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High-technology employment and R&D in cities: Heterogeneity vs specialization

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Abstract. This paper uses data from high technology industry clusters in U.S. cities to establish a strong positive relationship between city, industry cluster (and university) R&D, and subsequent employment in the same industry cluster and city. Perhaps surprisingly, in view of recent results that heterogeneity favors growth, we found no evidence for spillovers from R&D in any one high technology cluster to employment in any other. However, spillover benefits from specialization appear microeconomically plausible in our context, though the data panel is too short to obtain any conclusions regarding growth.

JEL classification: J23, J44, O30

1. Introduction

Why does economic activity cluster? According to Krugman (1991), economies of scale, transportation costs and market demand can interact to produce agglomerations even in the absence of any pure external economies. However, unless there are significant externalities, or other sources of social increasing returns, it is unlikely that economic growth can proceed at a constant, non-diminishing rate into the future (Griliches 1992).

What type of economic activity will promote positive externalities and, therefore, economic growth? This question is important given the debate in the literature about the nature of economic activity and how it affects economic growth. The Marshall-Arrow-Romer (MAR) externality concerns knowledge spillovers between firms in an industry. Arrow (1962) presented an early formalization; the paper by Romer (1986) is a recent and influential statement. Applied to cities by Marshall (1890), this view says that the concentration of an industry in a city facilitates knowledge spillovers between firms and, therefore the growth of that industry. According to this approach, externalities work within industries (Loesch 1954).

These theories of dynamic externalities are extremely appealing because they try to explain simultaneously how cities form and why they grow. MAR, in particular, predict that industries cluster geographically to absorb the knowledge spilling over between firms. In addition, they predict that regionally specialized industries grow faster because neighboring firms can learn from each other much better than geographically isolated firms.

A very different position has been attributed to Jacobs (1969). Jacobs perceives information spillovers between industry clusters to be more important for the firm than within-industry information flows. Heterogeneity, not specialization, is seen as the most important regional growth factor, so Jacobs theory predicts that industries located in areas that are highly industrially diversified should grow faster[1]. Glaeser et al. (1992) analyze the six largest industries in each of 170 U.S. cities. Their results are consistent with the presence of Jacobs type externalities. Industries will grow sluggishly in cities with high degrees of specialization. However, as Duranton and Puga (1999) point out in their survey of this area, the results may depend on the sector concerned. Thus, Henderson (1994) finds that traditional standardized goods tend to be produced in more specialized cities, and (relative) demand for these products has declined secularly as new product demand has grown.

While Glaeser et al. (1992), Henderson et al. (1995) and Henderson (1994) have all examined the role of heterogeneity and specialization in economic growth, none of these studies has directly examined the role of university or industrial R&D, the ultimate source of new and existing knowledge for economic growth. Recently, Jaffe (1989), Jaffe et al. (1993) and Varga (1998) found that R&D and other knowledge spillovers not only generate externalities, but that such knowledge spillovers tend to be geographically bounded within the region where the new economic knowledge was created. Anselin et al. (1997, 1999) confirmed the positive relationship between university research and innovative activity, and provided the first direct measure on the extent of knowledge spillovers that extended over a range of 50 miles from the innovating Metropolitan Statistical Area (MSA). However, these studies have only examined the effect of knowledge spillovers on patent and/or innovation counts but not on employment. The ultimate economic interest lies chiefly in the product markets and jobs that are generated by R&D.

In a recent paper, Acs et al. (1999) examined the spillover effects of university R&D on high-technology employment at the urban level. While our data was for a much shorter time period than Glaeser et al. (1992) and we only looked at high tech employment, by using BLS data instead of County Business Patterns data we did not have to estimate missing values. Moreover, we had data at the three-digit level, instead of the two-digit level, permitting a more disaggregated analysis. We found that after controlling for wages, prior innovations, state fixed effects and sample selectivity bias, university R&D spillovers have a significant effect on high technology employment within narrow industry bounds in MSAs.

In other words, university R&D spillovers appear to operate locally within a narrow set of industries from university research through innovation to high technology employment. There was no strong evidence of university R&D spillovers across industries or MSAs. The transmission of university knowledge spillovers across industries appears to be unimportant. It is certainly plausible that the usefulness of university research to the firm is greatest if it is

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[1] This paper does not address the issue posed by these studies and also Porter (1990) and Schumpeter (1942) on the role of competition and monopoly in promoting innovation and growth.

in the same three or four-digit SIC classification. Differing technologies and professional specializations also suggest that university research is likely to be less valuable to the firm, if it is carried out in different two-digit SIC codes. Thus, we found no support for Jacobs-type externalities for university R&D spillovers across industry clusters.

The purpose of this paper is to extend this research to industrial R&D. We test the MAR hypothesis that industrial R&D does not spillover across regional industry clusters. This is important for several reasons. First, the ratio of business R&D to total R&D is about 0.725, and even larger in selected three digit industries. Second, industrial R&D is more applied and closer to employment and economic growth than university R&D. Third, the empirical evidence suggests that R&D spillovers operate at the industry level and proximity does matter (Jaffe 1986).

In Sect. 2 we briefly summarize the literature on the search for R&D spillovers at the industry level. In Sect. 3 we examine some of the theoretical underpinnings of the heterogeneity and specialization hypotheses. Issues concerning the measurement of high technology employment and R&D are outlined in Sect. 4. After the empirical specification and econometric issues are discussed in Sect. 5, the results are presented in Sect. 6. The final section summarizes our conclusions. We find that the channels of knowledge spillover are similar for industrial R&D and university R&D. Both university and industry R&D spillovers may operate within, but certainly do not operate across, narrow three-digit industry groupings, thus supporting the specialization thesis in this context. However, these essentially cross-sectional data do not permit direct conclusions about employment growth.

2. The search for industrial R&D spillovers

What are R&D spillovers? There are two distinct notions. First, R&D intensive inputs are purchased from other industries at less than their full quality-adjusted price. This is a problem of measuring capital equipment, other inputs and their prices correctly and not really a case of pure knowledge spillovers. A good example of such productivity transfers would be the computer industry. It has experienced tremendous productivity growth. Different industries have benefited differentially from it depending on their rate of computer purchases. But these are not pure knowledge spillovers; instead they are just consequences of conventional measurement problems under uncertainty.

True spillovers are ideas borrowed by research teams of industry (or firm) i from the research results of industry (or firm) j. The photographic equipment industry (SIC 386) and the measuring and controlling device industry (SIC 382) may not purchase inputs from one another but may be in a sense working on similar problems and hence able to benefit considerably from each other's research.

To measure R&D spillovers directly, one has to assume either that their benefits are localized in a particular industry, or in a range of products. Or that there are ways of identifying the relevant channels of influence, so "that one can detect the path of the spillovers in the sands of the data" (Griliches 1992, p. S31). Arguably the usefulness of somebody else's research to you is highest if he is in the same four-digit SIC classification as you are. It is probably still high if she is in the same three-digit industry group. While research in your two-digit industry classification is less useful, it is still more valuable to you than research outside of your two-digit industry.

If there are R&D spillovers within industries then the computed returns should be higher at the industry than the firm level. A comparison of firm-based R&D results with those found using various industry aggregates does not, however, indicate consistently higher R&D coefficients at the aggregate level (Mairesse and Mohnen 1990). This result may be due to measurement error. These studies, for example, do not take into account explicitly the difference between private and social obsolescence rates (Griliches 1992).

Nevertheless, there are a significant number of reasonably well done studies all pointing in the same direction: R&D spillovers at the industry level are present, their magnitudes may be quite large, and social rates of return remain significantly above private rates. See, for example, Jaffe (1986), Griliches and Lichtenberg (1984), and Bernstein and Nadiri (1989).

3. Heterogeneity versus specialization

The importance of location to employment growth may seem paradoxical in a world of instant communications. However, as has been pointed out by Lucas (1988, 1993) and Black and Henderson (1999), it is localized information and knowledge spillovers, presumably through personal face-to-face contacts, that make cities the engines of economic growth. Cities grow faster than rural areas.

Despite the general consensus that knowledge spillovers within a given location stimulate employment growth, there is little consensus as to exactly how this occurs. The MAR model formalizes the insight that the concentration of an industry in a city promotes knowledge spillovers between firms and therefore would facilitate employment growth in a city industry observation. An important assumption is that knowledge externalities with respect to firms exist, but only for firms within the same industry. Thus, the relevant unit of observation is extended from the firm to the region in the theoretical tradition of the MAR model and in subsequent empirical studies, but spillovers are limited to occur within the relevant industry. The transmission of knowledge spillovers across industries is assumed to be non-existent or at least trivial.

However, according to Jacobs (1969), the emphasis on within industry spillovers may be misplaced. Jacobs' idea is that the crucial externality in cities is cross-fertilization of ideas across different lines of work and industries. New York grain and cotton merchants saw the need for national and international financial transactions, and so the financial services industry was born. Rosenberg (1963) discusses the spread of machine tools across industries and describes how an idea is transmitted from one industry to another. Because cities bring people together from different walks of life, they foster transmission of ideas. Lucas (1993) emphasizes metropolitan areas as the most natural context in which the compact nature of the geographic growth facilitates personal interchange, communication and knowledge spillovers both within and across industries.

Jacobs (1969) develops a theory which emphasizes that the variety of industries within a geographic region promotes knowledge externalities and ultimately employment and economic growth. A common science base facilitates the exchange of existing ideas and generation of new ones across disparate but complementary industries. Thus, in Jacobs' view diversity rather than specialization is the operative mechanism of economic growth.

A second issue is the role of university R&D[2]. University R&D by definition exists outside the industry. However, university R&D is a source of significant innovation generating knowledge which diffuses initially through direct personal contacts to adjacent firms. Since both basic and applied university research may benefit private enterprise in various ways, it induces firms to locate nearby (Jaffe 1989, and Anselin et al. 1997). Lund (1986) surveys industrial R&D managers and finds the proximity of university R&D to be important for the location decision due to the initial spillover from neighboring university research to commercial innovation. Of course, as research results are embodied in commercial products and disseminated, the initial learning advantage created by close geographic proximity between local high technology industrial activity and the university would fade but may persist for significant durations. Thus knowledge, both of a formal nature and embodied in the tacit skills of mobile human capital, flows locally through a variety of channels more easily and efficiently than over greater distances.[3]

4. Description of the data

Clusters are geographic concentrations of interconnected companies and institutions in a particular field or industry. Clusters encompass an array of linked industries and other entities important to competition. They include, for example, suppliers of specialized inputs such as components, machinery, and services and providers of specialized infrastructure (Porter 1990).[4] If Marshall-Arrow-Romer (MAR) externality concerns knowledge spillovers between firms in an industry, or cluster of industries, they most probably operate along these interconnections within clusters. We identified thirty two three-digit standard industrial classification (SIC) industries as high technology industries on the basis of a relatively high ratio of R&D to industry sales (Acs 1996). These industries were grouped into the five clusters of technologically closely related industries detailed in Table 1, namely Biotechnology and Biomedical, Information Technology and Services, High Technology Machinery and Instruments, Defense and Aerospace, and Energy and Chemicals.[5]

Employment and wage data corresponding to the five industry clusters were provided by the U.S. Department of Labor, Bureau of Labor Statistics (BLS). These are reported to the BLS by the State Employment Security Agencies (SESAs) of the 50 states as part of the Covered Employment and Wages Program (that is, the EC-202+ report). Employers in private industry provide SESAs with quarterly tax reports for an average of 90 million wage

[2] This is discussed in more detail in Acs et al. (1999).

[3] Note that we do not present here any tests for geographical spillovers, such as those conducted by Anselin et al. (1999). Research and development occurring in a given MSA may well have cross-regional employment impacts but consideration of the distinction between local and non-local spillovers is outside the scope of this paper.

[4] A rich literature has recently developed on industry clusters. See for example, Porter 1998; Braunerhjelm and Carlsson 1999; Acs 1996; Storper 1995. For a review of the literature see Muizer and Hospers 1998.

[5] In our previous paper (Acs et al. 1999) which did not consider industrial R&D, we were able to include the effect of university R&D on employment for the High Technology Research sector.

Table 1. Industry clusters

Biotechnology and biomedical	*Defence and aerospace*
Medicinals and botanicals (283)	Ordnance and accessories (348)
Medical instruments and supplies (384)	Aircraft and parts (372)
Ophthalmic goods (385)	Guided missiles and space (376)
	Search and navigation equipment (381)
Information technology and services	
Computer and office equipment (357)	*Energy and chemicals*
Electronic distribution equipment (361)	Crude petroleum and natural gas (131)
Audio and video equipment (365)	Industrial inorganic chemicals (281)
Communications equipment (366)	Plastic materials and synthetics (282)
Electronic components and accessories (367)	Industrial organic chemicals (286)
Communication services (489)	Miscellaneous chemical products (289)
Computer and data processing services (737)	Petroleum refining (291)
High technology machinery and instruments	
Engines and turbines (351)	
Construction and related machinery (353)	
General industrial machinery (356)	
Electrical industrial apparatus (362)	
Household appliances (363)	
Electric lighting and wiring (364)	
Miscellaneous electrical equipment and suppliers (369)	
Measuring and controlling devices (382)	
Photographic equipment and supplies (386)	

Source: Office of Management and Budget, Standard Industrial Classification Manual, 1987, Washington DC, 1988.

and salary workers in approximately 5.9 million reporting units. These reports covered approximately 98% of total wage and salary civilian employment and provide a virtual census of employees and their wages for nearly all sectors of the economy.

This study utilizes specialized data runs for 36 MSAs which are listed in Table 2 in descending order of total high technology employment in our five clusters. There is considerable variation in employment levels both between MSAs within an industry grouping and between sectors within a given city. Unfortunately, labor market data were unavailable for additional MSAs due to disclosure limitations.

In those cities and industries where there are only a few employers, the data cannot be released due to the problem of potentially revealing the details of individual records. This limits both the number of industries and the number of cities which can be studied using BLS data.

Although we could study employment in most of the 300 MSAs, disclosure problems prohibit access to data on specific high technology industries. This study of R&D spillovers, therefore, is necessarily confined to those cities that have a large number of high technology industries.

Our measure of industrial research and development (R&D) is a proxy based on data on professional employment in high technology research laboratories in the Bowker Directories (Jacques Cattell Press 1985). While imperfect, this approach allowed us to construct a private R&D variable for all MSAs. As indicated in Anselin, Varga and Acs (1997), our proxy variables are remarkably similar to the R&D expenditures used in Jaffe (1989).

Table 2. High technology employment by MSA and industry clusters, 1988

MSA	BB	DA	HTM	EC	ITS	TOTAL
Los Angeles	19535	219696	54176	24343	89321	407071
Boston	16481	44355	54176	5710	133252	253974
San Jose	10301	36315	40134	828	147266	234844
Chicago	11159	1587	59874	15835	80821	169276
Philadelphia	22026	19535	36315	22026	59874	159776
Dallas	3789	29732	12964	18033	80821	145339
Seattle	3714	98715	8184	464	15835	126912
Houston	1299	925	24343	73130	21162	120859
Minneapolis	12209	15063	29732	2565	59874	119443
Portland	5486	22026	73130	8184	8690	117516
Tucson	1224	3568	4188	1900	89321	100201
New York City	17676	4817	18215	6905	49020	96633
Rochester	7863	49020	9996	12835	14328	94042
Phoenix	2079	26903	5324	626	49020	83952
San Diego	6185	29732	14617	1286	29732	81552
Raleigh-Durham	5767	22026	5166	8184	26903	68046
Cleveland	2208	8103	24343	13766	10509	58929
Austin	2368	22026	3827	8184	22026	58431
Washington DC	2643	16155	7631	3789	26903	57121
Denver	4359	15214	4146	14328	15063	53110
Baltimore	2275	21162	6905	4402	17154	51898
Kansas City	437	22026	17154	8184	3568	51369
Cincinnati	4359	19341	11047	6502	7707	48956
Atlanta	2643	22026	953	8184	5377	39183
Pittsburgh	2892	259	15063	7707	12088	38009
Indianapolis	5271	3133	7785	2514	17154	35857
Orlando	1998	2344	14185	665	16647	35839
Nashville	837	14764	5431	249	11047	32328
Salt Lake City	3714	7115	2864	2018	14764	30475
San Francisco	3866	1998	2540	3197	16983	28584
Charlotte	1261	262	5166	9228	12209	28126
Columbus	1652	1685	9996	3751	10938	28022
St Louis	561	7785	2540	66	8866	19818
Miami	953	3361	7186	1808	6310	19618
Providence	1863	111	7942	2143	6438	18497
Louisville	6974	2253	2951	796	4769	17743

BB Biotechnology and biomedical; *DA* Defense and aerospace; *HTM* High technology machinery and instruments; *EC* Energy and chemicals; *ITS* Information and technology services.

The data on university R&D are measured in expenditure rather than employment terms. Total university R&D spending in each city is disaggregated by broad science department and allocated to each of the five industries. The assignment of research funds by academic department to each industrial grouping follows that used in Acs et al. (1999) which in turn was based on the mapping of Audretsch and Feldman (1996). The data are compiled from the National Science Foundation Survey of Scientific and Engineering Expenditures at Universities and Colleges for various years. Table 3 reports mean industrial and university R&D across the 36 MSAs by industrial grouping. Interestingly, there is an inverse relationship between our measures of average industrial R&D and university R&D by sector. The biotechnology sector, for example, has the smallest R&D laboratories in terms of employ-

Table 3. Mean industrial and university R&D by cluster

Industrial cluster	Industrial R&D (laboratory employment in 1985)	University R&D (annual expenditure 1988 to 1991 in $ millions)
Biotechnology and biomedical	644.6	112.8
Defense and aerospace	962.4	47.9
High technology machinery and instruments	1071.4	36.9
Energy and chemicals	1258.4	22.6
Information technology and services	1909.9	7.9

ment but the largest expenditures in terms of university R&D (departments of life sciences). This is because the more mature industries have higher industrial R&D and the newer clusters, such as Biotechnology and Biomedical that are rather young have larger university expenditures.

5. The empirical model

Since the data do not permit us to estimate a well specified labor demand equation, the employment equation is written down as a simple log linear reduced form in Eq. (1):

$$\begin{aligned} EMP_{MIT} = \alpha_0 + \alpha_1 W_{MIT} + \alpha_2 IRD_{MI} + \alpha_3 IRDSPILL_{MI} \\ + \alpha_4 URD_{MI,T-3} + \alpha_5 URDSPILL_{MI,T-3} \\ + \alpha_6 INNOV_M + \alpha_7 POP_{MT} + \alpha V + u_{MIT} \end{aligned} \tag{1}$$

where $M = 1 \dots 36$ indexes the MSA, $I = 1 \dots 5$ indexes industry grouping, and $T = 1988 \dots 1991$ indexes time, and all variables are in natural logarithms. EMP_{MIT} refers to high technology employment, W_{MIT} is the corresponding annual real wage per employee, defined as nominal wages deflated by the appropriate producer price index. Note that the panel is very short, including only four years of annual data, which compares unfavourably with, say, Glaeser et al. (1992), who use observations drawn from 1956 and 1987 to estimate employment growth equations. Since cross section variability dominates in our data set, attempts to estimate equations specified in terms of employment growth rates, rather than in levels, proved fruitless.

$URD_{MI,T-3}$ refers to university R&D deflated by the gross national product price deflator. Given the time span of the data set, it seems reasonable that the use of R&D with a three year lag provides an appropriate delay for the university research knowledge externality to be transmitted into commercial products and employment. Edwards and Gordon (1984), for example, find that innovations made in 1982 resulted from inventions made on average just over four years previously.

To test directly for spillovers to employment in each sector from university R&D expenditure outside of that matched to each industrial grouping, the variable $URDSPILL_{MI,T-3}$ was constructed. It is the sum of all hard science university R&D spending by MSA less the expenditure which corresponds to each industry.

IRD_{MI} is the industrial R&D proxy measured using employment in R&D laboratories. Data were collected by sector and city for a single year, namely 1985. The variable $IRDSPILL_{MI}$ captures any spillover from industrial R&D which is not specific to each industry grouping. It is constructed using the same method as that described for the university spillover variable.

$INNOV_M$ is a count of the number of product innovations by MSA in 1982, the year for which the data base of U.S. commercial innovations was compiled by the Small Business Administration. The count is based on an extensive review of new product announcements in trade and technical publications. The data are disaggregated by MSA but not by industry, so cross-industry spillover effects from the innovation count cannot be directly tested here[6]. In this model, the variable attempts to control for the effect of pre-existing commercial innovation, that ultimately leads to product development and marketing with substantial time lags, on subsequent employment levels.

POP_{MT} refers to MSA population and controls for local market size. Although the market may well extend beyond MSA boundaries, we do not have a more appropriate measure of demand. Finally V represents a vector of industry, state and annual time dummies. These control for fixed effects which may not have been captured by the continuous variables.

5.1. Sample selection bias

The disclosure limits of the BLS data described previously may introduce a selection bias in the results. This arises since the data are suppressed in those MSAs where high technology employment is low. A non-randomly selected sample is, therefore, effectively imposed by the BLS. This bias can be resolved econometrically by constructing a joint model which represents both the employment equation and the selection process determining when the dependent variable is observed[7]. If the selection rule is that employment is only reported if it exceeds an unobserved disclosure threshold, EMP^*_{MIT}, the model is described statistically as follows:

$$EMP_{MIT} = \beta' X_{MIT} + u_{MIT} \tag{2}$$

$$EMP^*_{MIT} = \gamma' Z_{MIT} + \varepsilon_{MIT} \tag{3}$$

$$EMP_{MIT} \text{ observed only if } EMP_{MIT} \geq EMP^*_{MIT}$$

where $(u_{MIT}, \varepsilon_{MIT})$ are i.i.d. drawings from a bivariate normal distribution with zero mean, variances σ_u^2 and σ_ε^2, and covariance $\sigma_{u\varepsilon}$. If this covariance is nonzero, the OLS estimates of β will be biased. X_{MIT} and Z_{MIT} are vectors of independent variables. The dependent variable EMP^*_{MIT} is unobserved but

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[6] For a discussion of their limitations see Edwards and Gordon (1984), Feldman and Audretsch (1999) and Varga (1998).

[7] See Maddala (1983).

Table 4. Summary statistics by variable

Variable	36 MSAs Mean	36 MSAs Coefficient of variation	77 MSAs Mean	77 MSAs Coefficient of variation
EMP_{MIT}	17308	1.55		
W_{MIT}	31723	0.24		
POP_{MT}	2370200	0.82	647000	0.96
$INNOV_M$	56	1.36	7	1.53
IRD_{MI}	1169	1.79	187	2.93
$IRDSPILL_{MI}$	4678	1.51	761	2.08
$URD_{MI,T-3}$	46	1.44	10	2.13
$URDSPILL_{MI,T-3}$	149	0.91	33	1.53

Note: (a) For ease of reading the table, the means are rounded to the nearest integer value; (b) the university R&D variables are measured in $ millions.

has a dichotomous observable realization I_{MIT} which is related to EMP^*_{MIT} as follows:

$$I_{MIT} = 1 \quad \text{if and only if} \quad EMP_{MIT} \geq EMP^*_{MIT}$$

$$I_{MIT} = 0 \quad \text{if and only if} \quad EMP_{MIT} < EMP^*_{MIT}$$

Equation (2) applies to the selected sample of 36 cities and summarizes the specification in (1). Additional data were obtained on the right hand side variables for a further 77 MSAs which are non-selected in the sense that no high technology employment observations were publicly available for these cases. The additional observations permit correction of the sample selection bias induced by censoring of the dependent variable using the two stage estimation procedure proposed by Heckman (1979). In the first stage the parameters of the probability that an MSA will be in the selected sample of 36 cities are estimated from a probit analysis of Eq. (3) using the full sample of $36 + 77 = 113$ MSAs. From these estimates the values of the inverse of Mills' ratio, denoted $\hat{\lambda}_{MIT}$, are computed for each observation in the selected sample. The second stage is to estimate the employment Eq. (2) by OLS with $\hat{\lambda}_{MIT}$ as an additional explanatory variable. It has been shown by Heckman and others that this correction term is a proxy variable for the probability of selection, measuring the sample selection effect arising from undisclosed observations on employment. This procedure gives consistent estimates of the parameters of Eq. (2).

Note that Z_{MIT} is a subset of X_{MIT}. Since the non-disclosure problems which apply to employment likewise afflict the wage data, the wage variable is excluded from the Z_{MIT} vector in the selection equation. The probability of hi-tech employment disclosure is likely to be strongly related to city size which is proxied here by the population variable. In addition, the innovation variable, and the industrial and university R&D variables together with their spillover counterparts are included. Table 4 provides basic summary statistics for all the variables in the model, disaggregated by disclosure status, and presented in their raw (unlogged) form[8]. The 77 MSAs for which high technology

[8] A human capital, labour supply variable for MSAs that was used with mixed results in our previous work, was insignificant and hence omitted here.

employment is not disclosed are clearly much smaller, with substantially fewer innovations and considerably lower R&D than those 36 MSAs for which employment and wage data are available.

6. Results

The first column of Table 5 reports the ordinary least squares regression results using 720 observations drawn from five high technology clusters in 36 MSAs over the four year period, 1988 to 1991. The absolute t-statistics in parentheses are based on White's heteroskedastic consistent estimates of the standard errors. The equation includes both state, time and industry fixed effects to control for unmeasured factors.

The coefficients on the fixed effects are not tabulated but their joint significance cannot be rejected by an F-test. Since the equation is estimated in natural logarithms the coefficients should therefore be interpreted as elasticities. These simple OLS estimates provide a baseline from which to assess the impact of sample selection on the employment equation. Column (2) of Ta-

Table 5. High technology employment estimates

Dependent variable	(1) OLS EMP_{MIT}	(2) PROBIT I_{MIT}	(3) OLS EMP_{MIT}	(4) OLS EMP_{MIT}
Constant	−22.69	−10.56	−22.03	−21.70
	(6.8)	(19.5)	(6.2)	(5.3)
W_{MIT}	2.61		2.61	
	(8.8)		(8.8)	
$W_{MI,T-1}$				2.60
				(7.6)
POP_{MT}	0.26	1.08	0.22	0.20
	(2.4)	(15.2)	(1.7)	(1.3)
$INNOV_M$	0.29	0.38	0.26	0.27
	(2.8)	(8.2)	(2.0)	(1.9)
IRD_{MI}	0.12	0.03	0.12	0.11
	(4.1)	(1.4)	(4.2)	(3.6)
$IRDSPILL_{MI}$	0.02	−0.07	0.03	0.04
	(0.5)	(3.1)	(0.7)	(0.7)
$URD_{MI,T-3}$	0.09	0.08	0.09	0.07
	(3.5)	(3.5)	(3.0)	(2.3)
$URDSPILL_{MI,T-3}$	0.06	0.15	0.05	0.06
	(1.5)	(5.1)	(1.0)	(1.1)
$\hat{\lambda}_{MIT}$			−0.19	−0.23
			(0.6)	(0.6)
$\bar{R}^2$	0.59	0.57	0.59	0.59
$\hat{\sigma}$	0.899		0.900	0.903
n	720	2260	720	540

Notes: (a) Absolute t-statistics based on White's heteroskedastic consistent standard errors are in parentheses; (b) All variables are in natural logarithms; (c) $\bar{R}^2$ is the adjusted multiple correlation coefficient, $\hat{\sigma}$ is the estimated standard error of the regression, and n is the number of observations; (d) Unreported dummy variables for industry, time and state are also included in each of these regressions except for the probit in column (2).

ble 5 reports the coefficient estimates of the disclosure probability equation estimated by maximum likelihood probit on the full sample of 113 MSAs over the four year period. The probit equation performs satisfactorily. All of the variables with the partial exception of industrial R&D, IRD_{MI}, are statistically significant at conventional levels, and the equation correctly predicts disclosure status in 84% of cases. Curiously, the signs on the two inter-industry spillover variables are opposite. Larger values for R&D spillovers assigned to a given MSA and industry (university) are likely to be associated with a smaller (greater) probability of employment disclosure, all else equal. Note, however, that the magnitudes of the R&D coefficients are comparatively small. It is mainly MSA size in terms of population, and to a smaller degree, the number of innovations that most powerfully determine disclosure probability.

Column (3) lists the estimated coefficients of the employment equation corrected for sample selection. Under the null hypothesis of no selection bias, the coefficient of the estimated inverse Mills' ratio, $\hat{\lambda}_{MIT}$, has a t-distribution. Using a t-test, we cannot reject the null at conventional levels of statistical significance. This outcome implies that there is no sample selection problem for these data. Hence including a term to capture sample selection makes very little difference respect to the remaining coefficients, as a comparison of the corrected equation in column (3) with the unadjusted equation in column (1) indicates.

There are several important findings in column (3). First, the major result is that the estimates suggest, if anything, a rejection of the heterogeneity hypothesis. Although the coefficient on the university R&D spillovers in other clusters, $URDSPILL_{MI,T-3}$, is slightly larger than that for the corresponding industrial R&D spillover, $IRDSPILL_{MI}$, both are statistically insignificant at conventional levels.

Second, industrial and university R&D are positive and statistically significant determinants of high technology employment. The employment elasticities are similar in magnitude, 0.12 and 0.09 respectively, though they are not strictly comparable given the different bases of measurement.

Third, and perhaps surprisingly, real wages and employment are positively related ceteris paribus. To correct for any possible simultaneity between employment and real wages, the equation was also estimated using lagged wages. The results are reported in column (4) and are very similar to those in columns (1) and (3). Neither unreported re-estimates with 2SLS or random effects models produced any difference in this result which thus appears to be robust to estimation technique.

Without a measure of output we cannot estimate a production function or a structural model of labor demand. Our reduced form relationship between wages and high technology employment suggests that we may have captured the dynamics of labor supply in the face of mobility costs and specific skills. Faster growing local industries may need higher wages to recruit scarce skills from further afield to compensate for relocation and transport costs. There is an analogy with the well known firm size-wage correlation, and of course higher employment is likely to imply larger firms on average[9].

[9] Higher wages and employment may be a legacy of faster growth in previous years not included in our short panel.

7. Conclusions

We have established a striking correlation between local R&D and subsequent high technology employment in the same MSA and three-digit industry cluster. There is apparently no spillover relationship from R&D in the other industry groups. This result may seem surprising in the light of much recent research which seems rather to support the Jacobs' (1969) view of the benefits of diversity. Of course, our essentially cross-sectional data cannot directly address the key issues of growth performance, which require longer panels. And we have only focussed on a narrow subset of industries, albeit important ones in the context of knowledge spillovers. In addition, our industry groupings offer no evidence on spillovers within groups, between the related industries we have aggregated and listed in Table 1, though such spillovers are to be expected among similar technologies, and would also not lend support to the diversity thesis.

From a microeconomic perspective, our evidence for the benefits of specialization, following MAR, does appear plausible in our context and raises several challenges for future research. These include extensions to other industries and longer panels which allow for further direct testing of spillovers from R&D to growth and productivity in other industries.

References

Acs ZJ (1996) American high technology clusters. In: de la Mote J, Paquet G (eds) Evolutionary economics and the new international political economy. Pinter, London pp 183–219

Acs Z, FitzRoy FR, Smith I (1999) High technology employment, wages and university R&D spillovers: Evidence from U.S. cities. Economics of Innovation and New Technology 8:57–78

Anselin L, Varga A, Acs ZJ (1997) Local geographical spillovers between university research and high technology innovations. Journal of Urban Economics 42:422–448

Anselin L, Varga A, Acs ZJ (2000) Geographic and sectoral characteristics of academic knowledge externalities. Papers in Regional Science 79(4):435–444

Arrow KJ (1962) Economic Welfare and the Allocation of Resources for Invention. In: Nelson RR (ed) The rate and direction of inventive activity. Princeton University Press, Princeton, NJ

Audretsch DB, Feldman MP (1996) Knowledge spillovers and the geography of innovation and production. American Economic Review 86(3):630–640

Bernstein JI, Nadiri MI (1989) Research and development and intra-industry spillovers: An empirical application of dynamic duality. Review of Economic Studies 56:249–269

Black D, Henderson V (1999) A theory of urban growth. Journal of Political Economy 107(2):252–284

Braunerhjelm P, Carlsson B (1998) Industry clusters in Ohio and Sweden, 1975–1995. Small Business Economics 1(4):279–293

Duranton G, Puga G (1999) Diversity and specialization in cities: Why, where and when does it matter? Centre for Economic Performance, Discussion Paper 433, August, London School of Economics and Political Science

Edwards KL, Gordon TJ (1984) Characterization of innovations introduced in the US market in 1982, the futures group. Report prepared for the U.S. Small Business Administration, The Futures Group, Washington D.C

Feldman MP, Audretsch DB (1999) Innovation in cities: Science-based diversity, specialization and localized competition. European Economic Review 43:409–429

Glaeser EL, Kallal HD, Scheinkman JA, Shleifer A (1992) Growth in cities. Journal of Political Economy 100(6):1126–1152

Griliches Z (1992) The search for R&D spillovers. Scandinavian Journal of Economics 94:29–47

Griliches Z, Lichtenberg F (1984) Inter-industry technology flows and productivity growth: A comment. Review of Economics and Statistics 66:324–329

Heckman JJ (1979) Sample selection bias as specification error. Econometrica 47:153–162
Henderson JV (1994) Where does an industry locate? Journal of Urban Economics 35:83–104
Henderson JV, Kuncoro A, Turner M (1995) Industrial development in cities. Journal of Political Economy 103(5):1067–1090
Jacobs J (1969) The economy of cities. Vintage, New York
Jaffe AB (1986) Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. American Economic Review 76(5):984–1001
Jaffe AB (1989) Real effects of academic research. American Economic Review 79(5):957–970
Jaffe AB, Trajtenberg M, Henderson R (1993) Geographic localization of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics 63:577–598
Krugman P (1991) Increasing returns and economic geography. Journal of Political Economy 99(3):483–499
Lund L (1986) Locating corporate R&D facilities, Conference Board Report No. 892, Conference Board, New York
Loesch A (1954) The economics of location. New Haven, Yale University Press
Lucas RE (1988) On the mechanisms of economic development. Journal of Monetary Economics 22:1–42
Lucas RE (1993) Making a miracle. Econometrica 61:251–272
Maddala GS (1983) Limited-dependent and qualitative variables in econometrics. (Econometric Society Monographs, No. 3.) Cambridge University Press, Cambridge
Mairesse J, Mohnen P (1990) Recherche-developpement et productivite: Un sorvolde la literature econometrique. Economie et Statistique, 237-8:99–108
Marshall A (1890) Principles of economics. Macmillan, London
Muizer AP, Hospers GJ (1998) Industry clusters ands SMEs. Small Business Research and Consultancy, Zoetermeer
Porter ME (1990) The competitive advantage of nations. The Free Press, New York
Romer PM (1986) Increasing returns and long run growth. Journal of Political Economy 94:1002–1037
Rosenberg N (1963) Technological change in the machine tool industry, 1840–1910. Journal of Economic History 23:414–443
Schumpeter JA (1942) Capitalism, socialism and democracy. Harper Collins, New York
Storper M (1995) The resurgence of regional economies, ten years latter: The region as nexus of untraded interdependencies. European Urban and Regional Studies 2(3):191–222
Varga A (1998) University research and regional innovation: A special econometric analysis of academic knowledge transfer. Kluwer Academic Publishers, Boston