	202	1.167
Northeast	0.035	0.224	2	2	12969	290	1.167
Knoxville	0.034	0.25	5	1	12763	398	1.167
Lorain-Elyria	0.034	0.128	2	2	12520	88	1.167
Portland	0.033	0.206	3	1	12272	230	1.167
Colorado Springs	0.032	0.236	5	6	11735	335	1.167
Pittsfield	0.032	0.106	2	2	11597	67	1.167
Waterloo-Cedar Falls	0.03	0.116	1	1	12941	96	1
Birmingham	0.029	0.283	6	1	10512	600	1.167
Trenton	0.029	0.252	8	29	10659	405	1.167
Kalamazoo-Portage	0.028	0.178	3	5	10417	164	1.167

Santa Barbara-Santa Maria-Lompoc	0.028	0.22	5	9	11890	429	1
Benton Harbor	0.026	0.137	2	1	9453	99	1.167
Fort Collins	0.023	0.186	3	6	8756	180	1.167
Burlington	0.022	0.126	2	3	9586	111	1
Janesville-Beloit	0.022	0.109	2	2	8254	70	1.167
Albuquerque	0.02	0.231	3	2	8766	509	1
Sacramento	0.019	0.329	7	7	7538	1056	1.167
Galveston-Texas	0.014	0.158	3	2	6285	127	1.167
Springfield	0.014	0.163	2	3	6824	191	1
Tacoma	0.012	0.223	4	2	5956	286	1.167
Fresno	0.011	0.224	2	1	6100	457	1
Spokane	0.011	0.195	1	3	6090	299	1
El Paso	0.01	0.2	3	7	5791	322	1
Lafayette-West Lafayette	0.01	0.117	2	1	5544	77	1.167
Lincoln	0.007	0.17	2	2	5275	210	1
Daytona Beach	0.005	0.202	2	1	4641	220	1.167
Hamilton-Middletown	0.003	0.136	2	4	4430	97	1.167
Madison	0.003	0.243	4	4	4385	365	1.167
Bloomington-Normal	-0.001	0.124	1	2	3845	84	1.167
Provo-Orem	-0.001	0.153	2	3	3822	120	1.167
Santa Cruz	-0.003	0.185	2	2	3624	179	1.167
Reno	-0.005	0.197	1	1	3215	312	1
Newburgh-Middletown	-0.006	0.164	2	3	3217	137	1.167
Stockton	-0.006	0.21	2	2	3273	243	1.167
Gainesville	-0.013	0.165	2	1	2552	139	1.167
Waco	-0.014	0.169	2	3	2450	147	1.167
Columbia	-0.016	0.086	1	1	2139	63	1
Salem	-0.024	0.188	2	1	1777	184	1.167
Bellingham	-0.045	0.107	1	1	852	68	1.167
Bryan-College Station	-0.048	0.131	1	2	765	92	1.167
Newport News-Hampton	-0.058	0.082	1	2	545	50	1.167
Norfolk-Virginia Beach-Portsmouth	-0.138	0.008	0	1	36	20	1.167

Notes: ELUR stands for elasticity of innovation with respect to university research; ELRD is elasticity of innovation with respect to industry research; PREDINN is predicted innovations; INNHT is observed innovations; HTEMP is high technology employment; BUS is employment in business services, and SM is the spatial multiplier (for further details see the main text).

Figure 1. Expected Innovations