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2 Agglomeration and the Role of Universities in Regional Economic Development

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2.1 Introduction

As Hungary has successfully been transformed into a country with a well-functioning market economy and a stable democratic political system the main economic issues are no longer related to transition but to modernization and the establishment of a sustainable long run growth path. Does the country have the capacity to follow the direction of knowledge-based economic development as perhaps the most promising way of modernization? Historical experience suggests that Hungary might have a good potential in this respect as indicated by the disproportionately high number of Hungarian-born Nobel laureates or the number of important inventions developed by Hungarian scientists in the last century. An economic development policy supporting certain scientific fields at universities and promoting collaboration between universities and the local industry could perhaps be a good instrument to fuel economic growth by scientific excellence. In this respect, as in many others, studying international experiences might be helpful to set more realistic expectations. One of the related key issues is the role of agglomeration (i.e., the size of the regional economy) in the efficiency of university-based regional economic development policies. This chapter*, based on data of one of the most targeted high technology sectors, the electronics industry, provides an analysis of the United States experience.

Since the early eighties, resulting from major structural changes in modern economies, a new wave of regional economic development policies has begun to emerge both in the US and in Europe (Atkinson 1991, Isserman 1994, Osborne1994). While traditional approaches (i.e., “smokestack chasing” via providing attractive financial conditions and business climate for relocating companies) were suitable tools for boosting localities in the era of mass production, they are no longer appropriate in the age of technology-led economic growth when economic globalization and the preeminence of knowledge and information in production have given rise to a renewed importance of regions (Acs 1999, Florida, Gleeson and Smith 1994, Scott 1996). This new set of policies, called “self-improvement” (Isserman 1994), or “high-performance economic development”

*This chapter draws on Varga (2000) and Varga (2001).

(Florida, Gleeson and Smith, 1994) aims at advancing a region's technology base and human infrastructure through the implementation of specific, technology related programs. In collaboration with the regional industry, governments support technology development, assist in industrial problem solving, provide start-up assistance, and help local firms finance new technologies (Coburn 1995).

Motivated by the success stories of Silicon Valley and Route 128, regional technology programs put a significant weight on promoting technology transfers from universities to the local industry. Not only has the direct support for university research increased (in the US academic R&D grew form $ 7 billion in 1980 to $ 17 billion in 1993 in 1987 dollars[1]), a major portion of technology related expenditures of regional governments is being spent on programs requiring different forms of university involvement. For example, according to the data in Coburn (1995), 30 % of the budget of state cooperative technology development programs in 1994 went directly to universities located in the state. This category of expenditures includes supporting university-industry technology centers, promoting university-industry research partnerships, and involvement in different forms of equipment and facility access programs. Moreover, about 70 % of the total budget of state technology programs is, in part, associated with some kind of university participation. University-industry research centers (UIRCs) appear to be the most favored vehicles of government involvement in academia-supported regional development. In 1990, federal and state governments spent about $ 1.9 billion on research and related activities at the estimated 1,056 UIRCs of the US (Cohen, Florida and Goe 1994). More than that, 40 US states maintain technology extension programs, many of them are located on university campuses. Additionally, 20 states support incubators and research parks, most of them assume significant university involvement (Coburn 1995).

Despite high expectations regarding positive regional economic effects of technology transfers from academia, scholarly evaluations of technology-based economic development programs are still rare in the literature[2]. Empirical economic research on regional university knowledge effects still struggles with data problems at lower levels of geographic and industrial aggregation and the absence of a comprehensive theory of regional innovation systems[3].

Studies carried out within the classical Griliches-Jaffe knowledge production function framework report strong and significant effects of technology transfers from university research laboratories to regional innovation both at the level of US

[1] National Science Board (1993)

[2] According to my knowledge, the study by Bania, Eberts, and Fogarty (1992) is the only major scholarly attempt in this area of research.

[3] Regarding university knowledge effects, modeling approaches belonging to the tradition of the neoclassical growth theory in Anderson (1981) and Anderson et al. (1989) and the regional investment model in Florax (1992) should be referred to here as major achievements in this research field. For a recent survey of the literature see Varga (2002).

states and metropolitan areas (Jaffe 1989, Acs, Audretsch and Feldman 1991, 1994, Anselin, Varga and Acs 1997). However, this effect exhibits notable sectoral variations (Anselin, Varga and Acs 2000a, 2000b).

Several observations support the hypothesis that the intensity of academic technology transfers is not stable across regions. For example, Acs, Herron and Sapienza (1992) and Feldman (1994b) point to the case of Johns Hopkins University and Baltimore. Despite the fact that Johns Hopkins is the largest recipient of federal research funds, no significant high technology concentration has emerged in the Baltimore area. 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. Regarding technology policy, these observations suggest that the same amount of university research support might affect regions differently, depending on the characteristics of their economic activities.

Besides definite differences in the scope and practical applicability of research programs at universities and regional variances in cultural traditions (Saxenian, 1994), it seems a reasonable assumption that agglomeration might play an important role in explaining spatial variations in university knowledge effects. To explain the modest university impact in Baltimore, Feldman (1994b) points to the possible role of the absence of a "critical mass" of high technology enterprises, the lack of producer services, venture capital and entrepreneurial culture.

In this chapter, the methodology developed in Varga (1998) is applied to study differences in the agglomeration effect on local university technology transfers. Applying a unique data set of innovation counts and professional employment in private R&D laboratories, an MSA level analysis is carried out within the Griliches-Jaffe knowledge production framework (Griliches 1979, Jaffe 1989). Section 2 presents the empirical model. It is followed by a data introduction and a discussion of estimation issues. Section 4 reports the regression results, while section 5 demonstrates the agglomeration effect on academic technology transfers. Concluding remarks follow.

2.2 The empirical model

A major obstacle of testing the effect of agglomeration on university technology transfers 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. However, these variables cover local academic knowledge spillovers only partially.

For modeling purposes, an implicit measure of academic technology transfers is proposed in Varga (1998). This measure is based on the Griliches-Jaffe knowledge production function (Griliches 1979, Jaffe 1989). 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. Jaffe points out that a positive and significant coefficient of the university research variable indicates university technology transfer effects on industrial knowledge production (Jaffe 1989: 957). As such, the magnitude of α_2 can be considered as a measure of 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[4].

The parameter expansion method of Casetti (1997) is applied in this chapter to test for the effect of agglomeration on academic knowledge spillovers measured by the coefficient of the university research variable in equation (1). Knowledge transfer mechanisms[5] are classified into three categories:

- information transmission via 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).

[4] Given that the coefficient of the university research variable in equation (1) reflects local academic technology transfers implicitly, this is not a perfect measure of knowledge spillovers. The absence of such a correct measure is the reason of its substitution with a "second best" solution applied in this chapter.

[5] The various mechanisms of local university knowledge transfers have been widely discussed in the literature (e.g., National Science Board 1983, Dorfman 1983, Johnson 1984, Rogers and Larsen 1984, Wicksteed 1985, Parker and Zilberman 1993, Saxenian 1994).

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[6]. 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 (Link and Rees 1990, Acs, Audretsch and Feldman 1994). Consequently, it is expected that *small firm concentration* enhances local university technology spillovers.

The following expansion equation models the dependence of academic knowledge transfers on the concentration of economic activities.

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

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 (as suggested by Link and Rees 1990, and Acs, Audretsch and Feldman 1994).

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 (Dosi 1988, Hippel 1988, Edwin Mansfield and Elisabeth Mansfield 1993). By enlarging the pool of available technical knowledge, concentration of production intensifies knowledge flows through the local networks 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, Audretsch and Feldman (1994) found that knowledge spillovers among private R&D laboratories 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:

[6] Regional technology transfers are being supported by different types of local service companies. Not only patent attorneys or management services but also several engineering services are considerable sources of significant support in technology spillovers. Unfortunately, industry classification does not support such details in data collection. A proxy, a measure of business service activities has been chosen as a rough indicator of local service input to technology transfers.

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

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 (1) provides the expanded knowledge production function:

(4) $$\begin{aligned}\log(K) = {} & \alpha_0 + \gamma_0 \log(RD) + \gamma_1 \log(PROD)\log(RD) + \\ & + \gamma_2 \log(BUS)\log(RD) + \gamma_3 \log(LARGE)\log(RD) + \beta_0 \log(URD) + \\ & + \beta_1 \log(PROD)\log(URD) + \beta_2 \log(BUS)\log(URD) + \\ & + \beta_3 \log(LARGE)\log(URD) + [\eta \log(RD) + \mu \log(URD) + \varepsilon]\end{aligned}$$

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 activities interacting with local agglomeration factors: concentration of production, business services and large companies.

2.3 Data and estimation

Estimation of equation (4) is based on the same unique data set of US metropolitan areas as in Anselin, Varga and Acs (2000a and 2000b). New technological knowledge (K) is measured by counts of product innovations introduced on the US market in 1982. Innovation counts come from the United States Small Business Administration (SBA) innovation citation database (Edwards and Gordon 1984). This data set is a result of an extensive survey of the new product sections of trade and technical journals. County and MSA aggregates of the innovation data are available in two-digit SIC industry details and only for 1982. To date the SBA data are the best available measure of US innovative activity[7].

Private research activities (RD) are proxied by professional R&D employment. The source of this data is the 17th edition of Industrial Research Laboratories of the United States (Jaques Cattell Press 1982)[8]. Following the common approach, university

[7] 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. A comparative analysis of innovation and patent counts as measures of new knowledge in the KPF context is provided in Acs, Anselin and Varga (2002).

[8] Although it is a reasonable approach to account for a four or five-year lag between innovations and research (as was done in Acs and Audretsch 1990, Acs, Audretsch and Feldman 1991, and in Feldman 1994), this approach is not followed here. The technical reason is that 1982 is the first year that the Classification Index of the Directory allows for appropriate industry level aggregations. Besides this technical impediment, the validity of the choice of the year 1982 is supported by the trends in R&D lab

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 the electronics industry is accounted for by the location quotient of sectoral employment in the metropolitan area[9]. Business services activities are measured by employment in SIC 73. The percentage of electronics firms with employment exceeding 500 accounts for the relative importance of large companies. For a more detailed description of the data see Anselin Varga and Acs (2000a, 2000b).

Three potential estimation problems of the expanded knowledge production function 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 (Belsley et al. 1980) are 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 the spatial econometrics literature (e.g. Anselin 1988, Anselin and Florax 1995, Anselin and 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) $$y = \rho W y + x\beta + \varepsilon$$

location. As reported in Malecki (1979, 1980a, 1980b), location patterns of R&D laboratories tend to be stable for a relatively long period of time. This observation suggests that a regression model on lagged research variables would not provide significantly different outcomes from those reported in this study.

[9] A location quotient relates local and national importance of an industry, based on its relative share in the local and in the national economy. Formally: LQ = $(EMPSEC_{MSA}/EMPTOT_{MSA})/(EMPSEC_{NATION}/EMPTOT_{NATION})$, where EMPSEC and EMPTOT stand for employment in the specific sector and total employment, respectively. LQ > 1 shows that industry employment is more concentrated in the region than on average in the nation.

where y is an N by 1 vector of dependent observations, W is a row standardized spatial weight matrix[10], 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.

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) $$\phi = \lambda W\varepsilon + \xi$$

where λ is the coefficient of spatially lagged autoregressive errors $W\varepsilon$ and ξ is an N by 1 vector of independent disturbance terms. The other notation is as before[11].

Three spatial weights matrices are 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 [12]. The presence of spatial dependence is tested for by Lagrange Multiplier test statistics (Burridge 1980, Anselin and Florax 1995). Empirical regressions are carried out in SpaceStat, an econometric software designed for the analysis of spatial data (Anselin 1992).

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[10] 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).

[11] The applied spatial econometric methodology is well suited for modeling the spatial extent of knowledge spillovers. Spatial dependence in the knowledge production function, either in the form of lag or error autocorrelation, is a sign of knowledge transfers among the spatial units of analysis. In any case of spatial dependence, the correctly specified spatial econometric equation accounts for spillovers both within and among the spatial units (Anselin, Varga, and Acs 1997, Varga 1998).

[12] 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.

2.4 Regression results

Parameter expansion results are reported in Table 2.1 for the electronics industry. The first column lists estimation results for equation (4). The extremely high value of multicollinearity (with condition number of 168) makes it impossible to reasonably evaluate the relative importance of different agglomeration factors in the processes of local knowledge transfers. In the second and third columns, parameters of the two research variables are expanded, separately.

Table 2.1. Regression results for Log (INN) in the Electronics industry (N=70, 1982)

Model	Full Model OLS	RD Model OLS	URD Model OLS	Final Model ML-Spatial Error
Constant	-0.315	-0.141	-0.130	-0.186
	(0.183)	(0.186)	(0.187)	(0.149)
log(RD)	-0.061	-0.595	0.174	0.139
	(0.409)	(0.201)	(0.061)	(0.053)
log(URD)	-0.183	0.081	-0.507	-0.424
	(0.292)	(0.042)	(0.140)	(0.116)
log(RD)log(PROD)	0.209	0.039		0.043
	(0.053)	(0.011)		(0.009)
log(RD)log(BUS)	0.022	0.173		
	(0.095)	(0.038)		
log(RD)log(LARGE)	-0.097	0.009		
	(0.079)	(0.031)		
log(URD)log(PROD)	-0.127		0.026	
	(0.039)		(0.009)	
log(URD)log(BUS)	0.094		0.134	0.123
	(0.069)		(0.029)	(0.024)
log(URD)log(LARGE)	0.073		0.004	
	(0.055)		(0.023)	
LAMBDA				0.376
				(0.111)
R^2 - adj	0.712	0.671	0.653	0.700
LIK	-3.194	-9.627	-11.476	-4.095
Multicollinearity	168	44	42	38
B-P for Heteroskedasticity	5.360	4.755	11.652	4.719
LM-Err (D75)	4.239	9.319	11.141	
LM-Lag (D75)	4.755	5.530	6.948	0.275
LR-Error (75)				9.638

Notes: estimated standard errors are in parentheses; critical values for the B-P statistic with respectively 8, 5, and 4 degrees of freedom are 15.51, 11.07, and 9.49 (p=0.05); critical values for LM-Err LM-Lag and LR-Err statistics are 3.84 (p=0.05) and 2.71 (p=0.10); the spatial weights matrixes are row-standardized: D50 is distance-based contiguity for 50 miles and D75 is distance based contiguity for 75 miles.

The results show that both university and industrial knowledge transfers are significantly and positively affected by the concentration of production and business services. Another common result is that the small firm effect is not significant for either form of research effects. However, high multicollinearity (an inherent shortcoming of the applied parameter expansion methodology) is a technical impediment to accounting for all the possible factors of agglomeration. Instead, the strongest effects are examined in the final model. The model in the fourth column exhibits the best properties in terms of regression fit and multicollinearity. Spatial dependence among regression error terms is taken care of by means of maximum likelihood estimation. Business services are the major agglomeration factors explaining technology transfers from universities while knowledge spillovers among research laboratories are dominantly promoted by production concentration.

2.5 University effect and agglomeration: a demonstration of the importance of a "critical mass" for successful technology transfers

Regression results in Table 2.1 clearly evidence that the available pool of technological knowledge at academic institutions exerts diverse impacts on the local economy, depending on the level of concentration of economic activities in a metropolitan area. However, the scale of local economic activities that is sufficient enough to yield substantial academic knowledge transfers still remains an important issue for the analysis.

In order to address the "critical mass" of local economic activities problem, MSAs in the samples are categorized into three different "tiers." The categorization is based on the intensity of local academic knowledge transfers measured by the estimated coefficients of the university research variables in the industrial knowledge production functions. Given that knowledge production is formulated in the form of a Cobb-Douglas function, these coefficients measure innovation elasticities with respect to university research spending.

Based on the final model in Table 2.1, the intensity of academic technology transfers in location j is calculated as follows:

(8) Elasticity [Innovation, University Research]$_j$ =

$$\delta \log(K_j) / \delta \log(URD_j) = -0.424 + 0.123 \log(BUS_j).$$

The first column of Table 2.2 lists average elasticities of innovation with respect to university research. It is clear that all the variables included in the table follow the same decreasing tendency of innovation elasticities. The third column lists average values of innovation predictions. These predictions are based on parameter estimates in Table 2.1. Compared to the respective average tier values of observed innovations, the estimated model of knowledge production provides good average predictions for the second and third tiers. However, the model consistently underpredicts average levels of innovation activities in the first tier. This observation suggests that for first tier MSAs actual university technology transfers are probably higher in their intensity than indicated by innovation elasticity predictions.

Table 2.2. Average values of innovation elasticities, innovation, R&D activities, employment and population by innovation elasticity categories for the Electronics industry

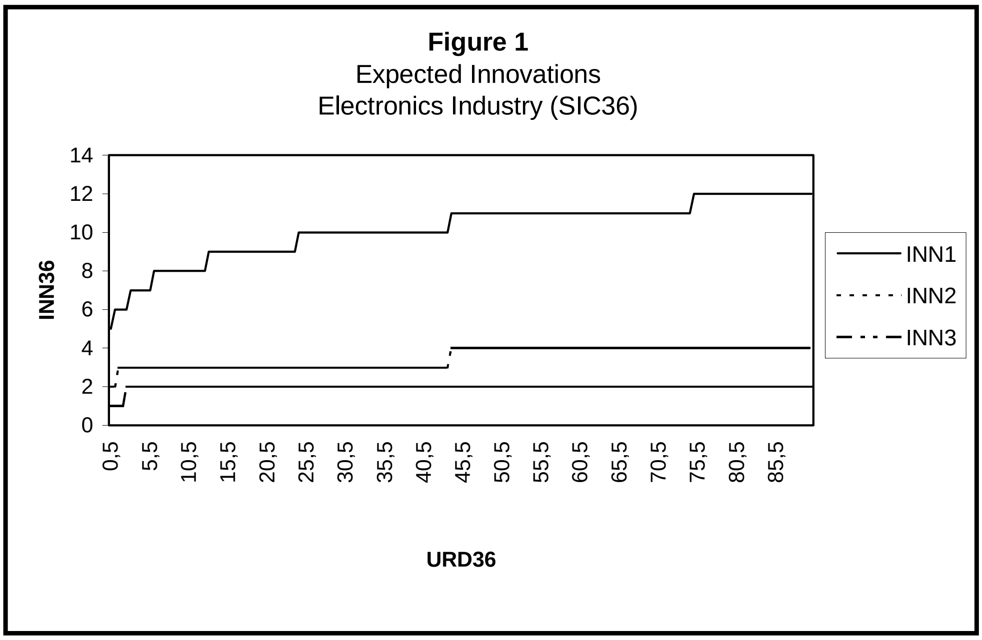
	EL(I,U)	INN36	INN36PR	RD36	URD36	EMP36	POP
Tier 1	0.164	23	9	2875	16154	38121	3.1
Tier 2	0.091	4	3	307	3950	9625	0.9
Tier 3	0.032	2	2	224	3119	5187	0.5

Notes: EL stands for elasticity of innovation with respect to university research; INN is the number of innovations in the MSA; INNPR is predicted innovations RD stands for R&D professional employment; URD is university research expenditures in thousands of US dollars; EMP is industry employment; POP is population in millions of inhabitants.

Figure 2.1 demonstrates the effect of agglomeration on local university technology transfers. In essence, this figure simulates the impacts of a *pure* university-based regional economic development policy in metropolitan areas exhibiting different levels of economic activities. In other words, the effects of increased university research expenditures on innovation are presented, while all the other characteristics of the MSAs are assumed to remain the same. The X axis represents university research expenditures, while the Y axis depicts expected innovations for university research spending sizes and for different MSAs in both figures. University research activities depicted on the X axis in the figure reflect the range between the highest and lowest levels of observed university research expenditures. The three curves stand for different expected innovation outcomes associated with the same amounts of university research spending. Expected innovations for each tier were calculated based on the final model in the last column of Table 2.1. For 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 calculations.

Figure 2.1 demonstrates the dramatic differences in the “productivity” of the same amount of university research spending depending on the size of economic activities in a geographic area. First tier metropolitan areas possess the “critical mass” of local economic activities, that is, those cities absorb university effects in the most efficient manner. This critical mass is characterized by population of around 3 million, electronics industry employment of about 40 thousands and the number of professional research staff in industrial laboratories of 3 thousands.

Figure 2.1 Expected innovations



While increased academic research expenditures have basically no effects on innovation activities in second and third tier cities, the impact of academic research in the first tier is remarkable. (Over the range of respective university research expenditures, innovation activity increases from 5 innovations to 12.)

A pure university-based regional development policy seems not to be effective enough to "upgrade" geographical areas in the second and third tiers to a higher level of innovative activity. With the exception of third tier cities (where knowledge production reaches the lowest level of second tier innovations after about 4 millions of university research expenditures), even the maximum amount of university research spending is not high enough to reach the lowest average level of knowledge production in the next tier of metropolitan areas.

Sensitivity of innovative activity to increased university research spending gradually decreases in first tier cities. While at lower levels of university research activities, boosting local universities seems to be a cost effective way of economic development, this advantage seems to disappear quickly: the larger the amount of university research spending, the higher the cost of each additional innovation.

2.6 Summary and conclusions

Universities have gained increased attention in modern, technology-based regional economic development policies. Despite high expectations regarding positive economic effects of university support, scholarly evaluations of policies promoting local technology transfers from universities are still scarce in the literature. An important area of research is the effect of spatial concentration of economic activities on university-based regional economic development policies. This chapter provided formal empirical evidence of the positive impact of agglomeration on local academic technology transfers for the US electronics industry.

Parameter expansion analyses were carried out within the classical Griliches-Jaffe knowledge production framework. Testing and correcting for spatial effects in regression equations earned a particular attention in the empirical investigations. University technology transfers are most sensitive to the presence of business services in the Electronics sector. It was demonstrated that the same amount of university research spending is associated with notable differences in knowledge production depending on the concentration of economic activities in the metropolitan area.

In addition, it was found that the presence of a “critical mass” of agglomeration in the metropolitan area is required in order to expect substantial local economic effects of academic research. To reach the critical mass a relatively high level of regional concentration of economic resources is needed: population size of around 3 million, electronics industry employment of about 40 thousands and the number of professional research staff in electronics industry laboratories of nearly 3 thousands. Simulations of university knowledge effects suggest that pure university-based regional economic development policies are not effective enough to “upgrade” localities to a higher tier of innovative activities. Simulation results also suggest that cost-effectiveness of university support is in an indirect relationship with the level of academic research expenditures.

A major message of the findings in this chapter is that strengthening universities in order to advance local economies seems be a good option for relatively well-developed metropolitan areas but not necessarily for lagging regions. For the latter group of localities a more comprehensive approach appears suitable including a complex regional economic development plan that targets not only local academic institutions, but also high technology employment, business services and small firms.[13]

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[13] To some extent, the applied data and methodology set the limitations on the interpretations of the results. Since the SBA innovation data are available for one year, only a static analysis is allowed in this study. Consequently, results reflect a “longer term” equilibrium under the assumption that economic variables do not go under significant changes. The innovation data set does not make it possible to differentiate among innovations based on their economic importance. It is possible that some places are over-represented because of their relatively numerous but not necessarily important

Results of the analyses reflect the general trend of agglomeration effect and should be interpreted this way. Individual cities can (and do) exhibit different combinations of regional economic features while maintaining the same intensity of academic technology transfers. The essence of the results is that individual metropolitan areas cannot be "too far" from the average size in order to preserve tier-specific university effects.

Despite its limitations, the analysis of this chapter strongly indicates that university-based economic development policies can be efficient tools for relatively matured high technology agglomerations. For less developed regions the results suggest reducing efforts on university-based regional economic development policies and concentrating more on the growth of high technology employment (via traditional "chasing" approaches) and widening the base of local business services[14]. This message could be very useful for Hungarian policy makers to consider universities as potential engines of local economic development from a more realistic perspective.

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product developments relative to others where only a few but fundamental innovations were reported. Due to its tendency for quickly increasing multicollinearity, the applied parameter expansion model reflects only the effects of the most important local agglomeration features on academic technology transfers and it cannot be used for a complete modeling approach.

[14] This result is robust: for the aggregate high technology sector essentially the same consequence was reached in Varga (1998, 2000).

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