Regional Innovation in the US over Space and Time [1]

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1 Introduction

Knowledge plays a central role in economic development as recently emphasized especially in endogenous growth models (e.g. Romer, 1986, 1990, Aghion and Howitt, 1999). Therefore, explaining the process of knowledge production is crucial to understand modern economic growth. Innovation activities have a predominant tendency to cluster spatially as demonstrated by recent empirical studies (e.g. for the US in Varga, 1998 and for the European Union in Caniels, 2000). Sensitivity of the transmission of tacit knowledge to distance provides a principal reason for the development of regional innovation clusters since the transfer of non-codified knowledge elements frequently requires close personal interactions (Polanyi, 1966, Dosi, 1988). Thus, relative spatial position of the actors in knowledge creation is a potentially significant factor of innovation. Endogenous growth theories provide models to study the role of knowledge in macroeconomic growth but leave out the regional dimension despite the substantial evidence provided in the recent empirical economics literature that a significant fraction of knowledge spillovers tends to be localized (Acs and Varga, 2002).

Four approaches have been developed in the recent empirical economics literature to estimate the role of localized knowledge flows in the process of innovation: surveys of industrial researchers (Mansfield, 1995), the study of the spatial patterns of patent citations (Jaffe, Trajtenberg and Henderson, 1993), regional innovation surveys (Cooke, 2000, Koschatzky and Sternberg, 2000) and econometric analyses within the knowledge production function framework. This framework has been widely applied in empirical studies of regional innovation in the US (e.g. Jaffe, 1989, Acs, Audretsch and Feldman, 1991, Acs, Anselin and Varga, 2002, Anselin, Varga and Acs, 1997, and Varga, 2000), in Italy (Audretsch and Vivarelly, 1994, Capello, 2001), in France (Autant-Bernard, 1999), in Germany (Fritsch, 2002 and in Austria (Fischer and Varga, 2003).

Building on a recently developed cross-sectional time-series data set of US inno-

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vation, private and university research and high technology employment, we continue our previous work in this paper. We provide a first-cut analysis of the data to shed some new light on the spatial and temporal aspects of US innovation. The novelty of this data set is that it opens up the possibilities to incorporate the time dimension into knowledge production function analysis at an appropriate level of spatial aggregation (i.e. US metropolitan areas) that has not been possible in empirical research yet. The following section introduces the methodology and the applied data, while the third and fourth sections highlight some important space-time aspects of US innovation. A summary concludes the paper.

2 Methodology and Data

The knowledge production function (KPF) framework was initiated by the work of Griliches (Griliches, 1979, 1986) and was first implemented in the spatial context in Jaffe (1989). Since then it has become a major methodological approach to understand the geography of innovation. A critique against knowledge production function studies (i.e. that the model does not allow for an explicit modeling of the way knowledge spillovers occur and as such it is difficult to separate spillovers from the correlation of variables at the geographical level as expressed e.g. in Feldman, 2000) is certainly valid to some extent. However, an important advantage of the knowledge production function analysis is that it can provide an account of innovation-related interactions on the basis of large number of geographical areas with the fraction of the costs of a similarly designed survey-based research given that KPF studies rely on secondary data sources. On the other hand, since the applied data do not refer to actual interactions, much care should be taken on econometric specification.

Formally, the knowledge production function is expressed as:

$$\log(K) = \alpha + \beta \log(R) + \gamma \log(U) + \delta \log(Z) + \epsilon \tag{1}$$

where K is a proxy for knowledge (either patents or innovation counts), R is industry R&D and U is university research, with ϵ as a stochastic error term. Z typically includes a measure of the concentration of a given activity (a proxy for innovation networks of manufacturing firms). The analysis is usually carried out for aggregate cross-sectional units (e.g. states, MSAs), possibly for several points in time and/or disaggregated by sector. Positive and significant coefficients for β, γ and δ indicate positive effects of different regional knowledge sources on industrial innovation.

We aggregated the data to the "high technology" sector, that is a set of industries where the intensity of knowledge inputs to production exceeds the industrial average. Table 1 provides more information on the set of specific industries included. Our panel data set comprises variables observed for three years (1985, 1988 and 1991) and aggregated to the level of US metropolitan statistical areas (MSAs). K is measured by patent applications (US Patent Office, 1998), R is professional employment in high technology industrial laboratories compiled from three editions of the Directory of American Research and Technology (1986, 1989, 1992), U is university research expenditures obtained from CASPAR data files (National Science Foundation, 1997) and

Z is high technology employment (Bureau of the Census, 1999).

As in our previous studies we apply the methodology of spatial econometrics in studying the geography of innovation. Spatial econometrics (Anselin, 1988, 2001, Anselin and Florax, 1995) turns out to be a very powerful analytical tool in empirically modeling localized knowledge spillovers when cross sectional data are applied. Spatial econometrics supplies both the appropriate statistics to test for potential misspecifications as well as different modeling approaches of spatial dependence with a high intuitive value in actually measuring inter-regional knowledge spillovers. SpaceStat, the software for spatial data analysis developed by Luc Anselin is used for spatial regressions throughout this paper.

Table 1: High technology industries

SIC (1972)	PTO
Drugs	
283 Drugs and medicines	14
Chemicals	
281 Industrial inorganic chemistry	6
282 Plastic materials and synthetic resins	8
286 Industrial organic chemistry	7
289 Miscellaneous chemical products	13
Information Technology	
357 Office computing and accounting machines	27
361, 3825 Electrical transmission and distribution equipment	35
365 Radio and television receiving equipment except communication types	42
366, 367 Electronic components and accessories and communications equipment	43
High Technology Machinery and Equipment	
351 Engines and turbines	23
353 Construction and related machinery	25
356 General industrial machinery and equipment	30
362 Electrical industrial apparatus	36
363 Household appliances	38
364 Electrical lighting and wiring equipment	39
369 Miscellaneous electrical machinery, equipment and supplies	40
Defense and Aerospace	
372 Aircraft and parts	54
376 Guided missiles and space vehicles and parts	47
Professional and Scientific Instruments	
38 Professional and scientific instruments	55

Notes: The list of industries is based on Acs (1996). Concordance between SIC codes and PTO sequence numbers is provided by the US Patent and Trademark Office

Table 2: Comparative statics. OLS knowledge production estimates with contemporaneous and lagged dependent variables

Variable	PATHT85 X85	PATHT88 X88	PATHT88 X85	PATHT91 X91	PATHT91 X88
Constant	-4.826	-3.676	-3.822	-4.284	-3.719
	(0.488)	(0.440)	(0.452	(0.482)	(0.475)
Log(RD)	0.166	0.224	0.218	0.163	0.189
	(0.043)	(0.039)	(0.040)	(0.039)	(0.041)
Log(URD)	0.086	0.067	0.071	0.093	0.090
	(0.026)	(0.024)	(0.024)	(0.027)	(0.026)
Log (EMPHT)	0.697	0.599	0.615	0.679	0.618
	(0.066)	(0.059)	(0.062)	(0.064)	(0.063)
CON50	0.244	0.260	0.236	0.328	0.268
	(0.127)	(0.121)	(0.118)	(0.128)	(0.130)
SOUTH and WEST	0.254	0.002	-0.002	0.149	0.010
	(0.125)	(0.118)	(0.116)	(0.127)	(0.127)
R^2-adj	0.80	0.81	0.82	0.79	0.79
Number of obs.	143	143	143	143	143

Notes: All dependent variables are in logarithm. Estimated standard errors are in parentheses; X denotes the dependent variables; RD is professional employment at industrial research and development laboratories; UR is university research expenditures; EMPHT is high technology employment; CON50 is a dummy variable: it takes 1 if at least one MSA is located within a 50 mile distance band and 0 otherwise; SOUTH and WEST is a dummy variable: it takes 1 if the MSA is situated in the South or West and 0 otherwise.

3 Space–Time Patterns of U.S. Innovation – Some Methodological Issues

Two important methodological issues are considered in this section. First, an examination of the extent to which parameters of lagged independent variables in the knowledge production function are stable over time with different time lags applied and, second, an exploration with respect to the stability of estimated parameters over spatial units.

The issue of the stability of estimated parameters for different time lags applied between the dependent variable and the explanatory variables is important in evaluating regression results when single cross sections are used and data constraints do not allow to apply time lags between innovation inputs and outputs (as, for example, in Anselin, Varga and Acs, 1997). In principle, time lags of 2–3 years are recommended (see Edwards and Gordon, 1984) when patent data are used in order to account for the time difference between the actual development of an invention and the approval of its patent.

In Table 2 the knowledge production function of equation (1) is extended with two additional dummy variables. CON50 accounts for potential effects of agglomeration on the intensity of localized knowledge spillovers (in case of a single metropolitan

Table 3: Pooled OLS estimates of the knowledge production function with regional dummies Variable Log(PATHT)

Variable	PATHT	PATHT	PATHT	PATHT
Constant	-4.079	-4.020	-4.069	-4.060
	(0.284)	(0.267)	(0.263)	(0.266)
Log(RD)	0.197	0.195	0.184	0.198
	(0.023)	(0.023)	(0.023)	(0.023)
Log(URD)	0.084	0.084	0.089	0.082
	(0.015)	(0.015)	(0.015)	(0.015)
Log (EMPHT)	0.635	0.628	0.646	0.632
	(0.038)	(0.037)	(0.037)	(0.037)
CON50	0.313	0.267	0.290	0.334
	(0.072)	(0.076)	(0.071)	(0.073)
Mid-West	0.019			
	(0.078)			
North East		0.150		
		(0.082)		
South			-0.264	
			(0.078)	
West				0.139
				(0.091)
R^2-adj	0.79	0.79	0.80	0.79
Number of obs.	429	429	429	429

Notes: All dependent variables are in logarithm. Estimated standard errors are in parentheses; for variable definition see notes to tables 2; PATHT is patent application counts in high technology; Mid-West, North East, South and West are dummy variables taking 1 if the MSA is situated in a given region and 0 otherwise.

area this variable takes the value of 0 and it is 1 if the MSA is part of a larger cluster of cities). The SOUTH and WEST dummy is included to test for potential differences between patterns of localized knowledge production in the US industrial heartland (the North East and the Mid-West regions) and the recently emerging "new economy" in the South and the West[2] of the country (Suarez-Villa, 2000). The connectivity dummy stays consistently significant, whereas the regional dummy remains insignificant.

A three-year time lag is applied between the date of patent approval and invention in the third and fifth columns. A comparison of the results with a time lag applied (third and fifth columns) to those without time lags (second and fourth columns) shows no significant differences between sizes, signs and significances of parameter estimates as well as regression fits. It is also shown in the table that the relative importance

[2]The North-East consists of Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, Pennsylvania, New Jersey, Delaware, Maryland, Washington DC, Virginia and West Virginia. The Midwest states are Minnesota, Michigan, Wisconsin, Iowa, Missouri, Illinois, Indiana, Ohio, Kentucky, North Dakota, South Dakota, Nebraska and Kansas. The South consists of Oklahoma, Texas, Arkansas, Louisiana, Mississippi, Tennessee, Alabama, Georgia, Florida, North Carolina and South Carolina. States in the West are Washington, Montana, Arizona, New Mexico, Wyoming, Idaho, Oregon, California, Nevada, Utah and Colorado.

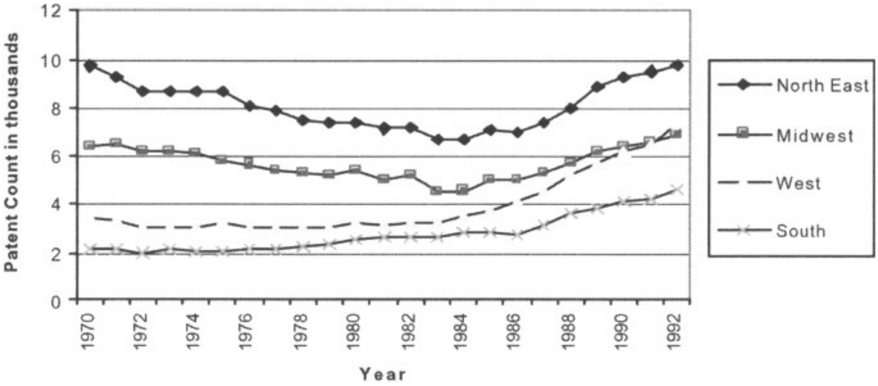

Figure 1: Regional trends in knowledge production in high technology (Source: Varga, 1999)

of different local sources of innovation remains the same no matter whether lagged or contemporaneous explanatory variables are used (i.e. interfirm knowledge flows dominate over research spillovers among local R&D laboratories and both are more important than knowledge transfers from regional universities).

The second research question relates to parameter stability over space. Compared to the South and West dummy a finer distinction among US regions is applied in Table 3 with the four regional dummies. In order to increase the level of information extracted from the data we run pooled time series cross-sectional regressions with 429 observations. Parameter values for local knowledge inputs as well as the connectivity dummy do not differ meaningfully, however, there are important differences as to the effect of regional dummies. Whereas no significant differences are reported for Mid-West, North East and the West, the significant (and negative) dummy for the US South suggests that local innovation systems in the newly emerging Southern high technology centers might differ in structure from the rest of the country. The following section focuses on this problem in more details.

4 Changing Geography of U.S. Innovation: Is There Any Role of Localized Knowledge Spillovers?

Perhaps one of the most fascinating issues in economic development is the recent emergence of high technology centers in the traditionally non-manufacturing sectors dominated US West and South, most notably in California, Texas, Arizona, Utah and Florida. Understanding the extent to which the impressive growth of these US regions is a result of consciously designed regional economic development policies (that can be learned and might be replicated in other parts of the World) may have relevance for currently lagging regions not only in the US, but in Europe as well. In Suarez-Villa

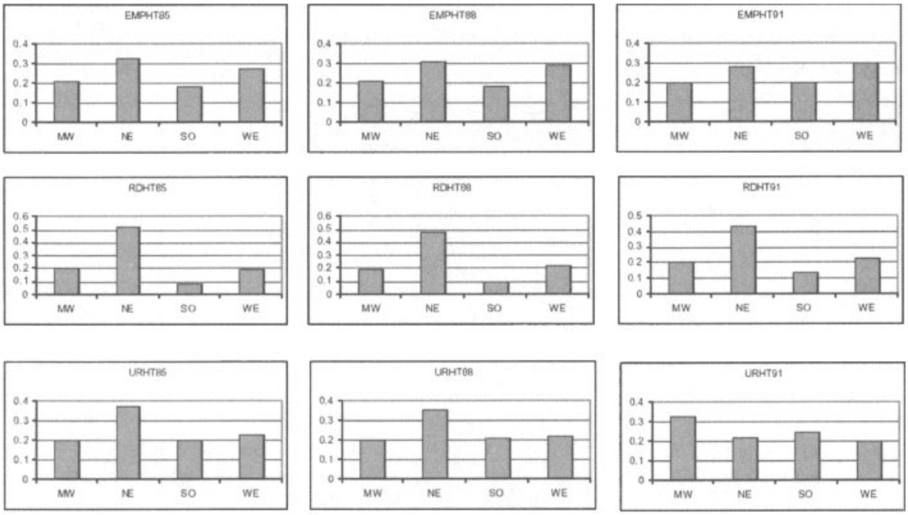

Figure 2: Geographical distribution of regional inputs to knowledge production between 1985 and 1991

(2000) the hypothesis that this growth is induced by previous investments in education and infrastructure is tested. In this section the focus is more on an exploration as to the potential differences in the relative importance of different regional factors of knowledge production.

Figure 1 shows regional trends in high technology knowledge production (measured by patent application counts) between 1970 and 1992. Whereas patenting activity followed a decreasing trend in the traditional manufacturing areas of the US (i.e. the North East and the Mid-West regions) until the early eighties, innovation activities of states in the South continuously increased, while in the West it stagnated during this period. However, after 1983 the differences among regional growth trends are dramatic and perhaps surprising. Although the North East maintained its traditional leading position in innovation during the whole time period, it seems that this position was increasingly challenged by the West, especially after 1989 when the rate of growth started to diminish in the North-East. Figure 1 shows that the North-East and the Midwest regions, which have been traditionally considered as leading manufacturing centers of the US, increasingly started losing their dominance in high technology innovation after 1983.

Differences in regional growth rates of patenting activity over the period of 1983–1992 also support this observation. While the North-East and the Midwest increased patenting by 45 and 53 percents, respectively, for the same time period growth rates of the West and the South were 128 and 79 percents. Moreover, while the North-East and the Midwest lost their share in total patents by 14 and 9 percents, the West and the South produced a substantial increase, 35 and 6 percents, respectively (Varga, 1999). This changing pattern might be induced by changes in the spatial distribution

Table 4: Maximum Likelihood Spatial SUR Regression Results for Log(Patents) at the level of US MSAs

Variable	National	North-East	Midwest	South	West
Constant	-4.783	-3.694	-3.534	-7.013	-4.955
	(0.449)	(1.066)	(0.822)	(0.949)	(0.526)
Log(RD85)	0.111	0.246	0.160	-0.001	0.123
	(0.035)	(0.064)	(0.071)	(0.060)	0.054)
Log(URD85)	0.097	0.007	0.091	0.187	0.156
	(0.024)	(0.044)	(0.043)	(0.053)	(0.041)
Log(EMPHT85)	0.711	0.624	0.570	0.906	0.688
	(0.059)	(0.130)	(0.120)	(0.105)	(0.090)
CON50	0.288	0.208	0.620	0.456	-0.304
	(0.125)	(0.241)	(0.246)	(0.280)	(0.223)
SOUTH and WEST	0.279				
	(0.123)				
Constant	-3.484	-2.639	-3.806	-3.934	-3.720
	(0.398)	(0.777)	(0.818)	(0.838)	(0.621)
Log(RD88)	0.194	0.255	0.141	0.188	0.161
	(0.030)	(0.046)	(0.075)	(0.050)	(0.054)
Log(URD88)	0.073	-0.003	0.069	0.135	0.061
	(0.022)	(0.036)	(0.044)	(0.047)	(0.039)
Log(EMPHT88)	0.588	0.565	0.632	0.570	0.666
	(0.051)	(0.092)	(0.123)	(0.085)	(0.096)
CON50	0.293	0.043	0.773	0.222	-0.079
	(0.118)	(0.197)	(0.250)	(0.272)	(0.248)
SOUTH and WEST	0.013				
	(0.116)				
Constant	-4.059	-3.384	-4.011	-5.239	-3.315
	(0.441)	(0.870)	(0.827)	(1.038)	(0.770)
Log(RD91)	0.141	0.171	0.112	0.125	0.195
	(0.031)	(0.047)	(0.073)	(0.049)	(0.065)
Log(URD91)	0.098	0.027	0.102	0.196	0.170
	(0.024)	(0.433)	(0.045)	(0.057)	(0.071)
Log(EMPHT91)	0.662	0.689	0.664	0.668	0.512
	(0.056)	(0.106)	(0.122)	(0.104)	(0.118)
CON50	0.353	0.098	0.627	0.588	-0.122
	(0.125)	(0.206)	(0.258)	(0.287)	(0.306)
SOUTH and WEST	0.153				
	0.124)				
R^2-adj	0.63	0.58	0.62	0.58	0.87
Number of observations	429	117	126	111	75
	Tests on spatial dependence				
D50 LM (error)	2.512	2.184	0.481	6.531*	0.834
D50LM (lag)	2.802	1.575	1.208	2.951	2.370
	Wald tests on parameter stability				
Log(RD)	8.875**	7.110**	0.349	10.682***	1.004
Log(URD)	2.975	2.026	1.025	2.907	14.612***
Log(EMPHT)	7.852**	4.037	0.577	15.220***	2.670
CON50	0.619	1.367	0.925	5.047*	2.100
SOUTH and WEST	9.246***				

Notes: Estimated standard errors are in parentheses; for variable definition see notes to tables 2 and 3; D50 is distance-based contiguity matrix for 50 miles; * denotes significance at least at 0.10; ** denotes significance at least at 0.05; *** denotes significance at least at 0.01.

of regional sources of innovation. However, a closer inspection of Figure 2 does not support this hypothesis. With the exception of the difference in the spatial patterns of university research between the last two time periods, no meaningful changes can be observed.

An alternative explanation is that there might be meaningful differences as to the "efficiency" with which the different local innovation systems combine their local knowledge resources (e.g. differences in local cultures with respect to the propensity of the actors to interact with each other as exemplified in Saxenian, 1994 for Silicon Valley and Route 128, or differences in the effectiveness in regional economic development policies). Comparison of sizes, signs and significances of parameter estimates over space and time might suggest some clues in this respect.

Table 4 lists spatial Maximum Likelihood Seemingly Unrelated Regression (SUR) results for the four large US regions and the nation for 1985, 1988 and 1991. This regression technique opens the possibility to compare estimated parameters over space as well as to test the stability of the coefficients. Perhaps the most striking difference relates to the university research parameter. This parameter is consistently non-significant in the North-East, which is perhaps a surprising result. This finding certainly needs a closer examination in the future, however heavy restructuring of the local economies of some North-Eastern metropolitan areas (such as Boston and New York as shown in Acs, 1996) characterized by major losses in high technology jobs during this time period could be behind this observation. On the other hand, parameter estimates of university research in the South are consistently higher than anywhere in the rest of the regions, which might suggest a more intensive local role of universities in economic development in the South than anywhere else in the country. This observation would certainly need further investigations, however it is definitely an interesting finding.

Regarding the rest of the parameters of local innovation inputs no comparable differences can be found across large regions. A further interesting result is the non-significant connectivity dummy for all the regions but the Mid-West. For this region CON50 stays consistently significant, indicating differences in local innovation systems between large agglomerations and smaller metropolitan areas. With the exception of the university research parameter, all the rest of the parameters of local innovation inputs are unstable in the South (as shown by the significant values of the Wald tests in Table 4). This might be taken as an additional support to the important role of local innovation inputs in the restructuring of metropolitan areas in the US South.

5 Summary

Local dimensions of knowledge production are gaining increasing attention in both theoretical and empirical research in economics. However, our understanding is still constrained by the availability of appropriate data on knowledge production-related activities. In this paper we presented results of a first-cut analysis based on a recently developed space-time data set of US innovation activities. The most important findings can be summarized as follows.

- No significant differences were observed between the regression results with lagged and contemporaneous explanatory variables, suggesting that within a relatively short period of time (e.g. in about three years) no meaningful changes occur in the performances of local innovation systems. This result has an important technical consequence: at least at the level of spatial aggregates the use of contemporaneous dependent and independent variables is acceptable in knowledge production function studies.
- Differences in the trends of knowledge production across large US regions do not seem to be the result of a changing spatial distribution of local innovation inputs.
- Differences are found regarding the importance of universities as local sources of new technological knowledge. Perhaps the most surprising result is the con-

sistently insignificant university effect in the North East.

- Compared to the rest of the country, the recently emerging US South seems to follow different patterns in combining local innovation inputs especially with respect to the role of local universities in supporting production of new technological knowledge. However, instability of most of the parameters indicates that the metropolitan areas in the region are in a reconstruction process of their innovation systems.

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