R&D Spillovers and the Geography of Innovation and Production

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More than most other economic activities, innovation and technological change depend upon new economic knowledge. Thus, Paul Romer (1986), Paul Krugman (1991a, b), and Gene Grossman and Elhanan Helpman (1991), among others, have focused on the role that spillovers of economic knowledge across agents and firms play in generating increasing returns and ultimately economic growth. In fact, several recent studies have identified the existence of spatially-mediated knowledge spillovers. An important finding of Adam B. Jaffe (1989), Zoltan Acs et al. (1992, 1994), and Feldman (1994a, b) is that investment in R&D by private corporations and universities "spills over" for third-party firms to exploit. If the ability to receive knowledge spillovers is influenced by distance from the knowledge source, then geographic concentration should be observed, especially in industries where knowledge spillovers are likely to play a more important role. The purpose of this paper is to examine the extent to which industrial activity clusters spatially and to link this geographic concentration to the existence of knowledge externalities. Of course, as Jaffe et al. (1993) point out, one obvious explanation why innovative activity in some industries tends to cluster geographically more than in other industries is that the location of production is more concentrated spatially. Thus, in explaining why the propensity for innovative activity to cluster geographically varies across industries, we need first to explain, and then to control for, the geographic concentration of the location of production.

As Alfred Marshall (1920) and, later Krugman (1991b) argue, there may be geographic boundaries to information flows or knowledge spillovers, particularly tacit knowledge, among the firms in an industry. Although the cost of transmitting information may be invariant to distance, presumably the cost of transmitting knowledge rises with distance. That is, proximity and location matter. While there is considerable evidence supporting the existence of knowledge spillovers, neither Jaffe (1989), Jaffe et al. (1993), nor Acs et al. (1992, 1994), and Feldman (1994a) actually examine the propensity for innovative activity to cluster spatially. But implicit in the knowledge production function model is the assumption that innovative activity should concentrate geographically in those industries where the direct knowledge-generating inputs are the greatest and where knowledge spillovers are the most prevalent. No one, to date, has examined the underlying propensity for industrial activity to cluster spatially. While one of the central themes in the industrial organization literature is to explain the degree of concentration of economic activity within an industry (F. M. Scherer and David Ross, 1990), the focus has typically been on the extent of dispersion across different enterprises and establishments within a single spatial unit—the country. The emerging importance of location as a unit of observation argues for examining both production and innovation within a geographic context. We empirically

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test for the importance of geographic location to different types of industries by linking the geographic concentration in manufacturing industries to industry specific characteristics, most notably the relative importance of knowledge spillovers.

In the following section of this paper, we examine the spatial distribution of innovative activity as well as the geographic concentration of production. An empirical model is specified in Section II, and the results are presented in Section III. In the final section, we provide a summary and conclusion. The empirical evidence suggests that, even after controlling for the degree of geographic concentration in production, innovative activity tends to cluster more in industries where knowledge spillovers play a decisive role. Although such industries also tend to exhibit a greater geographic concentration of production, the results suggest that the propensity for innovative activity to cluster is more attributable to the role of knowledge spillovers and not merely the geographic concentration of production.

I. The Spatial Distribution of Innovation and Production

To measure the spatial distribution of innovative activity we rely on the most recent and most ambitious major data base that provides a direct measure of innovative activity. The United States Small Business Administration (the Small Business Administration's Innovation Data Base or the SBIDB) compiled a data base of 8,074 commercial innovations introduced in the United States in 1982. A private firm, The Futures Group, compiled the data and performed quality control analyses for the United States Small Business Administration. A data base consisting of innovations by four-digit standard industrial classification (SIC) industries was formed from the new product announcement sections in over 100 technology, engineering and trade journals that span every industry.[1] These data were used by Acs and Audretsch (1988, 1990) to analyze the relationships between firm size and technological change, and market structure and technological change, and by Acs et al. (1992, 1994), Feldman (1994a, b), and Feldman and Richard Florida (1994) to examine the geography of innovation.

We adopt the state as the spatial unit of observation. While this is at best a crude proxy of the relevant economic market,[2] it does have one obvious appeal other than that it conforms to a number of data sources—the most relevant unit of policy-making is at the level of the state. Still, states are certainly not an entirely satisfactory unit of observation for the analysis of spatial phenomena. The analyses of spatial processes are handicapped by a lack of data for what might be considered to be the ideal observation. Certainly considerable progress would be made if data sources identifying innovation activity at the city or county level were made available.

Using the citation data base described above, an innovation is attributed to the state in which the establishment responsible for the development of that innovation is located. Some innovations are, in fact, developed by subsidiaries or divisions of companies with headquarters in other states. Since headquarters may announce new product innovations, the data base discriminates between the location of the innovating establishment and the location of the larger, innovating entity (Edwards and Gordon, 1984). For our purposes, the state identifier of the establishment is used to investigate the spatial distribution of innovation. Of the total number of innovations recorded in the data base, 4,200 were manufacturing innovations with information specifying location.[3]

Figure 1 shows the distribution of innovations by states. California is the state in which

[1] A detailed description of the U.S. Small Business Administration's Innovation Citation Data Base can be found in chapter two of Acs and Audretsch (1990), as well as in Acs and Audretsch (1988).

[2] As Krugman (1991b p. 57) emphasizes, "States aren't really the right geographical units," because of the lack of concordance between economic markets and political units.

[3] The SBIDB contains a total of 4,476 innovations in manufacturing industries. Of these, there are 276 innovations which are not used because they were developed by establishments outside the United States or did not have complete location information.

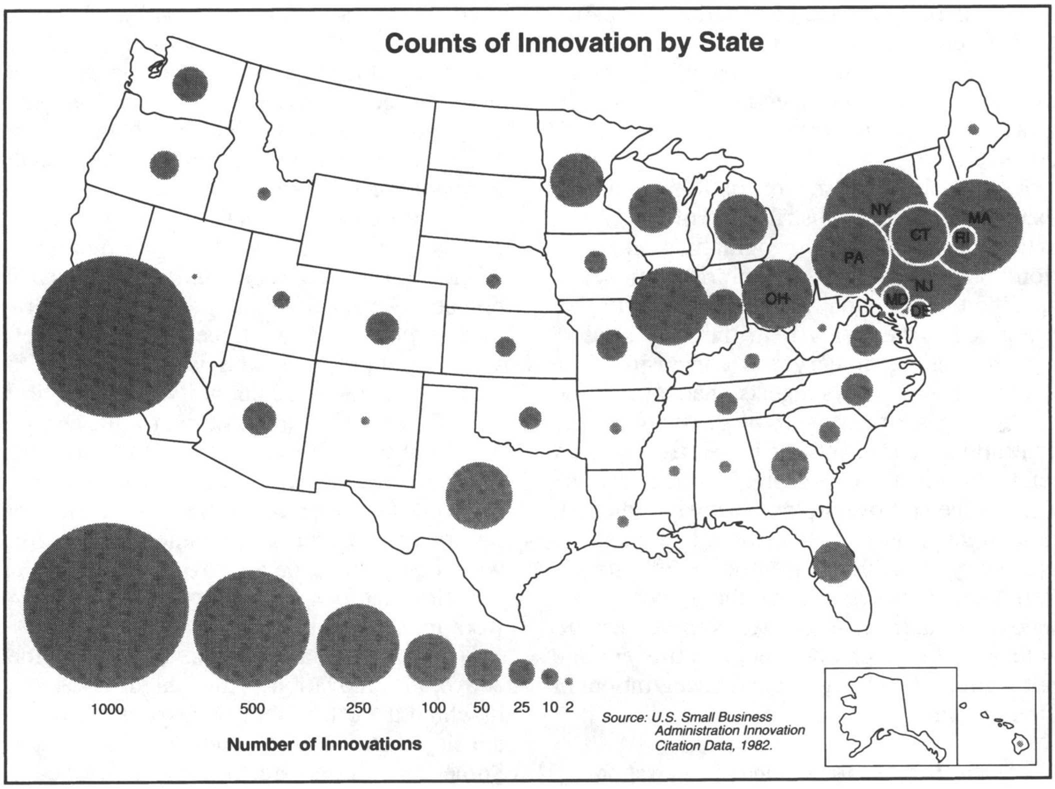

FIGURE 1. NUMBER OF INNOVATIONS BY STATE

the greatest number of innovations were registered, followed by New York, New Jersey, and Massachusetts. A particularly striking feature shown in Figure 1 is that the bulk of innovative activity in the United States occurs on the coasts, and especially in California and in New England. By contrast, no innovative activity is registered in certain Midwestern states such as North Dakota, South Dakota, Montana, and Wyoming.[4] States in the traditional manufacturing belt such as Ohio, Illinois, Michigan, and Pennsylvania are not at all particularly innovative. Thus, while the location of manufacturing activity may explain the spatial distribution of innovative activity to some degree, it is certainly not the only factor.

This presentation of the aggregate geographic distribution of innovative activity in the United States obscures the propensity for innovative activity to cluster spatially within specific industries. Thus, the distribution of innovative activity for the seven most innovative four-digit standard industrial classification (SIC) industries is shown in Table 1. A striking result is that the spatial concentration of innovative activity in particular industries is considerably greater than for all of manufacturing. For example, in the computer industry, 342 of the 821 innovations recorded, or 41.7 percent, are in California. And an additional 10 percent are recorded in Massachusetts.

[4] Of course, simply comparing the absolute amount of innovative activity across states ignores the fact that the manufacturing base of some states is larger than others. Presumably one of the most important determinants of innovative activity is the location of manufacturing activity. Additional information on the geographic distribution of the innovation data can be found in Feldman (1994b) and Feldman and Florida (1994).

TABLE 1—GEOGRAPHIC DISTRIBUTION OF INNOVATIVE ACTIVITY FOR MOST INNOVATIVE INDUSTRIES

SIC[a]	Industry[b]	State	Number of innovations	State share of industry innovations	Industry share of state innovations
3573	Computers	California	342	41.7	35.1
	(n = 821)	Massachusetts	78	9.5	21.7
		New York	58	7.1	12.7
		Texas	39	4.8	23.1
		New Jersey	38	4.6	8.9
		Illinois	28	3.4	12.1
3823	Process control instruments	California	80	17.2	8.2
	(n = 464)	Massachusetts	61	13.1	16.9
		New York	45	9.7	9.9
		Pennsylvania	40	8.6	16.5
		Illinois	32	6.9	13.9
3662	Radio and TV communications	California	105	31.0	10.8
	equipment	New York	40	11.8	8.8
	(n = 339)	Massachusetts	32	9.4	8.9
3674	Semiconductors	California	84	48.8	8.6
	(n = 172)	Massachusetts	17	9.9	4.7
		Texas	13	7.6	7.7
3842	Surgical appliances	New Jersey	43	28.3	10.1
	(n = 152)	California	17	11.2	1.7
		Pennsylvania	10	7.9	4.1
2834	Pharmaceuticals	New Jersey	50	39.4	11.7
	(n = 127)	New York	18	14.2	3.9
		Pennsylvania	10	7.9	4.1
		Michigan	8	6.3	7.1
3825	Measuring instruments for	California	37	32.2	3.8
	electricity	Massachusetts	22	19.1	16.9
	(n = 115)	New York	13	11.3	2.9

[a] The SIC is the standard industrial classification used in the U.S. Small Business Administration's Innovation Citation Data Base.

[b] The total number of innovations recorded in the four-digit industry is listed in parentheses.

Thus, these two states alone account for over one half of all the innovations in the computer industry. At the same time, the last column indicates that innovations in the computer industry accounted for slightly more than one third of all the innovations in California and a little more than one fifth of all innovations in Massachusetts. Similarly, nearly 40 percent of the 127 innovations in the drug industry (pharmaceuticals) were recorded in New Jersey, while an additional 14 percent were made in New York. Thus, over one-half of pharmaceutical innovations were in the New Jersey-New York area. At the same time, pharmaceutical innovations account for over one tenth of all innovations registered in New Jersey.

To measure the extent to which manufacturing in specific industries is concentrated geographically and the extent to which innovative activity tends to cluster spatially, we follow Krugman's (1991b) example and calculate Gini coefficients for the geographic concentration of innovative activity and for the location of manufacturing.[5] Table 2 provides

[5] The locational Gini coefficients for production are based on industry value-added. We calculate the amount of value-added in an industry and state divided by the national value-added for the industry. This ratio is normalized by the state share of total manufacturing value-added in order to account for the overall distribution of manufacturing activity. An industry which is not geographically concentrated more than is reflected by the overall distribution of manufacturing value-added would have a coefficient of 0. The closer the industry coefficient is to 1, the more geographically concentrated the industry would be. Cases in which state or industry data have been suppressed are omitted from the analysis. The Gini coefficients for innovation are based on the count of innovation in a state and industry and are calculated in a similar way. Further details are available from the authors upon request.

TABLE 2—GEOGRAPHIC CONCENTRATION OF PRODUCTION AND INNOVATIVE ACTIVITY FOR MANUFACTURING SECTORS (MEAN GINI COEFFICIENTS)[a]

Manufacturing sector	Value added	Employment	Innovations
Food and beverages	0.6973	0.5584	0.2567
	(0.1685)	(0.1828)	(0.2226)
Tobacco	0.6589	0.4137	0.3319
	(0.2559)	(0.1444)	(0.2043)
Textiles	0.7040	0.5670	0.1659
	(0.1149)	(0.1430)	(0.2347)
Apparel	0.6179	0.5160	0.0583
	(0.1589)	(0.1687)	(0.1469)
Lumber	0.6309	0.5605	0.1180
	(0.1007)	(0.1208)	(0.1235)
Furniture	0.5815	0.4632	0.4204
	(0.1373)	(0.1366)	(0.2347)
Paper	0.6036	0.5580	0.2363
	(0.1525)	(0.1568)	(0.3253)
Printing	0.5977	0.5325	0.1762
	(0.1491)	(0.1485)	(0.2220)
Chemicals	0.7003	0.5987	0.3881
	(0.1612)	(0.1790)	(0.1945)
Petroleum	0.6786	0.4766	0.2598
	(0.1512)	(0.1493)	(0.3674)
Rubber and plastics	0.5771	0.4569	0.3932
	(0.3089)	(0.2434)	(0.1952)
Leather	0.7186	0.5552	0.0646
	(0.1150)	(0.1300)	(0.1119)

[a] Standard deviations are given in parentheses.

the weighted mean Gini coefficients for value-added, employment, and innovative activity within each broad two-digit SIC manufacturing sector. Those sectors exhibiting the greatest geographic concentration of manufacturing activity include primary metals, transportation equipment, textiles, food and beverages, leather and chemicals. By contrast, those manufacturing sectors exhibiting the highest propensity for innovative activity to cluster spatially include transportation equipment, instruments, and electronics. That the propensity for innovative activity to spatially cluster cannot be simply explained by the geographic concentration of the location of manufacturing activity is evident from Table 2. This points to the importance of controlling for the geographic concentration of production in explaining the propensity for innovative activity to spatially cluster.

II. The Model

Why should innovations tend to cluster spatially more in some industries than in other industries? One obvious answer is simply that the location of production is more geographically concentrated in some industries than in others. This raises the issue of endogeny. Jaffe et al. (1993) identify two related critical issues which must be considered in trying to identify why the propensity for innovative activity to cluster spatially varies across industries. First, the extent to which the location of production is geographically concentrated must be controlled for, so that the relevant question becomes: *even after accounting for the geographic concentration of the production location, why does the propensity for innovative activity to cluster vary across industries?* And second, in trying to account for the degree to which the location of production is geographically concentrated, an important factor is the role which knowledge spillovers play in the industry. It is only after the geographic concentration of production has been controlled for, that the degree to which innovative activity clusters spatially can be addressed. Thus, to explain the propensity for innovative activity to cluster spatially we begin with the extent to which production is geographically concentrated.

While it is not possible to directly measure the extent to which knowledge externalities exist, as Kenneth J. Arrow (1962) and Krugman (1991a) point out, it is possible to identify industries in which new economic knowledge plays a relatively more important role. This is done on the basis of the industry R&D intensity, or R&D-sales ratio. The crucial assumption we make here is Arrow's (1962) argument that knowledge spillovers are more important in, and reflected at least to some degree by, highly R&D-intensive industries. By contrast, such knowledge externalities, while perhaps still present, play a less important role where the creation of new economic knowledge, as reflected by R&D intensity, is negligible. Thus, the location of production would be expected to be more concentrated in those industries where knowledge spillovers are prevalent, that is in industries which are R&D intensive.

Similarly, skilled workers endowed with a high level of human capital are a mechanism by which economic knowledge is transmitted. The greater the extent to which the industry

TABLE 3—DESCRIPTION OF VARIABLES

Variable	Description and source	Mean	Standard deviation
Gini of production	Gini coefficient of four-digit SIC industry value-added across states, weighted by national value-added for the industry in 1982 (U.S. Department of Commerce, Bureau of the Census, 1982 Economic Census).	0.56	0.13
Gini of innovation	Gini coefficient of four-digit SIC industry count of innovations across states, weighted by national innovation count for the industry in 1982 (Edwards and Gordon, 1984).	0.30	0.23
Natural resources	Share of total industry inputs purchased from mining and agriculture in 1976 (Input-output data as provided by U.S. International Trade Commission databank).	0.09	0.16
Scale	Mean size of the largest establishments accounting for one half of the industry value-of-shipments divided by industry value of shipments in 1982 (U.S. Department of Commerce, Bureau of the Census, 1982).	2.13	3.97
Transportation costs	Radius of the mean distance shipped in 1967 (Commodity Transport Survey of the United States Census of Transportation for 1967, taken from Weiss [1991]).	7.9549	4.0574
Industry R&D/sales	Industry expenditures on research and development divided by sales in 1977 (Line of Business Survey, U.S. Federal Trade Commission, 1977).	1.66	1.69
Skilled labor	Share of industry employment accounted for by professional and kindred workers, managers and administrators, plus craftspeople and kindred workers in 1970 (U.S. Department of Commerce, Bureau of the Census, 1972).	0.35	0.09
University research	Expenditures on university research for departments relevant to industry (Yale Survey of Industrial Managers in Levin et al. [1987] and National Science Foundation's (NSF) Survey of Science Resources Survey)	17.5946	13.851

work force is composed of skilled workers, the more important knowledge spillovers are likely to be. Thus, industries which rely on a higher component of skilled workers should tend to exhibit a greater tendency towards spatial concentration of industrial location.

Of course, while knowledge externalities may be important in influencing the degree to which the location of production is spatially concentrated, they are certainly not the only factors. Krugman (1991a) points out that the extent to which the location of production is geographically concentrated will be shaped by transportation costs. Transportation costs are inversely related to the mean distance shipped, so that a higher value of transportation costs should be associated with a lower geographic concentration of production. Similarly, industries which are highly dependent upon natural resource inputs are also going to tend to be geographically concentrated—presumably close to the source of those inputs. Augustus Loesch (1954) and Victor R. Fuchs (1962) argue that firms in industries with a high dependency on natural resource inputs will tend to locate in close proximity to those resources. Therefore, a higher content of natural resource inputs in an industry should result in a greater geographic concentration of the location of production. In addition, Robert C. Shelburne and Robert W. Bednarzik (1993) argue that industries which are more capital-intensive will tend to be geographically concentrated, since production will be concentrated among fewer enterprises. That is, as capital intensity and the importance of scale economies rise, fewer large establishments will be able to exist at a level of output in excess of the minimum efficient scale (MES) level of output.

The main hypothesis of this paper suggests that innovative activity will tend to cluster in industries where new economic knowledge plays an especially important role. In estimating the main influences on the geographic

TABLE 4—CORRELATION MATRIX

	Gini of production	Gini of innovation	Natural resources	Scale	Transportation costs	Industry R&D/sales	Skilled labor	University research
Gini of production	1.0	—	—	—	—	—	—	—
Gini of innovation	0.0090	1.0	—	—	—	—	—	—
Natural resources	0.1292	−0.1130	1.0	—	—	—	—	—
Scale	−0.2370	−0.1158	0.1009	1.0	—	—	—	—
Transportation costs	0.2076	0.1013	−0.1400	0.3010	1.0	—	—	—
Industry R&D/sales	0.3241	0.2254	−0.2148	0.2420	0.3225	1.0	—	—
Skilled labor	0.0563	0.2540	−0.2848	0.0997	0.0702	0.3961	1.0	—
University research	0.8730	0.5100	0.1199	−0.1077	0.0819	0.1946	0.0239	1.0

concentration of innovation we consider three sources of economic knowledge—industry R&D, skilled labor, and the size of the pool of basic science for a specific industry. Conceptually, there are great differences in the scope and commercial applicability of university research undertaken in different fields. Academic research will not necessarily result in useful knowledge for every industry; however, scientific knowledge from certain academic departments is expected to be more important for certain industries than for others. To capture the relevant pool of knowledge, academic departments are assigned to industries using the survey of industrial R&D managers by Richard C. Levin et al. (1987).[6] For example, basic scientific research in medicine, biology, chemistry and chemical engineering is found to be relevant for product innovation in drugs (SIC 2834).

III. The Results

Descriptive statistics for the variables used to estimate the model are provided in Table 3, and Table 4 provides the correlation matrix. There are 163 four-digit SIC industries for which comparable data for the different measures could be compiled.

Table 5 presents the regression results using ordinary-least-squares (OLS) estimates. Table 6 presents the results estimating the system of equations using three-stage least squares (3SLS).[7] The statistical results are generally quite consistent between the OLS and 3SLS methods of estimation.

In equation (1) of Table 5, the positive and statistically significant coefficient of the measure of natural resource utilization suggests that the degree to which inputs in an industry are composed of natural resources clearly tends to shape the geographic concentration of production. Resource dependent industries tend to be more geographically concentrated. The negative and statistically significant coefficient on the scale measure suggests that industries tend to be less, and not more, geographically concentrated when scale economies play a more important role. This result emerges even after controlling for the size of the industry. One explanation for this result

[6] To measure the relevance of a discipline to an industry a survey of industrial R&D managers was used. The question was asked, "How relevant were the basic sciences to technical progress in this line of business over the past 10–15 years?" The survey uses a Likert scale of 1 to 7 to assess relevance. We consider relevant science to be those academic departments that are rated with a relevance greater than a value of 5 on the scale.

[7] The system of equations was also estimated using two-stage least-squares estimation. The differences in the standard errors indicate the presence of cross-equation correlation. Thus, we estimate the model with 3SLS. The instruments used include all of the exogenous variables appearing on the right-hand side of the equations in the model.

TABLE 5—OLS REGRESSION RESULTS ESTIMATING GINI COEFFICIENTS ACROSS STATES[a]

	Gini of production			Gini of innovation		
	(1)	(2)	(3)[b]	(4)	(5)	(6)[b]
Gini of innovation	—	0.768	−0.125	—	—	—
		(0.143)	(−1.741)			
Natural resources	0.326	0.330	0.384	—	—	−0.108
	(4.950)	(5.261)	(5.058)			(−1.228)
Scale	−0.137	−0.160	−0.244	—	—	−0.007
	(−4.162)	(−4.173)	(−0.695)			(1.986)
Transportation costs	1.223	1.419	1.741	—	—	0.006
	(4.439)	(4.838)	(5.631)			(1.674)
Industry R&D/sales	0.455	0.436	0.608	0.469	0.565	0.543
	(7.791)	(7.170)	(2.860)	(2.137)	(2.405)	(2.341)
Skilled labor	1.094	1.058	1.318	0.466	0.657	0.645
	(15.044)	(12.483)	(15.031)	(4.910)	(4.581)	(4.686)
University research	—	—	0.034	0.108	0.116	0.118
			(2.147)	(7.920)	(8.093)	(8.139)
Gini of production	—	—	—	—	−0.119	−0.146
					(−1.587)	(−1.741)
Sample size	163	163	163	163	163	163
R^2	0.951	0.952	0.970	0.827	0.908	0.921
Standard error	0.15034	0.15079	0.18601	0.21443	0.21469	0.18487

[a] *t* values are given in parentheses.

[b] Columns (3) and (6) provide the unrestricted regression results. When the regression estimated for the Gini of production in column (2) is compared with the estimate of the unrestricted regression in column (3), the F test statistic (2,156) of 0.087 is computed for the overidentifying restrictions. Similarly, when the regression estimated for the Gini of innovation in column (5) is compared to the estimate of the unrestricted regression in column (6), the F test statistic (3,156) equals 2.662 for the overidentifying restrictions.

may be that this measure limits the size of the market to the United States, but when many manufacturing industries are global in scale, this measure will be understated.

There is little ambiguity concerning the two measures that are the primary focus of this paper—the relative importance of industry R&D in an industry and the extent to which the labor force is composed of skilled workers. The coefficient of industry R&D is positive and clearly statistically significant, supporting the hypothesis that industries where new economic knowledge tends to play a more important role will have a higher propensity to cluster together. Similarly, industries where skilled labor is relatively important also tend to exhibit a greater degree of geographic concentration of production.

An alternative specification which includes the Gini coefficient of innovation is presented in equation (2) of Table 5. To the extent that geographic proximity between R&D labs and production facilities is important to gain the benefits of R&D, we might expect that industries with closely clustered innovations may also have closely clustered factories. However, the coefficient of this variable cannot be considered to be statistically different from 0.

Equations (4) and (5) of Table 5 present the OLS regression results estimating the Gini coefficients of innovative activity across states. Equation (4) indicates that, when the extent to which production activity is geographically concentrated is not controlled for, the coefficients of all three types of knowledge-generating measures included—industry R&D, skilled labor, and university research—are positive and statistically significant. However, industries in which new economic knowledge plays a more important role also tend to exhibit a greater degree of spatial concentration. That is, without first controlling for the extent to which the location of production is geographically concentrated, it is not at all clear whether

TABLE 6—3SLS REGRESSION RESULTS ESTIMATING GINI COEFFICIENTS ACROSS STATES[a]

	Gini of production	Gini of innovation	Gini of production	Gini of innovation
Gini of innovation	—	—	0.224	—
			(0.416)	
Natural resources	0.331	—	0.347	—
	(5.145)		(5.261)	
Scale	−0.160	—	−0.166	—
	(−4.333)		(−3.589)	
Transportation costs	1.432	—	1.506	—
	(5.052)		(3.974)	
Industry R&D/sales	0.440	0.572	0.460	0.557
	(7.290)	(2.421)	(6.723)	(2.341)
Skilled labor	1.075	0.687	1.193	0.683
	(14.846)	(3.707)	(5.599)	(3.736)
University research	—	0.119	—	0.140
		(7.887)		(3.480)
Gini of production	—	−0.135	—	−0.158
		(−1.247)		(−1.391)
Sample size	163	163	163	163
Standard error	0.15523	0.21733	0.15571	0.21767

[a] t values are given in parentheses.

the greater propensity for innovative activity to cluster in industries where knowledge spillovers are more prevalent is attributable to the fact that knowledge externalities are more conducive to innovative activity or simply that the firms are already located within a relatively tight geographic area.

Thus, in equation (5) of Table 5, the Gini measure of the value-added across states is included. The coefficient of this variable is statistically insignificant, but the coefficients of the other explanatory variables remain virtually unchanged. Which is to say that, even after controlling for the extent to which the location of production is geographically concentrated, the three knowledge-generating variables are still found to have a significant impact on the propensity for innovative activity to cluster spatially.

Table 6 presents the 3SLS method of estimation. In the first set of equations the Gini coefficient of innovative activity across states is endogenous in both equations. In the second set of equations a fully specified simultaneous version of the model is presented in which the Gini coefficients of both innovative activity and production are endogenously included. Most importantly, the propensity for innovative activity to spatially cluster is found to be the result of new economic knowledge and not merely the existing geographic concentration of production.

The positive coefficients of industry R&D, skilled labor, and university research, even after controlling for the degree of concentration of production, using both the OLS and 3SLS methods of estimation, are certainly consistent with the following hypothesis. The propensity for innovative activity to cluster will tend to be higher in industries where new economic knowledge plays a more important role. Presumably, it is in such industries where new economic knowledge which generates innovative activity is transmitted tacitly through what has been described as knowledge spillovers. Therefore, innovative activity is more likely to occur within close geographic proximity to the source of that knowledge, be it a university research laboratory, the research and development department of a corporation, or exposure to the knowledge embodied in a skilled worker.

Industries where new economic knowledge plays a more important role also tend to exhibit a greater geographic concentration of production. However, based on the statistical results reported above it appears that the propensity for innovative activity to cluster spatially is more attributable to the influence of knowledge spillovers and not merely the geographic concentration of production.

IV. Conclusions

This paper examines the geography of innovation and production. In particular, by examining the concentration of economic phenomena, we re-focus the lens from the usual product dimension to a geographic or spatial dimension. A key assumption we make in examining the link between knowledge spillovers in an industry and innovative activity clustering spatially is that knowledge externalities are more prevalent in industries where new economic knowledge plays a greater role. New economic knowledge is captured by industry R&D, university R&D, and skilled labor.

One obvious complication in testing for this link is that innovative activity will be more geographically concentrated in industries where production is also geographically concentrated, simply because the bulk of firms are located within close proximity. Even more problematic, though, is the hypothesis that new economic knowledge will tend to shape the spatial distribution of production as well as that of innovation. Indeed, we find that a key determinant of the extent to which the location of production is geographically concentrated is the relative importance of new economic knowledge in the industry. Even after controlling for the concentration of production we find evidence that industries in which knowledge spillovers are more prevalent—that is where industry R&D, university research and skilled labor are the most important—have a greater propensity for innovative activity to cluster than industries where knowledge externalities are less important.

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