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Innovation in cities: Science-based diversity, specialization and localized competition

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Abstract

Whether diversity or specialization of economic activity better promotes technological change and subsequent economic growth has been the subject of a heated debate in the economics literature. The purpose of this paper is to consider the effect of the composition of economic activity on innovation. We test whether the specialization of economic activity within a narrow concentrated set of economic activities is more conducive to knowledge spillovers or if diversity, by bringing together complementary activities, better promotes innovation. The evidence provides considerable support for the diversity thesis but little support for the specialization thesis. © 1999 Elsevier Science B.V. All rights reserved.

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1. Introduction

In proposing a new theory of economic geography, Paul Krugman (1991b, p. 5) asks, 'What is the most striking feature of the geography of economic activity? The short answer is surely concentration… production is remarkably concentrated in space.' Perhaps in response to Krugman's concern, a literature has recently emerged which focuses on the implications of the concentration of economic activity for economic growth. Models posited by Romer (1986, 1990), Lucas (1993), and Krugman (1991a,b) link increasing returns to scale yielded by externalities within a geographically bounded region to higher rates of growth. The results of Jaffe (1989), Jaffe et al. (1993), Feldman (1994) and Audretsch and Feldman (1996) suggest that R&D and other knowledge spillovers not only generate externalities, but the evidence also suggests that such knowledge spillovers tend to be geographically bounded within the region where the new economic knowledge was created. New economic knowledge may spill over, but the geographic extent of such knowledge spillovers is bounded. Lucas (1993) emphasizes the most natural context in which to understand the mechanics of economic growth is in metropolitan areas where the compact nature of the geographic unit facilitates communication. Indeed, Lucas (1993) asserts that the only compelling reason for the existence of cities would be the presence of increasing returns to agglomerations of resources which make these locations more productive.

None of these studies, however, ask the question, 'Does the specific type of economic activity undertaken within any particular geographic region matter?' This question is important because a recent debate has arisen focusing precisely on the composition of economic activity within an agglomeration and how such externalities will be shaped by that composition of economic activity. One view, which Glaeser et al. (1992) attribute to the *Marshall–Arrow–Romer* externality, suggests that an increased concentration of a particular industry within a specific geographic region facilitates knowledge spillovers across firms.[1] By contrast, Jacobs (1969) argues that it is the exchange of complementary knowledge across diverse firms and economic agents which yields a greater return to new economic knowledge.

There are clear policy implications of this debate in terms of policies directed towards innovation and technological change. If the specialization thesis is correct, then policy should focus on developing a narrow set of economic activities within a geographic region in order to yield greater innovative output. On the other hand, if the diversity thesis is correct, then a geographic region comprised of a diverse set of economic activities will tend to yield greater output

[1] This mirrors an earlier debate summarized by Loesch (1954).

in terms of innovative activity. The key policy concerns would then become how to identify the commonalties and how to foster such diversity.

The purpose of this paper is to penetrate the black box of geographic space by identifying the extent to which the organization of economic activity is either concentrated, or alternatively consists of diverse but complementary economic activities, and how this composition influences innovative output. To consider this question we link the innovative output of product categories within a specific city to the extent to which the economic activity of that city is concentrated in that industry, or conversely, diversified in terms of complementary industries sharing a common science base. We use results on the relevance of academic departments to R&D from Levin et al. (1987) to identify complementary industries across which knowledge spillovers may be realized. We find a tendency for innovative activity in complementary industries sharing a common science-base to cluster together in geographic space. Industries which use the same base of scientific knowledge exhibit a strong tendency to locate together for both the location of production and the location of innovation.

In Section 2, we introduce the main theories alternatively favoring diversity or specialization in generating innovative activity. Issues concerning the measurement of innovative activity, the geographic unit of observation and the concepts of science-based diversity and specialization are examined in Section 3. After the model is presented in the Section 4, the empirical results are provided in Section 5. To explore the validity of our results, we extend our analysis to consider the impact of specialization versus diversity of economic activity within the firm on innovative activity in Section 6. We find considerable evidence rejecting the specialization thesis and in support of the diversity thesis. Based on the findings for both industries within specific cities as well as for individual firms, an organizational structure of economic activities that are diverse, but still complementary, apparently yields a greater innovative output than a specialization of economic activity.

2. Diversity versus specialization

The importance of location to innovation in a world increasingly relying upon E-mail, fax machines, and electronic communications superhighways may seem surprising, and even paradoxical at first glance. The resolution of this paradox lies in the distinction between knowledge and information. While the costs of transmitting information may be invariant to distance, presumably the cost of transmitting knowledge, especially what Von Hipple (1994) refers to as *sticky knowledge*, rises with distance. Von Hipple persuasively demonstrates that highly contextual and uncertain knowledge is best transmitted via face-to-face interaction and through frequent contact. Proximity matters in transmitting knowledge because, as Arrow (1962) pointed out, such sticky knowledge is inherently non-rival in nature and knowledge developed for any particular application can easily spill over and be applied to different use and applications. Indeed, Griliches (1992) has defined knowledge spillovers as 'working on similar things and hence benefiting much from each other's research'.[2]

Despite the general consensus that knowledge spillovers within a given location stimulate technological advance, there is little consensus as to exactly how this occurs. Glaeser et al. (1992) characterize three different models from the literature that would influence the production of innovation in cities. The *Marshall–Arrow–Romer* model formalizes the insight that the concentration of an industry in a city promotes knowledge spillovers between firms and therefore would facilitate innovation in that city-industry observation. This type of concentration is also known as industry localization (Loesch, 1954). An important assumption is that knowledge externalities with respect to firms exist, *but only for firms within the same industry*. Thus, the relevant unit of observation is extended from the firm to the region in the theoretical tradition of the Marshall–Arrow–Romer model and in subsequent empirical studies, but spillovers are limited to occur within the relevant industry. The transmission of knowledge spillovers across industries is assumed to be non-existent or at least trivial.

Restricting knowledge externalities to occur only within the industry may ignore an important source of new economic knowledge–inter-industry spillovers. Jacobs (1969) argues that the most important source of knowledge spillovers are external to the industry in which the firm operates and that cities are the source of innovation because the diversity of these knowledge sources is greatest in cities. Thus, Jacobs develops a theory that emphasizes that the variety of industries within a geographic region promotes knowledge externalities and ultimately innovative activity and economic growth. Of course, there should be some basis for interaction between diverse activities. A common science base facilitates the exchange of existing ideas and generation of new ones across disparate but complementary industries. Thus, in Jacobs' view, diversity rather than specialization is the operative mechanism of economic growth.

A second controversy involves the degree of competition prevalent in the region, or the extent of local monopoly. The Marshall–Arrow–Romer model predicts that local monopoly is superior to local competition because it

[2] Considerable evidence suggests that location and proximity clearly matter in exploiting knowledge spillovers. Not only have Jaffe et al. (1993) found that patent citations tend to occur more frequently within the state in which they were patented but Audretsch and Stephan (1996) and Audretsch and Feldman (1996) found that the propensity for innovative activity to cluster geographically tends to be greater in industries where new economic knowledge plays a more important role.

maximizes the ability of firms to appropriate the economic value accruing from their innovative activity. By contrast, Jacobs (1969) and Porter (1990) argue that competition is more conducive to knowledge externalities than is local monopoly.[3] It should be emphasized that by local competition, Jacobs (1969) does not mean competition within product markets as has traditionally envisioned within the industrial organization literature. Rather, Jacobs is referring to the competition for the new ideas embodied in economic agents. Not only does an increased number of firms provide greater competition for new ideas, but in addition, greater competition across firms facilitates the entry of a new firm specializing in some particular, new, product niche. This is because the necessary complementary inputs and services are likely to be available from small specialist niche firms but not necessarily from large, vertically integrated producers.[4]

3. Measurement issues

Krugman (1991a, p. 53) has argued that economists should abandon any attempts at measuring knowledge spillovers because '…knowledge flows are invisible, they leave no paper trail by which they may be measured and tracked'. But as Jaffe et al. (1993, p. 578) point out, 'knowledge flows do sometimes leave a paper trail' – in particular in the form of patented inventions and new product introductions.

In this paper we rely upon a direct measure of innovative output, rather than on a measure of intermediate output, such as patented inventions.[5] This United States Small Business Administration's Innovation Data Base (SBIDB) is the primary source of data for this paper.[6] The database consists of new product

[3] Porter (1990) provides examples of Italian ceramics and gold jewelry industries in which numerous firms are located with a bounded geographic region and compete intensively in terms of product innovation rather than focusing on simple price competition.

[4] A recent series of country studies assembled by Reynolds et al. (1994) show that new-firm start-up rates tend to be greatest in those geographic regions where the average number of firms per employee is the greatest.

[5] Scherer (1983), Mansfield (1984) and Griliches (1990) have all warned that the number of patented inventions is not the equivalent of a direct measure of innovative output. For example, Pakes and Griliches (1984, p. 378) argue that 'patents are a flawed measure of innovative output; particularly since not all new innovations are patented and since patents differ greatly in their economic impact'. In addressing the question, 'Patents as indicators of what?' Griliches (1990, p. 1669) concludes that, 'Ideally, we might hope that patent statistics would provide a measure of the innovative output … The reality, however, is very far from it. The dream of getting hold of an output measure of inventive activity is one of the strong motivating forces for economic research in this area'.

[6] A detailed description of the SBIDB is contained in Audretsch (1995).

introductions compiled form the new product announcement sections of over 100 technology, engineering and trade journals spanning every industry in manufacturing. From the sections in each trade journal listing new products, a database consisting of the innovations by four-digit standard industrial classification (SIC) industries was formed. These innovation data have been implemented by Audretsch (1995) to analyze the relationship between industry dynamics and technological change, and by Audretsch and Feldman (1996), Feldman (1994) and Feldman and Florida (1994) to examine the spatial distribution of innovation.

There are several important qualifications that should be made concerning the SBIDB. The trade journals report mainly product innovations. Thus, as is the case in the studies by Audretsch (1995) and Audretsch and Feldman (1996), the empirical analyses undertaken in this paper capture product innovation but not process innovation.

Another potential concern might be that the significance and 'quality' of the innovations vary considerably. In fact, each innovation was classified according to one of the following levels of significance: (1) the innovation established an entirely new category of product; (2) the innovation is the first of its type on the market in a product category already in existence; (3) the innovation represents a significant improvement in existing technology; and (4) the innovation is a modest improvement designed to update an existing product. About 87% of the innovations were in this fourth category and most of the remaining innovations were classified in the third category. However, the preliminary nature of such classifications leads us to treat the innovations as being homogeneous. While such an assumption will hopefully be improved upon in the future, it is consistent with the voluminous body of literature treating dollars of R&D, numbers of scientists and engineers, and numbers of patents as being homogeneous.[7]

An important strength of the database is that the innovating *establishment* is identified as well as the innovating *enterprise*. While this distinction is trivial for single-plant manufacturing firms, it becomes important in multi-plant firms. This is because some innovations are made by subsidiaries or divisions of companies with headquarters in other states. Even though the headquarters may announce new product innovations made by the company, the database still identifies the individual establishment responsible for the majority of the work leading to the innovation.

[7] An anonymous referee points out that the implicit assumption that innovations are homogeneous in their impact is found in most studies attempting to measure innovative activity. As Griliches (1990) emphasizes, this limitation has plagued studies using counts of patents, just as it has in those based on R&D expenditures or R&D scientists and engineers.

The innovations from the SBIDB are then classified according to the four-digit SIC industry of the new product and the city where the innovating establishment was located. We adapt either the Consolidated Metropolitan Statistical Area (CMSA) or the Metropolitan Statistical Area (MSA) as the spatial unit of observation. The analysis here is based on 3969 new manufacturing product innovations for which the address of the innovating establishment could be identified.[8]

In 1982 the most innovative city in the United States was New York. Seven hundred and thirty-five, or 18.5%, of the total number of innovations in the country were attributed to firms in the greater New York City area. Four hundred and seventy-seven (12.0%) were attributed to San Francisco and 345 (8.7%) to the Boston area and 333 (8.4%) to the Los Angeles area. In total, 1890, or 45% of the innovations, took place in these four consolidated metropolitan areas. In fact, all but 150 of the innovations included in the database are attributed to metropolitan areas. That is, less than 4% of the innovations occurred outside of metropolitan areas. This contrasts with the 70% of the population which resided in these areas.

Of course, simply comparing the absolute amount of innovative activity across cities ignores the fact that some cities are simply larger than others. Cities vary considerably in terms of measures of city size, and we expect that city scale will have an impact on innovative output. Table 1 presents the number of innovations normalized by the size of the geographic unit. Population provides a crude but useful measure of the size of the geographic unit. Cities in Table 1 are ranked in descending order by innovation rate or the number of innovations per 100,000 population. While New York has the highest count of innovation, it has the third highest innovation rate. The most innovative city in the United States, on a per capita measure of city size, was San Francisco, with an innovation rate of 8.90, followed by Boston, with an innovation rate of 8.69. By contrast, the mean innovation rate for the entire country is 1.75 innovations per 100,000 population. The distribution of innovation rates is considerably skewed. Only 14 cities are more innovative than the national average. Clearly, innovation appears to be a large city phenomenon.

To systematically identify the degree to which specific industries have a common underlying science and technology base, we rely upon a deductive approach that links products on their closeness in technological space. We use the widely acknowledge and established *Yale Survey of R&D managers*. This survey is documented in great detail in Levin et al. (1987) and has been widely used in studies linking various mechanisms of appropriability to R&D activity (Cohen

[8] Feldman (1994) provides a description of the data collection procedure. The results are invariant to using PMSAs.

Table 1
Counts of innovation normalized by population

Consolidated metropolitan statistical area	Innovations (1982)	1980 population (thousands)	Innovations per 100,000 population
San Francisco – Oakland	477	5368	8.886
Boston – Lawrence	345	3972	8.686
New York – Northern New Jersey	735	17539	4.191
Philadelphia – Wilmington	205	5681	3.609
Dallas – Fort Worth	88	2931	3.002
Hartford	30	1014	2.959
Los Angeles – Anaheim	333	11498	2.896
Buffalo – Niagara	35	1243	2.816
Cleveland – Akron	77	2834	2.717
Chicago – Gary	203	7937	2.558
Providence – Pawtucket	25	1083	2.308
Portland – Vancouver	25	1298	1.926
Cincinnati - Hamilton	30	1660	1.807
Seattle – Tacoma	37	2093	1.768
Pittsburgh	42	2423	1.733
Denver – Boulder	28	1618	1.731
Detroit – Ann Arbor	68	4753	1.431
Houston – Galveston	39	3101	1.258
Miami – Fort Lauderdale	13	2644	0.492

Source: 1980 Population is from the Statistical Abstract.

and Levinthal, 1990; Levin et al., 1987). The survey uses a Likert scale of 1 to 7, from least important to most important, to assess the relevance of basic scientific research in biology, chemistry, computer science, physics, mathematics, medicine, geology, mechanical engineering and electrical engineering. We assume any academic discipline with a value greater than 5 to be relevant for a product category. For example, basic scientific research in medicine, chemistry and chemical engineering is found to be relevant for product innovation in drugs (SIC 2834).

We then identify six groups of industries which rely on similar rankings for the importance of the different academic disciplines. These six groups, shown in Table 2, reflect distinct underlying common scientific bases. To facilitate identification of the groupings we assigned a name to each group that reflects not only the underlying science base but also the application to which this knowledge is directed. Thus, what we term as the ‘chemical engineering’ and ‘industrial machinery’ groups actually include the same critical academic departments (ranked differently), but applied to different types of industries.

While each industry within the group shares a common scientific base, the geographic space and product space differ across industries. For example, there

Table 2
The common science bases of industry clusters

Cluster	Critical academic departments	Most innovative industries
Agra-business	Chemistry (6.06);	SIC 2013: Sausages
	Agricultural Science (4.65);	SIC 2038: Frozen Specialities
	Computer Science (4.18);	SIC 2087: Flavoring Extracts
	Biology (4.09).	SIC 2092: Packaged Foods
Chemical engineering	Materials Science (5.32);	SIC 3861: Photographic Equipment
	Chemistry (4.80);	SIC 3443: Fabricated Plate Work
	Computer Science (4.50);	SIC 2821: Plastic Materials
	Physics (4.12).	SIC 3559: Special Ind. Machinery
Office machinery	Computer Science (6.75);	SIC 3576: Scales and Balances
	Medical Science (5.75);	SIC 3579: Office Machinery
	Math (5.49);	SIC 3535: Conveyors
	Applied Math (4.64).	SIC 2751: Commerial Printing
Industrial machinery	Materials Science (5.03);	SIC 3551: Food Processing Equipment
	Computer Science (4.76);	SIC 3523: Machinery
	Physics (3.94);	SIC 3546: Hand Tools
	Chemistry (3.88).	SIC 3629: Industrial Apparatus
High-tech computing	Materials Science (5.92);	SIC 3573: Computing Machinery
	Computer Science (5.63);	SIC 3662: Radio/TV Equipment
	Physics (5.45);	SIC 3823: Process Control Instruments
	Math (4.76).	SIC 3674: Semiconductors
Biomedical	Chemistry (5.53);	SIC 3842: Surgical Appliances
	Medical Science (5.47);	SIC 3841: Medical Instruments
	Computer Science (5.32);	SIC 2834: Pharmaceuticals
	Materials Science (5.02).	SIC 3811: Scientific Instruments

are 15 distinct industries included in the biomedical group. On average, each industry contributed 3.22 innovations. Their shared underlying knowledge base consists of chemistry, medical sciences, computer sciences and material sciences. Surgical Appliances (SIC 3842), Surgical and Medical Instruments (SIC 3841), and Pharmaceuticals (SIC 2834) are three of the 15 industries heavily dependent on this common underlying scientific knowledge base. There are 21 industries included in the Agra-Business group, 34 industries included in the Chemical Engineering group, 7 industries in the Office Machinery group and 11 industries included in the Industrial Machinery group. The largest science-based group is what we term High-tech Computing, which includes 80 industries.

The most innovative cities within each science-based industrial cluster are identified in Table 3. This recalls the well-known association between cities and

Table 3
Innovation in science-based industry clusters

Cluster	Prominent cities	Mean industry innovations per 100,000 workers
Agra-business	Atlanta	92.40
	Dallas	41.15
	Chicago	33.03
	St. Louis	91.74
Chemical engineering	Dallas	38.09
	Minneapolis	66.67
	San Francisco	43.89
	Wilmington	85.47
Office machinery	Anaheim-Santa Ana	92.59
	Minneapolis	31.86
	Rochester	72.20
	Stanford	68.40
Industrial machinery	Anaheim-Santa Ana	54.95
	Cincinnati	66.01
	Cleveland	141.51
	Passaic, NJ	90.90
High-tech computing	Boston	73.89
	Houston	62.08
	San Jose	44.88
	Minneapolis	181.74
Biomedical	Boston	38.71
	Cleveland	68.76
	Dallas	35.22
	New York	188.07

industries. For example, Atlanta is a prominent center for innovative activity stemming from the common science base of agra-business. While the national innovation rate was 20.34 innovations per 100,000 manufacturing workers, agra-business in Atlanta was almost five times as innovative.

A Chi-Squared test on the independence of the location of city and science-based industrial activity reveals that neither the distribution of employment nor the distribution of innovative activity is random. Industries which rely on a common science base exhibit a tendency to cluster together geographically with regard to the location of employment and the location of innovation. We conclude that the distribution of innovation within science-based clusters and cities appears to reflect the existence of science-related expertise.

4. Modeling framework

To test the hypothesis that the degree of specialization shapes the innovative output of an industry, we estimate a model where the dependent variable is the number of innovations attributed to a specific four-digit SIC industry in a particular city. To reflect the extent to which economic activity within a city is specialized, we include as an explanatory variable a measure of industry specialization which was used by Glaeser et al. (1992) and is defined as the 1982 share of total employment in the city accounted for by industry employment in the city, divided by the share of United States employment accounted by that particular industry. This variable reflects the degree to which a city is specialized in a particular industry relative to the degree of economic activity in that industry that would occur if employment in the industry were randomly distributed across the United States. A higher value of this measure indicates a greater degree of specialization of the industry in that particular city. Thus, a positive coefficient would indicate that increased specialization within a city is conducive to greater innovative output and would support the *Marshall–Arrow–Romer* thesis. A negative coefficient would indicate that greater specialization within a city impedes innovative output and would support Jacobs' theory that diversity of economic activity is more conducive to innovation than is specialization.

To identify the impact of an increased presence of economic activity in complementary industries, the presence of science-based related industries is included. This measure is constructed analogously to the index of industry specialization, and is defined as the share of total city employment accounted for by employment in the city in industries sharing the science base, divided by the share of total United States employment accounted for by employment in that same science base. This variable measures the presence of complementary industries relative to what the presence would be if those related industries were distributed across the United States. A positive coefficient of the presence of science-based related industries would indicate that a greater presence of complementary industries is conducive to greater innovative output and supports for the diversity thesis. By contrast, a negative coefficient suggests that a greater presence of related industries sharing the same science base impedes innovation and argues against Jacobs' diversity thesis.

The usual concept of product market competition in the industrial organization literature is typically measured in terms of the size-distribution of firms. By contrast, Jacobs' concept of *localized competition* emphasizes the extent of competition for the ideas embodied in individuals. The greater the degree of competition among firms, the greater the extent of specialization among those firms and the easier it will be for individuals to pursue and implement new ideas. Thus, the metric relevant to reflect the degree of localized competition is not the

Table 4
Variable definitions and descriptive statistics

Variable name	Definition	Mean	Standard deviation
Specialization	$\dfrac{\text{Industry employment in city/total employment in city}}{\text{Industry employment in US/total employment in US}}$	0.96	1.47
Science base diversity	$\dfrac{\text{Employment in cluster in city/total employment in city}}{\text{Employment in cluster in US/total employment in US}}$	0.37	0.51
Competition	$\dfrac{\text{Firms in city} - \text{industry/workers in city} - \text{industry}}{\text{Firms in US industry/workers in US industry}}$	0.57	2.08

size of the firms in the region relative to their number (because, after all, many if not most manufacturing product markets are national or at least inter-regional in nature) but rather the number of firms relative to the number of workers. In measuring the extent of localized competition we again adopt a measure used by Glaeser et al. (1992), which is defined as the number of firms per worker in the industry in the city relative to the number of firms per worker in the same industry in the United States. A higher value of this index of localized competition suggests that the industry has a greater number of firms per worker relative to its size in the particular city than it does elsewhere in the United States. Thus, if the index of localized competition exceeds one then the city is locally less competitive than in other American cities.

The data for these measures are from County Business Patterns. Table 4 presents the variable definitions and descriptive statistics for the measures of science-based diversity, specialization and competition.

5. Results

Table 5 presents the regression results based on the 5946 city-industry observations for which data could be collected. The Poisson regression estimation method is used because the dependent variable is a limited dependent variable with a highly skewed distribution.[9]

[9] The number of innovations in a city and product category is either zero or some positive integer. The mean of the distribution is 0.26 and the standard deviation is 2.96.

Table 5
Poisson regression estimation results

	Model 1	Model 2	Model 3	Model 4
Industry specialization	−0.209	−0.334	−0.527	−0.142
	(−8.360)	(−14.522)	(−17.684)	(−5.680)
Science-based related	0.168	0.104	0.089	0.069
industries	(3.812)	(2.122)	(2.405)	(2.091)
Localized competition	−0.175	0.576	0.221	0.168
	(−3.365)	(7.481)	(0.269)	(1.976)
City scale		1.044		1.004
		(28.216)		(20.917)
Technological opportunity			0.079	0.034
			(26.333)	(1.700)
n	5946	5946	5946	5946
Log-likelihood	−1296.793	−901.489	−693.046	−652.264

Note: The *t*-values of the coefficient is listed in parentheses.

Model 1 provides the results for the three measures which reflect the degree of specialization, diversity and localized competition. The negative and statistically significant coefficient of industry specialization suggests that innovative activity tends to be lower in industries located in cities specialized in economic activity in that industry. The positive and statistically significant coefficient for science-based related industries indicates that a strong presence of complementary industries sharing a common science base is particularly conducive to innovative activity. Taken together, these results provide support for the diversity thesis but not for the specialization thesis. The negative coefficient on the measure of localized competition suggests that less and not more localized competition promotes the innovative activity of an industry in a particular city.

One concern regarding the estimation of Model 1 is that larger cities might be expected to generate a greater amount of innovation in any particular industry, *ceteris paribus*, simply because of a greater degree of economic activity. In addition, the extent of localized competition might tend to be greater as the size of the city grows. Thus, when the total employment is included in the estimation of Model 2, the sign of the coefficient for localized competition switches from negative to positive, suggesting that a greater degree of localized competition is conducive to innovative activity. At the same time, the signs of the coefficients of the measures of industry specialization and science-based related industries remain unchanged.

Another concern regarding the estimation of Model 1 is that some industries are more innovative, or in a higher technological opportunity class than others. But even after controlling for the number of innovations recorded for the relevant industry in the estimation of Model 3 and Model 4, the basic results remain the same.[10]

The results in Table 5 generally provide support that it is diversity and not specialization that is more conducive to innovation. It should be emphasized here that even after we control for city scale and technological opportunity, specialization appears to have a negative effect on innovation, while science-based diversity has a positive impact on innovative output. In addition, the evidence suggests that a greater extent of localized competition and not monopoly tends to promote innovative output. Of course, the cross-sectional city level data do not provide any insight into whether these patterns are stable over time.

6. Diversity versus specialization at the firm level

The debate between specialization and diversity of economic activity and the impact on technological change is also relevant at the level of the firm and allows a further test of the effects of these influences on innovation. We expect a similar result in the organization of innovation within the firm – undertaking innovative activity across a range of science-based complementary activities will lead to greater innovative output than concentrating innovative activity within one industry. With this test we seek to ascertain if analogous processes operate at both the firm and the geographic level.

Jewkes et al. (1958) examined the histories of 61 innovations and found that a variety of different approaches within the firm are often pursued. It appears that diversity in terms of the number and the type of approaches used serves to reduce the uncertainty inherent in innovation by providing a greater number of unique ideas and outcomes. In an empirical examination of this question, Cohen and Malerba (1995) find a strong relationship between technological diversity and the rate of technical advance at the industry level. Our consideration of specialization examines the degree to which the firm focuses its innovative activity on one product category.

In order to model the effects of science-based diversity and specialization at the level, we follow the pioneering study of Scherer (1983) to estimate a

[10] The extent to which these relationships are non-linear was examined in the estimation with the inclusion of quadratic terms for industry specialization and localized competition. The results indicate that, in fact, cities which are highly specialized in economic activity may actually generate more innovative output in that industry. This result does not hold when city scale is included. It appears that scale is more important than the rate of change in the degree of specialization. The quadratic of localized competition suggests that there may be increasing returns to innovative output resulting for increased localized competition. Again, this result does not hold when urban scale is considered.

non-linear model which links R&D[11] to innovative output:

$$I_i = \alpha + \beta_1 RD_i + \beta_2 RD_i^2 + \beta_3 Innovative\ Diversity_i + \beta_4 Innovative\ Specialization_i + \varepsilon,$$

where I represents the total number of innovations attributed to firm I in the 1982 SBIDB.[12] RD represents the R&D expenditures of firm I.[13] To measure the extent to which the innovative activity of firm I is diversified across related product categories we calculate the share of innovations in the same common science base product categories divided by the total number of innovations introduced by the firm. Similarly, specialization, or own industry share, is measured as the proportion's of the firm's innovative activity in the primary industry identified with the firm.

R&D expenditures are taken from the *Business Week* 1975 sample of over 700 corporations for which R&D expenditures play an important role. An important feature of this sample is that it included more than 95% of the total company R&D expenditures undertaken in the United States. There is a seven year lag between the 1982 innovations and the 1975 R&D expenditures. This lag may be somewhat long in view of a number of studies in the literature. However, as long as firm R&D expenditures are relatively stable over a short period of time, differences in the assumed lag structure should not greatly impact the results.[14]

Table 6 indicates the most innovative firms in the database along with the corresponding R&D expenditures, sales, R&D/sales ratio and the number of innovations per R&D dollar. As we might expect a positive relationship can be observed between the size of the R&D budget and innovative output, but there is also great variation in the productivity of R&D. Some firms such as Data General appear to obtain a relatively high degree of innovation per R&D dollar expended. Other firms such as General Electric and RCA exhibit a considerably lower R&D yield.

The regression results from estimating the model of firm innovative activity are shown in Table 7. The positive relationship between R&D inputs and

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[11] R&D is generally observed to be the most decisive source of economic knowledge generating innovative activity.

[12] A log-log specification was estimated as well as the quadratic specification. The results for both specifications are consistent. We only report the results from the quadratic equations to facilitate comparisons with the earlier studies mentioned in the text.

[13] Note that the firm-level models are for the entire country and not for MSAs or states. It is not possible to identify firm-level R&D by location at this point.

[14] As an anonymous referee emphasizes, future research needs to explore distributed lags between R&D and innovative output.

Table 6
Firm innovation

	Number of innovations	R&D expenditure ($ million)	Sales ($ million)	R&D/ sales ratio	Innovation/ R&D[a]
Hewlett Packard Company	55	981.00	89.6	9.1	5.61
Minnesota Mining & Mfg.	40	3127.00	143.4	4.6	1.28
General Electric	36	13399.00	357.1	2.7	0.27
General Signal	29	548.00	21.2	3.9	5.29
National Semiconductor	27	235.00	20.7	8.8	11.49
Xerox	25	4054.00	198.6	4.9	0.62
Texas Instruments	24	1368.00	51.0	3.7	1.75
Pitney Bowes	22	461.00	10.5	2.3	4.77
RCA	21	4790.00	113.6	2.4	0.44
IBM	21	14437.00	946.0	6.6	0.15
Digital Equipment	21	534.00	48.5	9.1	3.93
Gould	20	773.00	23.1	3.0	2.59
Motorola	19	13112.00	98.5	7.5	1.45
Wheelabrator Frye	18	332.00	2.0	0.6	5.42
United Technologies	18	3878.00	323.7	8.3	0.46
Hoover	18	594.00	4.3	0.7	3.03
Honeywell	18	2760.00	164.2	5.9	0.65
Rockwell International	17	4943.00	31.0	0.6	0.34
Johnson & Johnson	17	2225.00	97.9	4.4	0.76
Eastman Kodak	17	4959.00	312.9	6.3	0.34
Data General	17	108.00	11.6	10.8	15.74
Exxon	16	4486.05	187.0	0.4	0.36
Du Pont	16	7222.00	335.7	4.6	0.22
Stanley Works	15	464.00	3.5	0.7	3.23
Sperry Rand	15	3041.00	163.5	5.4	0.49
Pennwalt	15	714.00	15.7	2.2	2.10
North American Philips	14	1410.00	22.5	1.6	0.99
Harris	14	479.00	21.1	4.4	2.92
General Motors	14	3572.05	1113.9	3.1	0.39

[a] Scaled by 100.

innovative output can be observed in Model 1. The negative coefficient of the quadratic term suggests that although innovative output tends to respond positively to increased investments in R&D inputs, the rate of increase in innovative output diminishes as R&D inputs increase.

When the measure of innovation diversity within industries sharing a common science base is included in Model 2, the positive coefficient provides support for the hypothesis that diversification across complementary economic activities is conducive to greater innovative output. When the measure of innovation specialization is included in Model 3, the positive coefficient suggests

Table 7
Regression results estimating firm innovative activity

	1	2	3	4
R&D	0.02804	0.0119	0.0178	0.0081
	(6.051)	(3.320)	(1.624)	(2.481)
R&D^2	−1.6945	−0.4157	−0.8940	−0.0323
	(−2.603)	(−0.878)	(−1.732)	(−0.075)
Innovative diversity	–	3.3081	–	9.2466
		(9.510)		(9.988)
Innovative specialization	–	–	2.8116	−7.4357
			(6.218)	(−6.819)
Number of observations	209	203	203	203
R^2	0.189	0.466	0.350	0.568
F	23.980	57.905	35.677	64.980

Notes: The t-value of the coefficient is listed in parentheses. The coefficients of R&D^2 have been divided by 100,000 for presentation purposes.

that greater specialization in innovation yields greater innovative output. When both specialization and diversity are included together in Model 4, the coefficient of specialization exhibits a negative coefficient suggesting that greater innovation specialization is less conducive to greater innovative output. On the other hand, holding R&D expenditures constant, greater innovative diversity within the common science base results in more innovative output.

The firms can also be grouped according to major two-digit SIC sectors. Results for six specific industrial sectors are listed in Table 8. There is interesting variation in these results across manufacturing sectors. For example, in instruments and telecommunications diminishing returns to R&D inputs can be observed. By contrast, increasing returns to R&D can be observed in the group of firms classified as conglomerates, and in electrical equipment and transportation no significant relationship can be observed between R&D and innovative output.

While the links between R&D inputs and innovative output vary substantially across sectors in Table 8, the relationships between specialization, innovation diversity and innovation remain remarkably constant across sectors. For all six sectors the coefficient of the measure of science-based innovation diversity remains positive and statistically significant, and the coefficient of the measure of innovation specialization also remains negative and statistically significant in all six sectors. Thus, the main finding that diversity in innovation activities within a common science base tends to promote innovative output more than does the specialization of innovation within just one single industry holds across a broad range of industrial sectors.

Table 8
Regression estimating firm innovative activity for specific sectors

Sector	R&D	R&D^2	Innovative diversity	Innovative specialization	n	R^2	F
Instruments	0.1796	−46.7294	7.7780	−7.3747	23	0.756	13.918
	(2.863)	(−2.344)	(3.167)	(−2.311)			
Telecommunications	0.0426	−81.0826	12.1458	−10.5068	31	0.681	13.857
	(1.757)	(−1.955)	(3.995)	(−2.888)			
Pharmaceuticals	0.0579	−21.2919	5.0999	−4.1984	24	0.732	12.951
	(1.162)	(−0.496)	(1.840)	(−1.501)			
Electrical	0.0328	−2.6788	11.8368	−9.5924	27	0.694	12.455
equipment	(0.908)	(−0.249)	(3.471)	(−2.310)			
Transportation	0.0025	0.5888	10.1231	−8.7190	20	0.859	22.934
	(0.357)	(0.880)	(4.985)	(−3.960)			
Conglomerates	−0.1074	0.0019	7.5160	−5.5113	25	0.926	62.866
	(−2.671)	(6.970)	(3.941)	(−2.671)			

Notes: The t-value of each coefficient is listed in parentheses. The coefficients of R&D^2 are multiplied by 100,000 for presentation purposes.

Table 9
Regression results estimating firm innovative activity for specific science bases

	High-tech computing (1)	High-tech computing (2)	Biomedical (3)	Biomedical (4)
R&D	0.0100	0.0059	0.6000	0.0501
	(2.293)	(1.497)	(2.056)	(1.723)
R&D^2	−0.2928	−0.1683	−25.7484	−18.6446
	(−0.522)	(0.300)	(−1.222)	(−0.889)
Innovation share within science base	3.7691	9.8348	1.4761	5.2878
	(7.831)	(8.524)	(1.925)	(2.120)
Innovation share within industry	–	−8.2150	–	−4.0457
		(−5.670)		(−1.601)
Number of observations	134	134	32	32
R^2	0.454	0.563	0.680	0.708
F	35.983	41.493	35.677	64.980

Notes: The t-value of the coefficient is listed in parentheses. The coefficients of R&D^2 have been divided by 100,000 for presentation purposes.

The results are confirmed in Table 9, which groups the firms according to two of the largest science bases – high-tech computing and biomedical products. Not only is the knowledge production function found to hold for firms in each of these distinct science bases, but again, diversity in innovation across economic activities with a common science base is found to increase innovation.

7. Conclusions

The nature and utility of knowledge is at the heart of the economics of R&D, innovation and technological change. Whether diversity or specialization of economic activities better promotes technological change has been the subject of a heated debate in the economics literature. This paper has attempted to shed light on that debate by linking the extent of diversity versus specialization of economic activities to innovative output. By focusing on innovative activity for particular industries at specific locations, we find compelling evidence that specialization of economic activity does not promote innovative output. Rather, the results indicate that diversity across complementary economic activities sharing a common science base is more conducive to innovation than is specialization. In addition, the results indicate that the degree of local competition for new ideas within a city is more conducive to innovative activity than is local monopoly.

A second perspective explored in this paper is the effect of diversity and specialization at the firm level. The results indicate that innovative activity tends to be lower when that innovation is specialized within a narrow industry than when it is diversified across a complementary set of industries sharing a common science base. Thus, the results at both the level of the firm as well as for the industry across geographic space present a consistent view of the returns to specialization versus diversity of economic activity. Our results suggest that diversity across complementary industries sharing a common base – a crucial qualification – results in greater returns to R&D.[15]

Increasingly scholars of technological change realize that external sources of knowledge are critical to innovation. Our results suggest that the boundaries of the firm are but one means to organize and harness knowledge. An analogous means of organizing economic activity are spatially defined boundaries. Geographic location may provide another useful set of boundaries within which to organize innovation. Geography may provide a platform upon which knowledge may be effectively organized.

[15] We underscore the descriptive nature of these results since there may be alternative explanations. Specifically, the relationships may be endogenous in a way that we have not considered. Firms which are more innovative may be more profitable and therefore, more likely to be able to engage in diverse activities. Similarly, regions which are successful at innovation in one industry may attract other activities. The cross-sectional nature of the data we use here does not allow us to examine these issues.

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