2006

Change in the Concentration of Employment in Computer Services: Spatial Estimation at the U.S. Metro County Level

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Abstract: This paper models the concentration of computer services activity across the U.S. with factors that incorporate spatial relationships. Specifically, we enhance the standard home-area study with an analysis that allows conditions in neighboring counties to affect the concentration of employment in the home county. We use county-level data for metropolitan areas between 1990 and 1997. To measure change in employment concentration, we use the change in location quotients for SIC 737, which captures employment concentration changes due to both the number of firms and the scale of their activity relative to the national average. After controlling for local demand for computer services, our results support the importance of the presence of a qualified labor supply, inter-industry linkages, proximity to a major airport, and spatial processes in explaining changes in computer services employment concentration, while finding little support for the influence of cost factors. Our enhanced model reveals inter-jurisdictional relationships among these metro counties that could not be captured with standard estimates by state, MSA or county. Using counties within MSAs, therefore, provides more general results than case studies, but still allows measurement of local interactions.

Introduction

Attracting software and other computer services to local areas is a highly desirable goal for many policy makers. Computer services jobs are perceived to pay relatively high wages, to be benign for the environment, and to act as a magnet for other high-tech employment. Thus, being known as a "high-tech" area is a sign of successful development for local policy makers. The analytical challenge is to understand what conditions are conducive to attracting these jobs in order that appropriate policies can be put in place.

The purpose of this paper is to estimate the factors that determine the location of computer services activity, and specifically what factors might explain why computer services jobs concentrate together, with a model that utilizes factors discussed in the literature and also incorporates spatial relationships. While local conditions are expected to matter to firms' location and expansion decisions, conditions in surrounding areas may matter as well. We use county-level data within metropolitan statistical areas (MSA) in the United States to analyze the change in the concentration of computer services employment between 1990 and 1997. Employment data capture change in computer services activity due to both new firms and those with changing payrolls.

Context and Motivation

Computer services firms have exhibited a tendency to locate together in clusters. Various externalities have been posited as explanations for clustering or agglomeration of similar firms (Le Blanc 2003). One type of externality is information spillovers. For example, a "learning advantage" may be created by close geographic proximity between high technology firms and major research universities (Acs, et al. 1998; Anselin et al., 2000). Another hypothesized factor in the development of high technology clusters, especially Silicon Valley, has been the creation of dense social and professional networks that serve as conduits for the dissemination of technical and market information (Saxenian 1998). Underlying these explanations is the idea that tacit knowledge is more easily transmitted from person to person the shorter the geographic distance between the individuals (Saxenian 1994, Audretsch and Stephan 1996). In these external, localized economies, there is an expectation that agglomeration spurs innovation, which then leads to productivity increases and growth (Audretsch, 2003; Feldman, 1999 & 2000).

A second type of externality associated with agglomeration has been postulated to enhance firm productivity via backward and forward linkages (Le Blanc 2003). These linkages include close proximity to suppliers and customers, transportation considerations or natural advantages such as found in the wine growing areas of California (Ellison & Glaeser, 1997, 1999).

The third type of externality leading to the concentration of similar firms results from the benefits derived from the existence of a large pool of labor with the appropriate skills (Le Blanc 2003). The potential benefits include lower search costs for firms, the ability to find qualified labor in the area due to an attractive job market, and more options and flexibility for both firms and labor.

A fourth approach suggests that externalities are critical in the start-up of new high-tech firms. Stuart & Sorenson (2003) develop an argument that social networks are needed to access the resources necessary to start a high-risk venture, and that co-location of such firms is due to the concentration of these networks of investors, customers, employees and collaborators (p.231). Once started, however, their study also shows that the conditions that draw new ventures are not necessarily the same set of conditions that are supportive of established firms.

A different strand of literature focuses on the potential costs associated with concentration. Factors such as higher prices due to resource competition, commuting costs, or unequal resource endowments important to particular industries would be expected to weigh heavily in firms' location decisions, and could even lead to dispersion of industry (Appold 1995, Beckmann 1999, Quigley 1998). In the Dixit-Stiglitz framework applied by Fujita et al. (1999), declines in concentration are represented by break points, where once some level of concentration is obtained, further declines in transport costs lead to a dissipation of that concentration. Due to technological improvements and competition, transport and communication costs have fallen sufficiently for some industries that they are no longer constrained by location decisions. In this case firms can choose any location that is most advantageous for them (Glaeser 1998, Le Blanc 2003). Theoretically, then, the effect of concentration of a particular industry on industry performance could be positive from externality effects or negative from competitive effects (Crozet, et al. 2003).

To measure the factors influencing employment concentration change in computer services, our study draws variables from this literature to include externality-type factors, as well as costs and local amenities.

Many studies of spatial clustering focus on one home area (Saxenian 1994, Walcott 1999), or use MSAs (Beardsell and Henderson, 1999; Quigley, 1998). There is some evidence that MSAs are an appropriate level of spatial analysis for looking at industry clustering (Sivitanidou 1999, Le Blanc 2003). However, the MSA level of aggregation cannot capture how near one center of concentration is to another within an MSA, or if firms are locating near, but not in, a particular center of concentration. Further, conditions vary substantially within MSAs. Some studies have used measures of population potential to try to overcome the restrictions of using MSAs or other definitions of home areas (Glaeser, 1998). Another study (Gabe, 2003) measures the effect of existing concentration on the growth of the number of new businesses in 16 counties and 344 industries in Maine between 1996 and 1999. This study, however, does not allow for spatial interaction. In contrast to these studies, we use county data within MSAs combined with distance-weighted variables in neighboring counties. As a result, we can measure the influence of concentration and other factors near the home county as well as within it.

A study that utilizes an approach similar to ours is Crozet et al. (2003). This study analyzes the location of foreign firms in France using 92 departments, which are an intermediate level of aggregation similar to U.S. counties. The authors apply distance-weighted variables to measure the influence of conditions in surrounding areas, but do not incorporate direct spatial lags. One of the contributions of our study is to utilize the MSA level of analysis across the U.S. for employment, rather than firms, and to measure the spatial relationship of key variables within MSAs at the county level. The results of our study suggest a more complicated spatial dynamic within MSAs than has been revealed using previous approaches.

The Computer Services Industry

The computer services industry (SIC 737) is defined as "computer programming, data processing, and other computer related services," and includes computer programming services, prepackaged software, computer integrated systems design, data processing and preparation, information retrieval services, computer facilities management, computer rental and leasing, computer maintenance and repair, and computer related services.[1] Because this is a relatively new and mobile industry, it is especially suitable for this study. One advantage is that it is unlikely that firms are located in a particular place because of past location factors that are no longer relevant, or due to inertia (Appold 1995, Feldman 2000, pp.383-384, Le Blanc 2003, p.461). Transportation costs should not matter to location decisions within this industry so that firms can locate anywhere, and yet we still observe high degrees of concentration (Le

Blanc 2003, pp.453-4). Our focus here is on understanding the factors behind that concentration.

Much of the computer services industry is also knowledge intensive, which has been found to have a direct relation to location concentration (Audretsch and Feldman 1996). High wages tend to be correlated with knowledge-based employment. The average wage within each of the nine sub-sectors of computer services (SIC 737) in 1997 was substantially higher than the average wage for all industries. If we take 150 percent of the average U.S. wage as a benchmark, then over 75 percent of employment in SIC 737 falls into this high wage category. The only two sub-sectors of computer services that did not meet this high wage rate criterion were data processing and computer maintenance and repair, although even these two categories had higher than average wages.

In addition, Le Blanc (2003) points out that the information technology sector includes a number of interrelated industries and that this fact helps to explain its cluster behavior via local complementarities. Le Blanc (2003) uses state level data for telecommunications plus most of the industries in SIC 737. Our study focuses on computer services and therefore does not include telecommunications. Within computer services, however, we expect there to be important interactions between the sub-categories of activities within SIC 737.

A detailed survey of computer software firms in southern California conducted by Sivitanidou (1999) investigated some of the standard theoretical factors proposed in the literature about firm location decisions.[2] Firms responding to questions about spatial preferences in general indicated that they cared most about access to a qualified labor force. The existence of amenities such as low crime rates and good environmental quality were also important but the responses indicated the reason good amenities mattered was to help attract and keep skilled labor. When asked about the importance of being close to other high-tech firms, the response was relatively weak in terms of advantages of being near other similar firms or near firms in other high-tech sectors. When clustering did matter to respondents it was most often due to facilitating business relationships, followed by benefits of labor concentration and potential knowledge sharing opportunities (Sivitanidou, 1999, p.126-127). In addition, being near universities generally mattered for labor supply more than for potential benefits from research spillovers (p.131), and access to airports no farther than 30 miles away was very important to about half the firms (p.137).

The Sivitanidou study is a thorough look at company preferences of those firms who responded to the survey in southern California. In our study the importance of these and other factors are investigated empirically using employment data across the U.S., and is based on the actual location of employment concentration change rather than on what firms report.

The Spatial Model

Both theory and data considerations suggest that spatial processes should be incorporated into the model. If there are local networks that influence firm location or expansion and hiring decisions, the spatial framework can capture the interaction of variables across space. Our specification allows for the possibility of a variety of spatial interdependencies. Using metro areas within the U.S. is representative of changes across the country, as the MSAs accounted for over 96 percent of all U.S. employment in this industry in 1990. By using county level data within metro areas, we can analyze the local factors underlying these employment concentration changes. Therefore the results of this study are more general than case studies of a single county or MSA but are still able to capture local interactions.

Firms make location and growth decisions based on economic factors while county boundaries are administratively determined. The spatial approach taken here considers both employment conditions in neighboring counties as well as changes in employment in each home county. This allows us to overcome, to some extent, the limits of county level data. Clearly, this approach improves on analyses that measure activity in individual counties alone, especially given the expectations of firm interaction motivated by theories of learning (Glaeser, 2000, pp.88-89) and social and professional networks (Stuart and Sorenson, 2003).

The spatial specification is based on the classic formulations of spatial processes (Cliff & Ord, 1973; Anselin, 1980). In our model, the variable of interest is the location quotient, or LQ (Vias & Mulligan, 1999; Mulligan and Schmidt, 2005). LQ is defined in the standard way, as the proportion of computer services jobs to total employment in county (i) relative to the same proportion nationally. LQs give a precise measure of relative concentration of jobs in a particular industry, and therefore of clustering or agglomeration. Therefore a change in the location quotient is a precise measure of the change in an area's concentration of jobs in a particular industry. Using the change in employment in computer services as the dependent variable is another option. However, growth in these jobs is highly correlated with growth in MSAs generally, and would not be as good a measure of the change in job concentration as a change in the location quotient

In our spatial model, we specify that nearby counties have the most direct correlations and allow the conditional mean of LQ_i to be a direct function of LQ in neighboring counties, with neighbors defined as counties within a 50 mile radius of the home county.[3] The spatial process in the dependent variable is modeled as $\rho W \bullet LQ$, where the matrix W captures the pattern of correlations across counties. This specification is often referred to as a spatial lag model, and it implies that LQ_i is affected by a distance-weighted average of the level of the location quotient in nearby counties. We allow for the possibility that the explanatory variables also have effects that go beyond county borders. The most general model, then, is represented by equation (1):

(1) $$LQ = \rho W \bullet LQ + X\beta_1 + WX\beta_2 + u,$$

where the weight matrix W is specified so that the diagonal values are all zero and the elements in each row are normalized to sum to one. We assume that the idiosyncratic errors, u, are independently normally distributed.[4]

The dependent variable, ΔLQ, is the change in employment concentration as measured by the location quotient for computer services (SIC 737) in counties between 1990 and 1997. The vector x_i contains the explanatory variables for county (i), the home county.

Additionally, we allow for the possibility that distance-weighted averages of these variables in neighboring counties (within a 50 mile radius) affect the growth in the relative concentration of employment in computer services, so that WX is included on the right hand side. These effects are measured by the vector β_2.

Our model includes ten independent variables. The level of the location quotient in computer services in a county in 1990 is used to measure how important existing activity in this industry is to the creation of new activity by 1997. The level of the location quotient in computer manufacturing is used to measure how important the existence of a related industry is to new computer service activity. These variables reflect the hypotheses in the literature of learning externalities and linkages, respectively, as reasons for firms to locate together. If these externalities are important, we would expect a positive relationship between the initial levels and the change in employment concentration in computer services.

For the home demand effect, we use the concentration of workers in managerial and professional occupations as reported in the 1990 Census of Population to measure the local demand for computer services. We expect local demand to be an important determinant of changes in employment concentration. However, some firms in the computer service sector will have the ability to expand or choose locations independent of local demand. Thus, once local demand is controlled for, we can test to see if other variables are important in explaining the variation in employment concentration changes.

To test the importance of the presence of qualified labor as a determinant of growth in this industry, we use the number of graduates with a Masters or Ph.D. degree in computer science in the 1990-91 academic year (fall 1990 to spring 1991). The number of graduates is based upon information on the total number of students graduating with a degree in computer programming at all universities in the county as measured by the

Integrated Postsecondary Education Data System (IPEDS) (United States Department of Education, National Center for Education Statistics).

We use three measures for amenities. The first is the crime rate reported by county. Here, of course, we expect a higher crime rate to be negatively related to changes in job concentration. This measure is provided by the Federal Bureau of Investigation as reported in USA Counties, 1998 (U.S. Department of Commerce).[5]

The second amenity is a favorable climate. Conventional wisdom suggests that because these types of high wage jobs can locate anywhere, they tend to go where the weather is good. We use the average temperature in January to test this idea, and we would expect a positive relation in that mild winters should be attractive. [6]

The final amenity is access to a major airport. We use the number of enplanements (measured as per 1000 population) at major airports to see if increases in a county's computer services employment concentration is related to the presence of a major airport. Enplanements are a count of all revenue paying passengers boarding commercial aircraft at the 407 primary airports in the United States in 1995 as published by the U.S. Bureau of Transportation Statistics and stored at the National Transportation Library.

Cost factors are measured with proxies for labor, land and taxes. Labor costs are measured by the average wage in the computer services industry in 1990. Land costs are proxied with population density. The population density is measured as the population (in 1,000s) per square mile, and is calculated by dividing the July 1, 1992 population by the square miles of land area (area covered by lakes and rivers is excluded) as reported by the census bureau in 1990. We expect that higher land costs (higher population density) would be negatively related to changes in computer services concentration. For tax costs we use property tax as a share of personal income, since state or federal taxes would not vary by county. In this case we expect a lower value to be positively related to changes in computer services job concentration. The information on property taxes reflects the total property taxes paid in the county in the 1992 fiscal year as reported to the Census Bureau divided by the personal income in calendar year 1992.

All of the independent variables are then included in the X_2 matrix to capture the importance of characteristics of neighboring counties to employment growth in a home county. We did not have *a priori* information leading us to hypothesize that a particular sub-set of these variables would have spatial spillovers, and therefore we include them all.

The Data

The data used in the regressions include information on all counties contained in metropolitan areas as defined by the U.S. Office of Management and Budget as of June 2003 that had non-zero employment in the computer services industry in 1990.[7] These area definitions include the new micropolitan areas (areas that are too small to be a metropolitan area, but have a central urban area) as well as the traditional metropolitan areas with a total of 1313 counties. The descriptive statistics are presented in table 1.

The industry employment and wage measures are from the U.S. Department of Labor's Quarterly Census of Employment and Wages (QCEW) data series.[8] The data do not include self-employed workers. The QCEW data series is based upon administrative records of all employees covered by state or federal unemployment insurance programs.

Approximately 98 percent of all wage and salary workers are included in this data series. Because the QCEW series is a universe of the employment records of virtually all employers and it is an average of 12 months of data, it is preferable to other series that only rely upon one month of data or a sample of employers. In some counties the data were suppressed to avoid disclosure of establishment specific information. In these cases

Table 1: Descriptive Statistics Across Counties in MSAs

N = 1313					
Variable description		Min	Max	Mean	Std. Dev.
Change in computer services concentration, 1990-97	chlq9097	-9.06	3.46	-.0172	0.6309
Concentration of computer services employment in 1990	lq73790	0	13.86	0.4737	1.001
Concentration of computer manufacturing employment in 1990	lq35790	0	33.12	0.5478	2.5731
Concentration of managers and professionals in 1990	lqmp90	0.3993	2.0731	0.8748	0.2130
Graduates with a masters or Ph.D in computer science, academic year 1990-91	compg91	0	526	7.55	33.96
Crime rate in 1990	crate90	141	20899	4381	2337
Average temperature in January	jantemp	3.1	67.2	33.96	11.63
Property tax as a share of personal income, 1992	prtaxpi	0.0022	0.1786	0.0283	0.0135
Enplanements per 1000 population, 1995	enp95pc	0	98524	737.7	4314
Average wage in computer services, 1990	Aw73790	4463	130912	27081	11357
Population density (1000's people per square mile), 1992	Popsqm	0.0011	257.6935	0.9227	9.8693

the missing information was estimated using the statewide share of sub-industry categories present, but missing, in the county where the industry data was suppressed.[9] All of the initial county employment and wage bill estimates were then adjusted so that the sum of all counties in a state equaled the statewide total.

Results

The estimation results are given in Table 2. The key spatial parameter, ρ, is statistically significant, indicating the existence of spatial processes across the counties thereby supporting the model specification used.[10]

The level of employment concentration in computer services in 1990 has a significant and negative coefficient indicating that counties beginning with higher levels of employment concentration in 1990 experienced either less of an increase, or a decrease, in their change in concentration in this industry by 1997. This result implies that when other variables are controlled for, and in particular, potential demand for computer services, the factors driving dispersion of computer services jobs are overwhelming the factors driving concentration as measured at the county level. This result runs counter to the hypothesis that similar firms will locate together to take advantage of learning externalities but is consistent with the Stuart and Sorenson (2003) hypothesis that start-up firms co-locate to utilize network resources but that they disperse later. However, this interpretation is suggestive only since our data is employment and not number of firms.

The other key aspect in interpreting the negative coefficient on the change in home concentration in computer services employment is accounting for the spatial spillover effects that are central to our specification. The ρ coefficient measures the influence of the weighted change in the concentration of computer services employment in neighboring counties on the change in concentration of the home county's computer services jobs through 1997. This coefficient is significantly different from zero and positive suggesting that spatial relationships are present. In other words, having an established presence in the industry by 1990 put a damper on future increases in the concentration in the home county, but having nearby counties with growing employment concentration spilled over as an indirect, positive effect on home county employment concentration.

The next nine explanatory variables are the control variables hypothesized to explain changes in home county employment concentration. Inter-industry linkages have been hypothesized to influence employment, and in our case the level of employment concentration in computer manufacturing in 1990 was significant. Having a base in computer manufacturing helps explain increases in the concentration of new computer services jobs by 1997.

The effect of the number of graduates in computer science in the home county with a Masters or Ph.D. degree in computer science was positive and significant as expected based on skill supply externalities.

Our measure of home market demand for computer services is the level of the relative concentration of managers and professionals in 1990. This coefficient was positive and significant, indicating that other things held constant, a disproportionately large presence of end users of computer services was a good predictor of the growth in employment concentration in computer services. The demand factor, however, clearly

Table 2: General Spatial Model Estimates

Dependent variable: Change in employment location quotient for computer services (SIC 737), 1990-97				
Variable description	Variable	Coefficient	Asymptotic t-ratio	Probability value
	Constant	-0.553653	-6.276555	0.000000
	rho (ρ)	0.074999	2.152901	0.031326
Level of employment location quotient for computer services in 1990	lq73790	-0.528341	-38.658126	0.000000
Level of employment location quotient for computer manufacturing in 1990	lq35790	0.035155	7.378790	0.000000
Graduates with a masters or above in computer science, academic year 1990-91	compg91	0.001382	3.364371	0.000767
Level of location quotient for managers & professionals in 1990	lqmp90	0.760017	10.523850	0.000000
Crime rate, 1990	crate90	-0.000001	-0.145748	0.884120
Average temperature in January	jantemp	-0.000368	-0.157947	0.874498
Number of enplanements per 1000	enp95pc	0.007816	2.747890	0.005998
Property tax as a share of income	prtaxpi	-0.555478	-0.473087	0.636151
Average wage in computer services, 1990	aw73790	0.000003	2.485695	0.012930
Population density	popsqm	-0.003970	-2.853168	0.004329
Variables interacted with weighted average of nearby counties:				
Level of employment concentration in computer science, 1990	Wlq73790	0.072504	2.557555	0.010541
Level of employment concentration in computer manufacturing, 1990	Wlq35790	-0.019919	-2.139324	0.032409
Computer science graduates, academic year 1990-91	Wcompg91	-0.000025	-0.022785	0.981822
Concentration of managers & professionals, 1990	Wlqmp90	-0.017254	-0.172388	0.863133
Crime rate, 1990	Wcrate90	0.000009	0.890522	0.373186
January average temperature	Wjantemp	-0.001830	-0.771924	0.440159
Average wage in computer services, 1990	Waw73790	0.000004	2.891822	0.003830
Property tax as a share of income	Wprtaxpi	-2.195693	-1.402403	0.160795
Population density	Wpopsqm	0.000657	0.180055	0.857109
Number of emplanements per 1000	Wenppc	0.023447	20421298	0.015465

is not the only driving factor behind increases in computer services concentration, as our results indicate that there are a number of other significant factors underlying this process.

The amenity measures have mixed results. The coefficient on the crime rate was negative, as expected, but not significant. Our measure of climate was also not significant, suggesting sun-belt counties do not have an advantage over others in attracting concentrations of computer services jobs. The presence of a major airport in the home county, however, was significant, indicating that access to an airport does matter to job concentration in this industry.

The basic cost factors also had mixed results. When costs matter to location decisions we expect them to have a negative coefficient implying that higher costs would discourage firms from locating in that county, dampening any tendency for concentration of jobs. In our study, land costs (proxied with population density) were negative and significant as expected, tax costs were negative but insignificant, and wage rates were positive and significant.

Mixed results on factor costs in high-tech industries have also been found in other work on high-tech industries. For example, using U.S. MSA data from 1977 to 1992, Beardsell and Henderson (1999, p.447) found no consistent effect of wages and taxes on location of employment in the computer industry. The Crozet et al. (2003) study of foreign firms' location decisions in France found an unexpected positive coefficient on wages in some of their estimates suggesting possible endogeneity.[11] In contrast, the Gabe (2003) study generally found the expected signs and significance for tax and wage costs.

However, the Gabe results were from a variety of sectors such as manufacturing, transportation and construction, but were weakest for services, which would be the best comparison with computer services.

In the context of our study, the tax variable can have a dual interpretation, which might explain its statistical insignificance. While higher taxes might be associated with higher costs, taxes also buy government services. To the extent that positive public goods, such as good schools, are associated with higher local taxes, we would expect a counter influence with respect to that variable.

There is also some evidence that wages behave differently than expected in certain industries. Glaeser (1998, p.142) found that a "wage premium" was paid to workers in urban areas, even controlling for the typical factors affecting wage levels. While this evidence does not mean that high-tech firms seek out high wages, it does imply that they are willing to pay them, most likely because of the increased productivity gained. Research suggests the wage premium reflects learning, experience, or skill acquisition rather than simply higher cost-of-living wages or a union derived economic rent (Glaeser, 1998, p.148; Glaeser and Mare, 2001). The negative effect of higher wages on employment growth is expected to be more significant for traditional industries such as manufacturing rather than knowledge-based industries such as computer services.

The next set of variables contains the spatial interaction terms matrix between the home county and the weighted average of nearby counties included in the X_2 matrix to see whether our variables might matter to home counties' computer services employment concentration. Our hypothesis was that being close to these factors might have a spillover effect on home counties, although we did not have a reason to choose some over others or know whether the effects would be supportive or competitive. From Table 2 we can see that four of the weighted variables had significant county spillover effects: the level of computer service job concentration in 1990, the level of computer manufacturing concentration in 1990, enplanements and the average wage (which again has a positive sign). The result for neighboring levels of concentration of computer service jobs in 1990 indicates a positive effect on the change in home county employment concentration. This result is consistent with the earlier one showing that changes in nearby employment concentration were positively related to changes in home county concentration as indicated by a positive ρ. Both indicate positive county-level spillovers, which counter to some extent the tendency for the concentration in high concentration counties in 1990 to fall. In addition, we need to remember that falling concentration does not mean necessarily the number of jobs is falling, but rather that the concentration of computer services jobs relative to total jobs in the county as compared with the U.S. total is less in 1997 than in 1990.

In the case of computer manufacturing, there is the opposite, competitive effect in nearby counties. In other words, if employment concentration in computer manufacturing is increasing nearby, it has a negative effect on the concentration on computer service jobs in the home county. With the enplanements variable we find that having a major airport in a nearby county has a positive effect on computer services employment in the home county.

Conclusion

This study utilizes a model that incorporates county-level and neighboring influences within MSAs across the U.S. Our results underscore the importance of incorporating activity in neighboring areas when estimating statistical relationships between the change in an industry's concentration in an area and possible factors to explain that change. We find statistically significant spatial relationships through the spatial lag coefficient, ρ, and through some of the distance interaction variables. Thus, using a spatial model is necessary to capture the interdependence across space.

While cost factors and even amenities, except for airports, were not found to be important in explaining the concentration of computer services jobs overall, our findings lend support for three of the four externalities effects outlined in the literature, namely industry linkages, labor market spillovers and network externalities. The fourth externality, information or learning spillovers, may be important, but since in our study counties with high concentrations of computer service jobs tended to see that concentration fall relative to the national average, we find evidence of similar firms becoming less agglomerated, at least in home counties. Our results suggest, instead, that the concentration in this industry may be driven by regional characteristics rather than by benefits derived from being located very close to competing firms in the same industry. For policy, this result suggests that county governments should focus on improving their own characteristics, such as educating a quality workforce, but good regional characteristics help attract these prized jobs as well.

The significant spatial relationships that emerged from our modeling of the change in computer services employment concentration suggest that more research would be useful. Studies that use cross-sectional samples of counties or MSAs, or look at home areas alone, miss some of the interesting relationships. Future research could seek to identify the causal relationships through which some variables propagate through space.

It would also be useful to explore other industries to see if, and why, the spatial relationships we found vary by economic activity.

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Endnotes:

[1] Standard Industrial Classification Manual 1987, Office of Management and Budget.
[2] This study also analyzes the survey responses based on the age of the companies, whether they are single or multi-unit, and the size based on number of employees. Since our study looks at employment concentration changes by county, we are interested in the overall preferences reported.
[3] We define neighbors within a 50 mile radius to exclude the most distant counties within an MSA and to include nearby counties even if they are in a different MSA. This specification also avoids any definitional problems with attempting to use contiguous counties, and the fact that in some areas counties are very large. We calculate distances based on spherical geometry, as does Stuart and Sorenson (2003) and others.
[4] Additional regularity assumptions on the weight matrix, the matrix of explanatory variables, and the innovations are required in order to establish the consistency and asymptotic normality of the maximum likelihood estimator for this model. These conditions seem to have been established in the literature only very recently. See Lee (2005) and Kelejian and Prucha (1998 and 1999) for more information.
[5] USA Counties CD issued May 1999, U.S. Department of Commerce, U.S. Census Bureau.
[6] http://www.ers.usda.gov/data/NaturalAmenities/
[7] We would like to use all counties, even those that did not have employment in computer services in the base year, but one of the explanatory variables, the average wage in computer services in 1990, requires that a county have some non-zero employment in computer services in 1990.
[8] http://stats.bls.gov/cew/home.htm
[9] For example, in Autauga Alabama (FIPS 01001), employment in computer services in 1990 was suppressed, however employment in the aggregate industry category, business services (SIC 73) totals 71 employees and it is known that employment in two sub-aggregate industries (SICs 734 and 738) total 42. Subtracting the known sub-aggregate industry employment from the aggregate industry total leaves 29 employees distributed among six industries (SICs 731, 732, 733, 735, 736, and 737) covered by disclosure restrictions. Employment in computer services (SIC 737) was then estimated using the statewide distribution of employment in these six industries.
[10] In a naïve test of the model, we estimated an OLS regression without the spatial lag variables. The results were qualitatively similar to the results presented here, but the coefficient estimates are inconsistent if the spatial lag is omitted.
[11] In the survey study of computer software firms by Sivitanidou (1999), none of the questions in the survey dealt with direct cost issues.