Geographic Determinants of High-Tech Employment Growth in U.S. Counties

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1. Introduction

Spurring growth in the high-tech sector has been a pervasive focal point of regional economic development efforts (Partridge, 1993; Buss, 2002). The interest in high-tech firms stems from their research intensiveness and role in innovation and raising standards of living. A critical issue, however, is how likely it is that the successes of high-technology centers such as Silicon Valley, Route 128 (Bania, 1993) and North Carolina's Research Triangle (Goldstein, 2005) can be replicated elsewhere. The academic literature has focused extensively on the role of clusters and universities in the development of the high-tech sector (e.g., Maggioni, 2004; Smilor et al., 2007; Florida et al., 2008). Prominent in these investigations is the role of geographic distance.

Numerous developments in recent decades suggested that the role of geographic distance in determining economic activity may have changed. Technological advances in communications have reduced the costs of the transmission and processing of information (Jovanovic, 2003), potentially reducing the role of geography. Distance may have diminished in importance as products became standardized (Wojan, 1998) or as organizational structures formed capable of information transmission across regions (Crescenzi et al., 2007) or internationally (Waxell and Malmberg, 2007). Such trends were popularly highlighted in proclamations of the "death of distance" (Cairncross, 1995) and that the "world is flat" (Friedman, 2005). Others have argued that rather becoming flatter, the world became more curved or spiky (Florida, 2005; Florida et al., 2008; McCann, 2008). New information technology may have increased the frequency of personal interactions (McCann, 2007), making them complementary rather substitutable. There may be an urban bias in the provision and adoption of new technology (Sinai and Waldfogel, 2004; Forman et al., 2005.). Urban household amenities also may have become more important for highly educated and skilled workers (Glaeser et al., 2001).

To be sure, Partridge et al. (2008a; 2008b) found U.S. employment and population growth as increasingly dependent on geographic proximity to larger core urban areas in the latter part of the twentieth century. The trend appeared to continue throughout the 1990s and generally was consistent across major industries. Only for rural manufacturing did distance appear to become less of a barrier to growth (Partridge et al., 2008a). Because of the prevalence of high-tech firms among new high growth firms (Buss, 2002), and potential links to research universities and clusters, the question naturally rises regarding whether high tech employment growth has been differentially affected by geographic proximity and recent trends than all sectors generally.

Therefore, in this paper we examine the role of geography in high-tech employment growth for U.S. counties in the lower 48 states from 1990 to 2006. Included in the analysis are measures of clustering, urban agglomeration, human capital, access to research universities, and proximity to larger core areas. These measures can be related to high-tech employment growth through numerous channels, potentially emanating both from firm and household location considerations. If distance ceased to be a consideration in the location of firms and households involved in the high-tech sector the measures should be unrelated to high-tech employment growth during the period. In addition, previous advantages should have been capitalized into factor prices, so growth differences related to geographic proximity would only occur if it was growing in importance.

A notable contribution of the study is the extensive use of Geographic Information Systems data in constructing the various geographic measures. Geographic proximity measures for counties are calculated to capture spillovers within industries, human capital spillovers, spillovers emanating from research-intensive industries, and economic effects of remoteness in the urban hierarchy. Another novel feature of the study is the use of four-digit NAICs data for high-tech industries, including estimates for data that are suppressed by the government to preserve firm confidentiality. This is particularly crucial for examining less-populated counties. We split the sample into metropolitan and nonmetropolitan counties to allow for different growth generating processes between them. For both sub-samples, we examine whether high-technology employment growth differs from growth in their respective industries generally or that of the overall economy. Further, we examine whether there are employment growth differences in manufacturing and services high-technology industries, as well as in information technology, bio-technology and natural resource technology sub-sectors.

The conceptual framework and discussion of relevant literature follow in the next section, which is followed by the empirical model and implementation in Section 3. Section 4 presents and discusses the results. Among our primary findings, there is not any evidence of cluster growth benefits, either within the county or across nearby counties. In fact, within the county the results suggest negative growth effects from clustering. There is some evidence of beneficial agglomeration economies for the high-tech sector in both metropolitan and nonmetropolitan counties, which appear to be of greater importance than for the overall economy. In addition, there were growth penalties for greater distances from larger core urban areas, consistent with positive urban agglomeration effects. Human capital also is found to be more important for high-tech employment growth than for employment growth on average. However, besides their contribution to human capital, proximity to research universities did not appear to stimulate high-tech employment growth. Regarding differences across high-tech subsectors, urban agglomeration economies appeared to play a much smaller role for metropolitan bio-technology and natural resource high-technology industries. Human capital generally was localized in effect, except for the information technology and bio-technology sub-sectors in metropolitan counties, in which human capital in nearby counties positively influenced employment growth. Section 5 briefly summarizes and concludes the paper.

2. Conceptual Framework and Relevant Literature

We view regional employment growth differentials as primarily arising from shifts in site specific characteristics or of their importance to the location of firms and households. For growth to be differentially affected across space, such changes cannot have been anticipated and capitalized into factor prices. In the absence of any unanticipated influences, the economy is thought to follow a spatially-balanced growth path (Partridge et al., 2008a). Although many of the factors underlying employment growth generally also apply to high-tech employment growth, significant differences might be expected, including differences across high-tech sectors.

Higher profits in local high-tech firms lead to their expansion and the emergence of new firms in the region, stimulating labor demand. Many of the factors affecting high-tech firm profits are those affecting profits of all firms in the region. For example, broad considerations of access to markets for inputs and products can influence high-tech firms (King et al., 2003; Rosenthal and Strange, 2003; Andersson and Hellerstedt, 2009). There also is an extensive literature on the importance of human capital and education in determining economic growth of regions (Glaeser et al., 1995; Simon, 1998, Simon and Nardinelli, 2002). Yet, the influences on high-tech firms may differ from the average across firms, and even vary across differing sectors of high-tech firms.

Of particular interest in this study is the degree to which geography influences regional high-tech employment growth in the United States. U.S. county employment and population growth during the 1990s was stronger the nearer the county was to larger core urban areas (Partridge et al., 2008a; 2008b). This suggested increasing economic disadvantages in remote areas. Using hedonic analysis, Partridge et al., (2010) classified the growing disadvantages of areas in the lower levels of the urban hierarchy primarily as firm-based.

From endogenous growth theory (Romer, 1990), innovation plays a central role in economic growth. Spending by firms on research and development can create knowledge and spur innovation. Yet, firms may not fully appropriate the benefits of their innovative efforts (Crescenzi, 2005), as the benefits may spill over to co-located firms. Knowledge spillovers occurring between firms within the same industry in the area generally are referred to as Marshall-Arrow-Romer (MAR) externalities, while those between firms among diverse industries often found in large urban areas are referred to as Jacobian externalities.[1] Negative

[1] For a review of the localization (MAR externalities) versus urbanization (Jacobs externalities) debate see Beaudry and Schiffauerova, (2009).

spillovers from co-location also are possible if the firms are competitors (Rosenthal and Strange, 2003; Tallman et al., 2004). Often viewed as a leader in innovation, knowledge spillovers may be particularly associated with the high-tech sector, (Partridge and Rickman, 1999).

However, for the broad sectors of manufacturing, retail, and services larger initial employment levels were negatively related to subsequent growth in the 1990s, though total initial employment levels spurred growth in rural counties in all three sectors (and for manufacturing in metropolitan counties) (Partridge et al., 2008a). Feser et al. (2008) also report that employment in Appalachian counties did not grow faster in the presence of a corresponding industry cluster. Glaeser et al (1992) and Partridge and Rickman (1999) similarly find more evidence of Jacobian dynamic externalities than within industry externalities.[2] To be sure, agglomeration has been found to increase innovation even after controlling for other factors such as human capital and public research and development infrastructure (Sedgley and Elmslie, 2004).

In addition to knowledge spillovers obtained from co-located firms, firms may receive spillovers from geographically proximate public institutions such as universities, and suppliers and customers (Maine et al., 2010). Specifically, Braunerhjelm et al. (2000) find evidence supporting the existence of knowledge spilling over from public universities to high-tech firms. In addition to spillovers accruing directly to firms, universities may increase human capital spillovers, indirectly raising firm productivity and worker wages (Rauch, 1993). Spillovers emanating from local supply chains have been reported by Porter and Stern (2001).

The transmission of knowledge spillovers may be costly and diminish with distance (Audretch and Feldman, 1996), though they may extend beyond the boundaries of the immediate region (Rodriguez-Pose and Crescenzi, 2008). Even if most of the spillover-generating face-to-face interactions occur within a narrow geographic area (Crescenzi, 2005), migration between regions can transmit knowledge (Crescenzi et al., 2007). Gallie and Legros (2007) suggest that the existence of spillovers depends on the degree of cooperation between public and private

[2] However, the only evidence of high-tech spillovers to the rest of the economy reported by Partridge and Rickman (1999) was through increasing the share of productive industries.

researchers and may dominate location in importance. In fact, Weterings and Ponds (2009) provide evidence that information contained in regional flows of information may be more important than information obtained through local face-to-face interactions.

Knowledge has to be both diffused and assimilated for spillovers to occur (Rodriguez-Pose and Crescenzi, 2008). The capacity of a region to translate spillovers into innovation and growth may depend on the region's human capital, and economic, political and social institutions (Rodriguez-Pose, 1999). If remoteness is associated with lower human capital and limited institutional capacities, distance negatively affects both the diffusion and assimilation of knowledge spillovers and hence growth. To be sure, Varga (2000) finds evidence that university spillovers lead to greater innovation when they occur in metropolitan areas with sufficient mass.

The ability of a region to attract high-tech workers also affects regional growth prospects. For example, universities not only may create knowledge spillovers but they also may increase the cultural attractiveness and tolerance of the area, which may particularly attract innovative and high human capital individuals, members of the so-called creative class (Florida, 2002). Other features of an area that may be attractive to these individuals include cultural amenities offered in large urban areas (Glaeser et al., 2001) or natural amenities (McGranahan and Wojan, 2007). Existence of a creative class has been reported to spur overall employment growth in metropolitan and nonmetropolitan areas (McGranahan and Wojan, 2007), new firm formation and high-tech specialization in metropolitan areas (Lee et al., 2004), and various measures of economic performance in the high-tech sector for U.S. metropolitan regions (Bieri, 2010).

The influence of distance can differ across high-tech sectors. Arauzo-Carod and Viladecans-Marsal (2009) found that the higher the technological level of the industry the more firm establishments preferred to locate in the center of the largest metropolitan areas of Spain. For the U.S., Anselin et al. (2000) found evidence of university spillovers in the two-digit SIC industries of Electronics and Instruments, but not for Drugs and Chemicals, or Machinery. Bania et al. (1993) found university research associated with firm births in Electronics but not in Instruments. Maine et al. (2010) find larger benefits of clustering and proximity to universities for biotech firms, which they attribute to their reliance on tacit knowledge that decays significantly with greater distance because it is not easily codified and typically is transmitted by personal interactions. They find supply chain effects available in a diverse metropolitan area as benefiting information and communication technology firms. Ketelhohn (2006) reports evidence of spillovers from buyers for the semiconductor industry, which may be of greater importance than within industry spillovers, but did not find evidence of supply chain spillovers.

Therefore, through the varied channels outlined above, local high-tech employment growth (HTGRW) can be expressed in reduced form as related to the initial level of high-tech employment in the area (CLUSTER), urban agglomeration (AGGLOM), geographic proximity in the urban hierarchy (GEOG), presence of a public university (UNIV), human capital (HUMCAP) and natural amenity levels (AMENITY):

(1) HTGRW = f(CLUSTER, AGGLOM, GEOG, UNIV, HUMCAP, AMENITY).

In reduced form, a single variable can potentially influence high-tech employment growth in several ways. For example, urban agglomeration (AGGLOM) may be associated with Jacobian knowledge spillovers, supply chain effects, urban cultural amenities, and a greater ability to translate knowledge spillovers into innovation, all of which may directly or indirectly increase economic growth. Likewise, as discussed in the next section, geographic proximity in the urban hierarchy likely reflects access to the potential array of benefits contained in large urban areas. Hence, we are not able to separately identify all the specific channels through which geography influences high-tech employment growth. We instead aim to establish whether geography mattered for high-tech employment growth during the period of 1990 to 2006 in the United States.

3. Empirical Implementation.

The period under consideration is 1990 to 2006, which is long enough to capture long-term trends in advanced technology industries and to smooth over various shocks such as the "dot.com" bubble at the end of the 1990s and the 2001 recession. To avoid the severe business cycle effects of the Great Recession, the period ends before its onset in 2007. The period reflects a broadening globalization of advanced technology industries that started with offshore sourcing of the manufacturing of basic components to out-sourcing higher-level jobs beginning in the latter 1990s (e.g., the stereotypical outsourcing of programmers to India).

We use county-level data for the lower 48 states and the District of Columbia, dividing the counties into metropolitan and nonmetropolitan sub-samples using the June 2003 metropolitan area definitions.[3] We considered further delineations such as splitting the nonmetropolitan sample into those micropolitan versus non-micropolitan (non-core rural) and splitting the metropolitan counties into samples using a 250,000 overall metropolitan population as the dividing point (based on a 1990 population). However, those results were not particularly different, so we compressed our findings to a simple metropolitan/nonmetropolitan division for brevity and ease of interpretation.

Our dependent variables are various measures of employment growth over the 1990 to 2006 period. We first focus on overall high-technology employment growth, determining whether high-technology employment growth behaves differently than overall total employment growth and growth in manufacturing and private services. We then decompose high-technology employment into alternative sub-sectors: (1) manufacturing high-technology; (2) service high-technology, and (3) information high-technology; (4) biotechnology high-technology; and (5) natural resource high-technology subsectors.[4] Our definition of high-technology industries is that developed by the U.S. Bureau of Labor Statistics (Hecker, 2005). Appendix Table 1 lists the high-technology industries and their classification.

The data for high-technology employment are from the consulting firm EMSI (EMSI.com), which have been used in a variety of published studies such as Nolan et al. (2011) and Fallah et al. (forthcoming). The importance is that the definition of high-technology industries is at the four-digit NAICS level, which is not reported by government agencies due to confidentiality

[3]A metropolitan area is defined for counties that surround a city of at least 50,000. The counties are typically determined based on commuting linkages.

[4]Note that biotechnology and natural-resource intensive are sub-sets of the first three major categories. Also, the information sector is, partly, a subset of service and manufacturing high tech major categories. (See Appendix Table 1).

reasons. EMSI employs an algorithm to estimate these data gaps using a variety of sources including the *Quarterly Census of Employment and Wages* from the U.S. Bureau of Labor Statistics, *County Business Patterns* from the U.S. Census Bureau, and Bureau of Economic Analysis regional data. EMSI has confirmed with state employment agencies that their estimates are remarkably close at even the six-digit level. Thus, we believe we have the most comprehensive study of high-technology employment growth using the fine levels of industry data that define high-technology employment.

A key feature of the empirical model is the exogenous and/or predetermined nature of the explanatory variables, though we conduct sensitivity analysis to assess this claim. The base specification for employment growth in a given industry (EMPI) in a given county i, located in state s is then represented as:

$$(2)\ \%\Delta \mathrm{EMPI}_{is(t\text{-}0)} = \alpha + \beta \mathbf{EMPI}_{is0} + \rho \mathrm{WEMPI}_{is0} + \boldsymbol{\varphi}\, \mathbf{AGGLOM}_{is0} + \boldsymbol{\delta} \mathbf{EDUC}_{is0} + \boldsymbol{\gamma} \mathbf{AMENITY}_{is0} + \boldsymbol{\lambda} \mathbf{X}_{is0} + \sigma_s + \varepsilon_{is(t\text{-}0)},$$

where the dependent variable is the percent change in employment between periods 0 (1990) and t (2006) for each of the industry classifications described above. **EMPI** is the initial-period (1990) employment level to account for agglomeration effects—in particular localization and clustering effects of the particular industries due to information spillovers, labor market pooling, better access to inputs, or congestion effects due to competition.[5] **W**EMPI accounts for the average employment in industry i for the nearest 5 counties.[6] This accounts for possible spillovers across county borders including knowledge spillovers and input sharing. **AGGLOM** is a vector that includes variables measuring incremental distances to different tiers in the urban hierarchy and population variables to reflect urbanization effects. **AMENITY** represents natural amenities and **X** represents other standard control variables described below. The regression coefficients are α, $\boldsymbol{\varphi}$, $\boldsymbol{\gamma}$, $\boldsymbol{\lambda}$, and $\boldsymbol{\delta}$; σ_s are state fixed effects that account for common growth factors within a state; and ε is the residual. Appendix Table 2 presents the detailed variable definitions and sources.

[5] In the overall total employment model, the proper interpretation for the lagged employment variable is urbanization effects.

[6] Note that measuring the average employment in the nearest 10 counties instead did not affect the results.

The **AGGLOM** vector includes several variables to assess whether it is access or proximity to agglomeration economies that are driving the results. First, for nonmetropolitan counties, we include the county's own population and the population of the nearest metropolitan area. For metropolitan counties, we include the overall metropolitan area population. Then to more accurately account for spillovers over distance, the **AGGLOM** also includes several spatial distance measures to reflect proximity to metropolitan areas differentiated by their status in the hierarchy. Partridge et al. (2008a, 2008b, 2009) found these distance measures to be highly associated with job and population growth as well as wages and housing values dating back to the mid-20th Century. For a county that is part of a metropolitan area, the first distance is from the population-weighted center of the county to the population-weighted center of the metropolitan area. Inside a metropolitan area, the influence of longer distances would largely reflect any offsetting effects of agglomeration or congestion effects. For a nonmetropolitan county, the variable is the distance from the county center to the center of the nearest metropolitan area.[7]

Beyond the nearest metropolitan area, we also include the incremental distances to larger higher-tiered metropolitan areas to reflect added spillovers from higher-ordered cities. They reflect the incremental or marginal costs to reach each higher-tiered (larger) metropolitan areas. First, are incremental (or additional) distances to reach metropolitan areas of at least 250,000, and then at least 500,000, and finally over 1.5 million population.[8] The largest category generally reflects national and top-tier regional cities. There may be measurement error bias when using straight-line distance rather than travel time, but this classic measurement error would bias the distance

[7]If it is a one-county metropolitan area, this distance term is zero. Population-weighted county centroids are from the U.S. Census Bureau. The metropolitan area population category is based on initial 1990 population.

[8]If the county is already nearest to a metropolitan area that is either larger than or equal to its own size category, then the incremental value is zero. For example, ifthe county's nearest metro area of any size is already over 250,000 people and 60kms away, then the nearest metropolitan area is 60kms away and the two incremental distance values for nearest metro area of any size and the nearest metro area> 250,000 are both equal to zero. As another example, suppose nonmetropolitan county A is 100kms from its nearest metro area of any size (say 100,000 population), 140kms from a metro area >250,000 people (say 350,000 population), 320kms from a metro area >500,000 (which happens to be 2.5 million). Then the incremental distances are 100kms to the nearest metropolitan area, 40 incremental kms to a metro area >250,000 (140-100), 180 incremental kms to a metro area >500,000 (320-140), and 0 incremental kms to a metro area >1.5million.

regression coefficients toward zero, suggesting a larger distance effect than we report.[9]

The **EDUC** vector controls for human capital and includes variables for the initial 1990 percent of the population 25 years or older that has (1) at least a high school degree but no further education, (2) some college/university but no degree, (3) Associates Degree but no further degree, and (4) at least a Bachelors degree. We expect that a greater share with a Bachelors degree to be positively linked to high-technology growth. But for assembly-line positions in manufacturing there may be a need for workers with medium skill or education levels. Likewise, to account for knowledge spillovers from research-intensive universities, we include a dummy variable for being located within 100 miles of a Carnegie Classification research-intensive university including major Land Grant universities. We also tried a dummy for being located within 50 miles, but the results were virtually identical.

Akin to the within-industry knowledge spillovers accounted for by the surrounding county industry employment, we also include the average share of the population with at least a Bachelors degree in the nearest 5 counties.[10] Greater human capital in nearby regions may have spillovers or allow the focal county to be more innovative or technologically progressive through a greater ease in adopting innovation spillovers (Rodriguez-Pose and Crescenzi, 2008). Neighboring county educational attainment may also have labor market impacts because it may increase the available labor supply for local firms in the focal county through commuting. Alternatively, it may reduce local employment growth because high-technology firms would rather locate in the neighboring county due to better access to an educated workforce.

Natural **AMENITIES** are measured using a 1 to 7 scale developed by the U.S. Department of Agriculture (see Appendix Table 2). This variable assesses the hypothesis that high-technology workers may be more footloose than other workers and that these firms may be better able to locate in areas preferred by its workforce. The **X** vector controls for other factors that potentially influence growth including population-age composition shares and race and ethnic population

[9]Nevertheless, we expect that with the developed U.S. road system, this measurement error is small. For example, Combes and Lafourcade (2005) find that the correlation between distances and French transport costs is 0.97.
[10]Note that measuring this for the nearest 10 counties did not affect the results.

shares described in Appendix Table 1. We also account for the average of median household incomes in nearby counties to account for nearby markets. State fixed effects account for state-specific factors including tax and expenditure policies, regulatory differences, geographic location with respect to coasts, and settlement period.

4. Empirical Results

Table 1 reports descriptive statistics for the dependent and independent variables. Tables 2 and 3 respectively report the metropolitan and nonmetropolitan regression results for overall high-tech employment growth and for corresponding non-high-tech categories: overall total employment growth, manufacturing employment growth, and private services employment growth.[11] For each industry category, the first column of results report a parsimonious model that does not include the demographic variables including educational attainment, total population, age, and racial/ethnic population shares. These more parsimonious models help us assess whether multicollinearity is greatly affecting the results and whether there is demographic self-sorting (such as whether college-educated workers self-sort into places they expect to have better long-term employment prospects).[12]

4.1 High-Technology vs Aggregate Industry Categories

Comparing the parsimonious model results to the base model results in both Tables 2 and 3 suggests that the results are relatively stable. One exception is that the magnitude of the regression coefficient for the log of initial employment generally becomes much more negative in the parsimonious model. For example, the magnitude of the coefficient approximately doubled in the overall high-technology employment and overall total employment cases. Thus, there is some evidence of a correlation between the initial demographic composition and the initial industry employment. Nonetheless, given that the results did not significantly change, we focus on the more fully-specified base models.

[11] A handful of counties are omitted for very small counties due to the Bureau of Economic Analysis not disclosing manufacturing employment data for confidentiality reasons.

[12] By controlling for the initial 1990 high-technology employment share, presumably any self-sorting related to the initial employment share is then accounted for.

Regarding the base high-technology results in column (2), the initial 1990 employment share is negative and statistically significantly related to subsequent high-technology employment growth in both the metropolitan and nonmetropolitan samples, in which the size of this response is larger for high-technology employment than for overall total employment. The negative influence supports arguments that industry employment growth "reverts to the mean" and that greater competition within one local area for factors and customers reduces subsequent growth (e.g., Desmet and Fafchamps, 2005; Partridge et al., 2008a), and is inconsistent with the argument that clusters are an important source for employment growth.

The spatial lag of 1990 initial high-technology employment is statistically insignificant in both the base metropolitan and nonmetropolitan models, which is consistent with arguments that knowledge spillovers are very localized (Rosenthal and Strange, 2001), although knowledge spillovers across high-technology industries broadly defined may be more limited. Thus, this result may not apply for the more narrowly defined high-technology groupings described below. Nonetheless, these findings do not support those who contend that "regional innovation systems" are a dominant feature in describing high-technology industry growth.

Consistent with urbanization or diversity economies (Glaeser et al., 1992), the results suggest that 1990-2006 high-technology employment growth is positively related to own-county growth in the nonmetropolitan sample and overall metropolitan area population in the metropolitan sample. These findings suggest that access to nearby inputs, customers, or Jacobs spillovers, is more important than the size of the industry itself, though urban size also may be important because of cultural amenities or better translation of spillovers into innovation. Comparing the high-technology and overall employment growth coefficients on population of the county and population of the metropolitan area (compare col 2 vs. col 4) shows that the coefficient is considerably larger in the high-technology model, especially in the nonmetropolitan sample. Hence, while industry diversity and urbanization are critical to overall growth, they appear to matter even more in the high-technology sector.

The distance from larger cities in the urban hierarchy is negatively associated with high-technology employment growth as well as growth in overall employment, manufacturing, and services. Remoteness appears to be an even stronger deterrent to growth in nonmetropolitan settings, in which the negative distance relationship is particularly strong for the high-technology sector compared to other sectors. Conversely, proximity to even larger urban areas has the smallest negative relationship for metropolitan high-technology growth compared to overall metropolitan total employment growth and growth in manufacturing and services.

The human capital variables have their expected effects in which a larger share of the initial 1990 adult population with a Bachelors degree or higher is associated with greater high-technology growth and overall total employment growth. In both the nonmetropolitan and metropolitan samples, the point estimate on high-technology growth is about three-times greater than for overall employment growth. In addition, there is a similar pattern for the population share with some college (but no college degree). The importance of higher education should also be viewed within the context of controlling for state fixed effects, size and proximity to urban areas, and amenities. That is, even after controlling for the possibility that more educated people may want to locate in particular states, near urban areas, and in high amenity locations, there is still a strong independent effect for the college graduate labor supply to influence growth within a given state. While the direct routes of causation are difficult to untangle, the results suggest that availability of a good workforce or the availability of high human capital entrepreneurs is related to faster employment growth.

While local availability of college-educated workers appears to be positively linked to high-technology employment growth, the 1990 share of the population with at least a Bachelors' degree in the nearest 5 counties has a statistically insignificant relationship with metropolitan high-technology employment growth and a negative relationship in nonmetropolitan counties. This result again suggests rather limited spatial spillovers in terms of knowledge and human capital. Indeed, the nonmetropolitan result suggests that more educated counties are actually pulling high-technology firms away from the focus county. Likewise, the dummy for proximity to research universities (including major Land Grant universities) is statistically insignificant, consistent with Faggian and McCann's (2009) findings that universities most important role in augmenting regional innovation is as a source of supply for human capital, not for localized knowledge spillovers. Overall, the results suggest that high technology employment growth is more influenced by access to urban markets and localized access to human capital and less by knowledge spillovers.

For the base metropolitan and nonmetropolitan total and service employment models, amenities are positively related to employment growth. However, for the high-technology employment growth model, the amenity index is statistically insignificant. Past research may have suggested the opposite result, because if (some) high-technology firms are more footloose, and try to locate near relatively educated and high-income workers who demand natural amenities, then amenities would be expected to have a particularly large influence (McGranahan, and Wojan, 2007). We examine this though for specific high-technology industry groupings below as high-technology workers (say) in software development may be more footloose than those who are forced to be near R&D facilities.

4.2 High-Technology Subsectors

Tables 4 and 5 respectively consider metropolitan and nonmetropolitan subsectors within the high-technology sector. We separately consider high-technology industries in manufacturing, services, information, biotechnology, and natural resource based. The latter two sectors are more prone to have values of zero in both 1990 and 2006. To assure that these cases do not exert too much leverage on the regression results, we include an indicator variable for cases where there was zero employment in *both* 1990 and 2006 and then another indicator variable when just 1990 employment equals zero.[13]

Across the high-technology sectors in both Tables 4 and 5, the biotechnology model is less precisely estimated and has a much smaller R^2 statistic, suggesting a less systematic process for

[13] The employment growth variable is constructed as 100 × ($Employment_{2006}$ – $Employment_{1990}$)/ employment 1990. For the biotechnology and natural resource technology subsectors, if there was zero employment in both years, we set percent change in employment growth equal to zero. If emp90 >0 and emp06 =0, then employment growth is -1. Also, if emp90=0 and emp06>0 then employment growth =1. While this process adjusts for cases of zeros in the beginning and ending year, it does produce a different scaling than the other industries in Tables 4 and 5.

its employment growth. In both the metropolitan and nonmetropolitan models, there is a strong inverse association between the 1990 log of initial employment in each of the high-tech sub-sectors and the subsequent 1990-2006 employment growth. Thus, even when using more disaggregated industries groupings that are more homogenous the results do not support the classic notion of localization economies or the more recent version of clusters (Porter, 1998). Instead the findings support Feser et al.'s (2008) results regarding the absence of any connection between industry clusters and employment growth in the Appalachian region.

The average subsector employment in the nearest five counties remains statistically insignificant with the exception of the natural resource based high-technology industries, in which there is a statistically significant positive relationship. This again suggests that the range of spatial spillovers is geographically limited even when using finer industry breakdowns. The natural resources subsector exception likely relates to clustering due to natural resource availability rather than knowledge spillovers.

Metropolitan area population and access to larger metropolitan areas have the strongest positive association for the metropolitan manufacturing, services, and information high-technology industries, especially the latter two. The metropolitan high-technology manufacturing result is somewhat surprising because of cost considerations near more urban settings, but this pattern suggests that access to inputs and customers may be the dominant features for even manufacturing. There are similar distance and own-county population patterns in the nonmetropolitan results in Table 5. However, urban-access effects play a much smaller role for metropolitan biotechnology and natural resource high-technology industries. The latter is not surprising, but the result for biotechnology is somewhat surprising, but is consistent with a more 'random' or nonsystematic distribution for biotechnology growth.

The continued pattern is that having a higher share of university educated workers is positively linked to metropolitan high-technology employment. The educational attainment result is localized for every sector except biotechnology, in which it is the Bachelors degree share in the surrounding five counties that has the primary effect. The association between high-technology employment and the four-year college degree share is a little weaker in nonmetropolitan areas with the direct share being statistically insignificant for the high-technology service and the high-technology natural resource subsectors. There are no nonmetropolitan cases where there is a positive relationship for surrounding county average college graduate share—again suggesting no positive knowledge spillover or labor market linkages. In fact, the average college graduate share in neighboring counties is actually negative and statistically significant in the manufacturing and natural resource based high-technology industries.

Continuing a pattern observed in Tables 2 and 3, there is no statistical link to being within 100 miles of a research intensive or major Land Grant university, further suggesting that universities play their biggest role as providers of human capital, not through localized knowledge spillovers. That does *not* mean that U.S. research universities are unimportant to the development of high-technology industries through their research role, but the knowledge likely leaks across the country and throughout the world. Clearly, with the both human capital (i.e., graduates) and the knowledge that universities generate, relying on a model of state funding means that universities will be underfunded if their knowledge spillovers are national or international—i.e., one state cannot internalize these effects. Finally, we observe no positive association between high-technology employment and natural amenities, further suggesting that reports of high-technology firms as footloose and locating in nice places due to the preferences of their employees and owners are likely over exaggerated—supporting the findings of Dorfman et al. (2011) for the most research-intensive firms.

5. Summary and Policy Conclusions

We examined the role of geography in high-tech employment growth for U.S. counties from 1990-2006. Geographic factors considered included the presence of within county and nearby county high-tech clusters, human capital within the county and in nearby counties, proximity to a research university, urban agglomeration economies and proximity in the urban hierarchy. Control variables included natural amenities and demographic characteristics of the local population. Overall, our findings suggest that geography and human capital significantly influenced high-tech employment.

We did not find any evidence of cluster benefits, either within the county or across nearby counties. In fact, the initial within-county level of high-tech employment is negatively related to subsequent growth. There is evidence of beneficial agglomeration economies for the high-tech sector in both metropolitan and nonmetropolitan counties, which appear to be of greater importance than for the overall economy (particularly for nonmetropolitan counties). Urban agglomeration economies appeared to play a much smaller role for metropolitan bio-technology and natural resource high-technology industries. Human capital also is found to be more important for high-tech employment growth than for employment growth on average. Human capital generally was localized in effect, except for the information technology and bio-technology sub-sectors in metropolitan counties, in which human capital in nearby counties positively influenced employment growth. Besides their contribution to human capital, proximity to research universities did not appear to stimulate high-tech employment growth. Natural resource high-tech employment growth was affected by similar employment in nearby counties, but this simply may have resulted from broader region natural resource availability. In contrast to the results for overall employment growth, quality of life did not affect high-tech employment growth.

The absence of positive clustering effects casts doubt on the expected efficacy of the Obama Administration's Regional Innovation Cluster initiative that is a defining characteristic its place-based policy approaches. Combined with the importance of agglomeration economies and proximity in the urban hierarchy, and the lack of significance of natural amenities, the absence of cluster benefits particularly points to the likely futility of such a strategy for more remote U.S. areas. The greater importance of education for high-tech employment growth points to more fundamental factors as the drivers of innovativeness and growth. Thus, as suggested by Varga (2000) more comprehensive economic development approaches are needed to spur high-tech growth.

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Table 1: Descriptive Statistics

Variables	Metropolitan counties mean	std	Nonmetropolitan counties Mean	Std. Dev.
Employment Growth Variables (1990-2006)				
Percentage change in total employment	38.8	61.4	0.167	0.264
Percentage change in Biotech	143.0	585.9	0.279	3.106
Percentage change in Natural resources HT	69.6	303.13	63.11	415.4
Percentage change in total HT	27.7	81.1	-2.5	75.8
Percentage change in Information HT	61.3	125.9	20.6	111.6
Percentage change in Manufacturing HT	-3.6	111.1	-2.71	122.8
Percentage change in Private Service HT	71.1	118.7	29.4	124.5
Percentage change in Manufacturing	7.3	106.7	13.6	137.5
Percentage change in Private Service	6.26	105.3	32.1	40.1
1990 employment variables				
Total Employment	90535	90535	7965	8344
Biotechnology	634	2395	25	133
Natural resources HT	415	2420	64	157
Total HT	11190	33153	716	932
Information HT	5257	17610	932	275
Manufacturing HT	4183	15688	289	412
Private Service HT	6280	17708	309	600
Manufacturing	13596	37269	1722	2411
Private Services	55398	33153	3730	4292
Distance Variables in kilometers				
Dist to nearest/actual urban center	24.4	19.8	96.7	58.2
Inc dist to metro>250k	36.8	74.5	67.0	106.4
Inc dist to metro>500k	36.573	68.256	42.855	66.134
Inc dist to metro>1500k	91.579	131.827	88.935	111.164
Proximity to research univ-100m	0.798	0.402	0.536	0.499
1990 Demographic and other variables				
Natural Amenity Rank	3.582	1.089	3.437	1.020
Total population	191967	434755	22308	20451
Population of nearest MA	1082961	2236041	279335	412487
Median HH income in the surrounding counties	28302	5271	25894	4271
Percent of agricultural employment	4.12	4.03	10.82	8.89
Percent pop under 6 years	10.261	1.311	9.992	1.507
Percent pop 7-17 years	16.251	2.259	17.090	2.318
Percent pop 18-24 years	10.218	3.263	8.578	3.322
Percent pop 55-59 years	4.306	0.630	4.693	0.745
Percent pop 60-64 years	4.284	0.861	4.930	0.968
Percent pop 65+ years	12.552	3.626	16.275	4.116
Percent HS graduate	33.260	6.217	35.018	5.958
Percent of some college, no degree	17.761	4.416	15.666	4.386
Percent of associate degree	5.700	1.859	5.153	2.207
Percent of bachelor degree and above	16.471	7.837	11.757	4.737
Spatial lag of percent of bachelor degree and above	15.562	5.330	12.382	3.560
Percentages of Hispanic	4.472	9.651	4.353	11.665
Percentages of Asian	10.056	13.326	7.696	14.686
Percentages of African American	1.105	1.949	0.316	0.430
Percentages of native American	0.745	2.123	1.827	6.734

Percentages of other races	1.868	4.046	1.785	4.850

Notes: See Appendix Table 2 for variable definitions.

Table 2: Employment Growth: Metropolitan Counties

Variable	Total Emp-HT		Total Emp		Manufacturing		Services	
	-1-	-2-	-3-	-4-	-5-	-6-	-7-	-8-
1990 log initial employment	-0.11	-0.28	-0.11	-0.21	-0.27	-0.32	-0.16	-0.26
	(-3.27)	(-7.98)	(-2.31)	(-2.7)	(-3.31)	(-3.56)	(-2.41)	(-2.29)
1990 spatial lag of initial employment†	1.26	-0.44	3.97E-07	1.98E-07	-0.09	0.19	1.33	1.14
	(1.35)	(-0.50)	(1.90)	(1.16)	(-0.26)	(0.42)	(2.25)	(2.22)
Distance to Center of Own MA	-0.007	-0.005	-0.005	-0.005	-0.012	-0.011	-0.006	-0.007
	(-3.76)	(-3.14)	(-2.01)	(-2.65)	(-2.41)	(-2.040	(-1.70)	(-2.46)
Inc distance to MA >250 k	-0.003	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003	-0.003
	(-5.59)	(-3.69)	(-4.84)	(-5.40)	(-3.08)	(-2.69)	(-3.83)	(-3.36)
Inc distance to MA >500 k	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002
	(-2.81)	(-2.18)	(-3.34)	(-3.21)	(-2.31)	(-1.84)	(-2.47)	(-2.28)
Inc distance to MA >1500 k	-0.001	-0.001	-0.001	-0.001	-0.001	-0.0003	-0.001	-0.001
	(-2.12)	(-1.90)	(-2.82)	(-3.38)	(-1.69)	(-0.78)	(-1.37)	(-1.78)
Proximity research univ 100mi.	-0.001	-0.056	0.004	-0.033	-0.066	-0.092	0.013	-0.053
	(-0.01)	(-0.72)	(0.08)	(-0.70)	(-0.65)	(-0.85)	(0.13)	(-0.57)
Amenity Rank	0.03	0.03	0.08	0.08	-0.02	-0.05	0.12	0.16
	(0.55)	(0.8)	(1.54)	(2.2)	(-0.25)	(-0.64)	(1.28)	(1.99)
1990 population ofOwn MA		3.01E-08		1.84E-08		2.69E-08		2.24E-08
		(2.24)		(1.73)		(1.54)		(2.04)
1990 Education attainment shares								
High School graduate		0.01		-0.02		-0.02		-0.04
		(-0.69)		(-1.86)		(-1.36)		(-2.13)
Some college, no degree		0.04		0.03		0.04		0.04
		(3.07)		(2.32)		(1.96)		(1.68)
Associate degree		-0.02		-0.03		-0.04		-0.07
		(-0.68)		(-1.53)		(-1.01)		(-1.83)
Bachelor degree and above		0.03		0.01		-0.004		0.006
		(3.99)		(2.46)		(-0.43)		(0.89)
1990 spatial lag of college graduates†		0.001		-0.009		-0.002		-0.02
		(0.22)		(-1.2)		(-0.25)		(-2.06)
Other Explanatory Variables††	Y	Y	Y	Y	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y	Y	Y	Y	Y
Constant	1.32	2.11	1.39	4.25	3.43	5.42	1.39	6.2
	(-3.6)	(-1.86)	(-5.46)	(-1.89)	(-3.26)	(-2.35)	(-2.65)	(-1.73)
N	1040	1040	1040	1040	1040	1040	1040	1040
R-sq	0.161	0.344	0.228	0.394	0.209	0.245	0.178	0.287

Note: Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://wwkes w.bea.doc.gov/bea/regional/docs/econlist.cfm

†The spatial lagged variablesis the average value of the nearest 5 counties. The weight matrix used is normalized so that rows sum to 1.

††This includes agecomposition shares, race/ethnic shares, and median household income in BEA region.

Table 3: Employment Growth: Nonmetropolitan Counties

Variable	Total Emp-HT		Total Emp		Manufacturing		Services	
	-1-	**-2-**	**-3-**	**-4-**	**-5-**	**-6-**	**-7-**	**-8-**
1990 log initial employment	-0.15	-0.3	0.02	-0.05	-0.24	-0.38	-0.02	-0.16
	(-4.01)	(-6.69)	-2.78	(-3.04)	(-5.36)	(-6.04)	(-1.44)	(-4.92)
1990 spatial lag of initial employment†	1.14	0.35	1.57E-07	-2.14E-07	1.01	1.47	-0.002	0.05
	(1.83)	(0.6)	(0.3)	(-0.39)	(1.94)	(2.56)	(-0.01)	(0.26)
Distance to Nearest MA	-0.002	-0.002	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001
	(-2.97)	(-3.72)	(-4.26)	(-4.25)	(-2.09)	(-1.38)	(-4.65)	(-4.54)
Inc distance to MA >250 k	-0.0008	-0.0008	-0.0005	-0.0004	-0.0004	-0.0001	-0.0009	-0.0007
	(-2.86)	(-2.17)	(-3.71)	(-3.24)	(-0.51)	(-0.16)	(-4.8)	(-3.7)
Inc distance to MA >500 k	-0.0002	-0.0007	-0.0004	-0.0004	-0.0008	-0.0008	-0.0006	-0.0005
	(-0.62)	(-1.76)	(-2.76)	(-2.72)	(-1.65)	(-1.62)	(-2.62)	(-2.44)
Inc distance to MA >1500 k	-0.0001	-0.0002	-0.0001	-0.0001	0.0004	0.0001	-0.0002	-0.0002
	(-0.78)	(-0.96)	(-1.18)	(-1.11)	(1.28)	(0.34)	(-1.13)	(-1.40)
Proximity to research univ-100m	-0.06	-0.05	0.01	0.01	0.04	0.02	0.02	0.01
	(-1.35)	(-1.24)	(0.7)	(0.68)	(0.56)	(0.22)	(0.71)	(0.51)
Amenity Rank	0.05	-0.02	0.07	0.04	-0.06	-0.06	0.09	0.05
	(2.02)	(-0.61)	(7.14)	(4.01)	(-1.37)	(9-1.43)	(5.1)	(3.13)
1990 population		1.11E-05		1.44E-06				4.98E-06
		(6.85)		(2.31)		(4.51)		(4.11)
1990 population of nearest MA		3.39E-08		4.08E-09		1.81E-08		1.71E-08
		(0.64)		(0.29)		(0.29)		(0.63)
1990 Education attainment shares								
High School graduate		-0.004		-0.003		0.0004		-0.005
		(-0.83)		(-1.67)		-0.05		(-1.97)
Some college, no degree		0.028		0.007		0.002		0.002
		(2.03)		(2.52)		(0.11)		(0.38)
Associate degree		0.014		-0.001		-0.021		-0.002
		(1.02)		(-0.13)		(-0.87)		(-0.25)
Bachelor degree and above		0.03		0.01		-0.01		0.01
		(2.45)		(3.82)		(-1.31)		(3.95)
1990 spatial lag of college graduates†		-0.03		0.003		0.016		-0.005
		(-2.65)		(1.08)		(1.53)		(-1.15)
Other Explanatory Variables††	Y	Y	Y	Y	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y	Y	Y	Y	Y
constant	1.23	4.27	0.02	0.18	2.26	2.08	0.47	1.38
	(3.85)	(3.12)	(0.18)	(0.55)	(5.18)	(1.48)	(2.1)	(2.66)
N*	1963	1963	1963	1963	1959	1959	1963	1963
R-sq	0.141	0.262	0.211	0.291	0.118	0.158	0.363	0.300

Note: Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://wwkes w.bea.doc.gov/bea/regional/docs/econlist.cfm

† The spatial lagged variables is the average value of the nearest 5 counties. The weight matrix used is normalized so that rows sum to 1.

††This includes age composition shares, race/ethnic shares, and median household income in the BEA region.

* The number of observations slightly varies across regressions due to missing employment data as a result of BEA disclosure.

Table 4: High Tech Employment Growth: Metropolitan Counties

Variable	Manufacturing-HT	Services-HT	Information-HT	Biotech†-HT	Nat.Resources†-HT
	1	2	3	4	5
1990 log initial employment	-0.23	-0.45	-0.46	-0.89	-0.83
	(-5.08)	(-9.04)	(-7.05)	(-6.26)	(-6.42)
1990 initial employment -spatial lag.‡	0.81	0.57	-0.68	78.85	27.04
	(0.39)	(0.28)	(-0.24)	(1.4)	(2.81)
Distance to Center of Own MA	-0.007	-0.01	-0.009	-0.019	-0.01
	(-2.9)	(-3.79)	(-3.07)	(-1.30)	(-1.44)
Inc distance to MA >250 k	-0.002	-0.004	-0.004	-0.002	-0.0003
	(-2.94)	(-4.99)	(-4.67)	(-0.57)	(-0.15)
Inc distance to MA >500 k	-0.001	-0.002	-0.002	-0.005	-0.001
	(-1.39)	(-2.79)	(-2.19)	(-1.4)	(-0.55)
Inc distance to MA >1500 k	0.0002	-0.001	-0.106	-0.006	0.001
	(0.32)	(-2.13)	(-0.98)	(-2.38)	(0.84)
Proximity to research univ.-100mile	-0.06	-0.01	-0.11	0.28	-0.25
	(-0.57)	(-0.08)	(-0.97)	(0.66)	(-0.73)
Amenity Rank	-0.11	0.07	0.07	-0.03	-0.04
	(-1.64)	(1.02)	(1.03)	(-0.17)	(-0.23)
1990 population of Own MA	2.83E-08	4.52E-08	5.46E-08	1.07e-07	3.79E-08
	(1.78)	(2.48)	(2.98)	(1.14)	(1.3)
1990 Education attainment shares					
High School graduate	-0.005	-0.024	-0.001	-0.068	-0.034
	(-0.37)	(-1.97)	(-0.06)	(-0.90)	(-0.94)
Some college, no degree	0.01	0.06	0.04	0.12	0.1
	(0.74)	(3.58)	(2.24)	(1.72)	(1.81)
Associate degree	0.05	-0.02	0.03	0.11	-0.09
	(0.98)	(-0.44)	(0.75)	(0.48)	(-0.81)
Bachelor degree and above	0.03	0.04	0.05	0.03	0.09
	(2.84)	(3.4)	(3.66)	(0.69)	(2.41)
1990 spatial lag of college graduates‡	0.007	0.008	0.025	0.09	0.028
	(0.67)	(0.78)	(2.03)	(1.76)	(1.1)
Other Explanatory variables††	Y	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y	Y
Constant	-0.14	3.6	3.11	-0.04	-4.28
	(-0.07)	(2.12)	(1.44)	(-0.01)	(-0.89)
N*	1033	1038	1038	1040	1040
R-sq	0.172	0.349	0.389	0.121	0.216

Note: Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://wwkes w.bea.doc.gov/bea/regional/docs/econlist.cfm

†As described in the text, there are some changes when the 1990 or 2006 employment value equals zero for the biotechnology and natural resource high-technology industries.

‡ The spatial lagged variables is the average value of the nearest 5 counties. The weight matrix used is normalized so that rows sum to 1.

††This includes age composition shares, race/ethnic shares, and median household income in BEA region.

* The number of observations slightly varies across regressions due to missing employment data as a result of BEA disclosure.

Table 5: High Tech Employment Growth: Nonmetropolitan Counties

Variable	Manufacturing-HT -1	Services HT -2	Information-HT -3	Biotech†-HT -4	Nat. Res†-HT -5
1990 log initial employment	-0.19	-0.67	-0.51	-0.50	-1.1
	(-5.12)	(-6.78)	(-8.6)	(-4.10)	(-4.27)
1990 spatial lag of initial employment‡	2.91	-0.12	3.41	-18.54	44.14
	(1.15)	(-0.06)	(1.12)	(-0.97)	(2.22)
Distance to Nearest MA	-0.002	-0.003	-0.001	-0.002	-0.003
	(-2.98)	(-2.74)	(-2.18)	(-1.49)	(-1.00)
Inc distance to MA >250 k	-0.001	-0.001	-0.001	-0.002	-0.002
	(-0.51)	(-1.99)	(-2.24)	(-1.71)	(-1.02)
Inc distance to MA >500 k	-0.001	-0.002	-0.001	-0.005	-0.0003
	(-0.65)	(-3.28)	(-2.74)	(-3.34)	(-0.11)
Inc distance to MA >1500 k	-0.0001	-0.0003	-0.001	-0.0004	-0.0009
	(-0.22)	(-1.04)	(-2.81)	(-0.35)	(-1.10)
Proximity to research university-100 mile	0.05	-0.09	0.03	-0.22	-0.54
	(0.53)	(-1.39)	(0.4)	(-1.01)	(-1.57)
Amenity Rank	-0.12	-0.04	0.05	-0.11	-0.05
	(-2.52)	(-0.77)	(1.29)	(-1.07)	(-0.39)
1990 population	8.67E-06	1.90E-05	1.55E-05	2.15E-05	2.46E-05
	(4.46)	(5.55)	(6.68)	(3.20)	(3.35)
1990 population of nearest MA	-1.46E-08	9.64E-08	5.11E-08	9.58E-08	-1.58E-08
	(-0.28)	(1.8)	(0.82)	(0.28)	(-0.09)
1990 Education attainment shares					
High School graduate	-0.004	-0.0002	0.008	-0.003	-0.02
	(-0.47)	(-0.02)	(-0.97)	(-0.18)	(-0.72)
Some college, no degree	-0.01	0.01	0.03	-0.05	0.03
	(-0.56)	(0.61)	(1.93)	(-1.11)	(0.82)
Associate degree	0.054	0.023	0.004	0.005	0.09
	(1.43)	(1.38)	(0.22)	(0.13)	(0.73)
Bachelor degree and above	0.03	0.02	0.04	0.13	-0.01
	(2.11)	(1.15)	(3.95)	(2.29)	(-0.41)
1990 spatial lag of college graduates‡	-0.017	-4.244E-04	0.011	0.013	-0.125
	(-1.71)	(-0.03)	(0.98)	(0.43)	(2.56)
Other Explanatory variables††	Y	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y	Y
constant	0.27	7.45	0.53	1.6	2.34
	(0.21)	(3.22)	(0.49)	(0.45)	(0.5)
N*	1900	1954	1945	1963	1963
R sq	0.1049	0.2111	0.2802	0.0998	0.1668

Note: Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://wwkes w.bea.doc.gov/bea/regional/docs/econlist.cfm

† As described in the text, there are some changes when the 1990 or 2006 employment value equals zero for the biotechnology and natural resource high-technology industries.

‡ The spatial lagged variables is the average value of the nearest 5 counties. The weight matrix used is normalized so that rows sum to 1.

††This includes age composition shares, race/ethnic shares, and median household income in BEA region.

*The number of observations slightly varies across regressions due to missing employment data as a result of BEA disclosure.

Appendix Table 1: High Tech Industries: NAICS Classifications

High Tech	NIACS Code	Industry Name
Biotechnology	3254	Pharmaceutical and medicine manufacturing
Natural resources	1131,1132	Forestry
	2111	Oil and gas extraction
	3241	Petroleum and coal products manufacturing
Information	5415	Computer systems design and related services
	3333	Commercial and service industry machinery manufacturing
	3342	Communications equipment manufacturing
	3344	Semiconductor and other electronic component manufacturing
	3345	Navigational, measuring, electromedical, and control instruments manufacturing
	5112	Software publishers
	5161	Internet publishing and broadcasting
	5179	Other telecommunications
	5181	Internet service providers and Web search portals
	5182	Data processing, hosting, and related services
	3333	Commercial and service industry machinery manufacturing
	3343	Audio and video equipment manufacturing
	3346	Manufacturing and reproducing, magnetic and optical media
	4234	Professional and commercial equipment and supplies, merchant wholesalers
	5416	Management, scientific, and technical consulting services
	5171	Wired telecommunications carriers
	5172	Wireless telecommunications carriers (except satellite)
	5173	Telecommunications resellers
	5174	Satellite telecommunications
	8112	Electronic and precision equipment repair and maintenance
	3341	Computer and peripheral equipment manufacturing
Manufacturing	3254	Pharmaceutical and medicine manufacturing
	3251	Basic chemical manufacturing
	3252	Resin, synthetic rubber, and artificial synthetic fibers and filaments manufacturing
	3255	Paint, coating, and adhesive manufacturing
	3259	Other chemical product and preparation manufacturing
	3332	Industrial machinery manufacturing
	3333	Commercial and service industry machinery manufacturing
	3336	Engine, turbine, and power transmission equipment manufacturing
	3339	Other general-purpose machinery manufacturing
	3341	Computer and peripheral equipment manufacturing
	3342	Communications equipment manufacturing
	3343	Audio and video equipment manufacturing
	3344	Semiconductor and other electronic component manufacturing
	3345	Navigational, measuring, electromedical, and control instruments manufacturing
	3346	Manufacturing and reproducing, magnetic and optical media
	3353	Electrical equipment manufacturing
	3364	Aerospace product and parts manufacturing
	3369	Other transportation equipmentmanufacturing
	3241	Petroleum and coal products manufacturing
	3253	Pesticide, fertilizer, and other agricultural chemical manufacturing

Appendix Table 1 Continued: High Tech Industries: NAICS Classifications

High Tech	NAICS	Sub Industries
Services	4234	Professional and commercial equipment and supplies, merchant wholesalers
	4861	Pipeline transportation of crude oil
	4862	Pipeline transportation of natural gas
	4869	Other pipeline transportation
	5112	Software publishers
	5161	Internet publishing and broadcasting
	5171	Wired telecommunications carriers
	5172	Wireless telecommunications carriers (except satellite)
	5173	Telecommunications resellers
	5174	Satellite telecommunications
	5179	Other telecommunications
	5181	Internet service providers and Web search portals
	5182	Data processing, hosting, and related services
	5211	Software publishers
	5232	Securities and commodity exchanges
	5413	Architectural, engineering, and related services
	5415	Computer systems design and related services
	5416	Management, scientific, and technical consulting services
	5417	Scientific research-and-development services
	5511	Management of companies and enterprises
	5612	Facilities support services
	8112	Electronic and precision equipment repair and maintenance

Dependent Variables		
Employment change	Percentage change in total or major sector employment for 1990-2006	U.S. BEA, REIS
HT Employment change	Percentage change in HT total or the HT subsector employment for 1990-2006	EMSI
Independent Variables		
Dist to nearest/actual metropolitan area	Distance (in km) between centroid of a county and population weighted centroid of the nearest urban center, if the county is not in an urban center. Distance to the centroid of its own urban center if the county is a member of an urban center.	1990 Census, C-RERL
Inc dist to metro>250k	Incremental distance to the nearest/actual metropolitan area with at least 250,000 population in 1990 in kms	Authors' est.
Inc dist to metro>500k	Incremental distance to the nearest/actual metropolitan area with at least 500,000 population in 1990 in kms	Authors' est.
Inc dist to metro>1500k	Incremental distance to the nearest/actual metropolitan area with at least 1,500,000 population in 1990 in kms	Authors' est.
Nearest/Actual Urban Center pop	Population of the nearest/actual urban center measured as metropolitan area 1990.	Authors' est.
Natural Amenity Rank	The amenity scale combines six measures of natural amenities; warm winter, winter sun, temperate summer, low summer humidity, topographic variation, and water area. The scale ranges from 1 to 7, with a higher value reflecting more natural amenities.	ERS USDA
Economic/Demographic variables, 1990		
Agriculture share	Percent employed in agriculture sector 1990	1990 Census, Geolytics
Percent pop under 6 years	Percent population under 6 years, 1990.	1990 Census, Geolytics
% of pop 7-17 years	Percent population 7-17 years, 1990.	1990 Census, Geolytics
% of pop 18-24 years	Percent population 18-24 years, 1990.	1990 Census, Geolytics
% of pop 55-59 years	Percent population 55-59 years, 1990.	1990 Census, Geolytics
% of pop 60-64 years	Percent population 60-64 years, 1990.	1990 Census, Geolytics
% of pop 65+ years	Percent population over 65 years, 1990.	1990 Census, Geolytics
% of HS graduate	Percent population 25 years and over that are high school graduates, 1990.	1990 Census, Geolytics
% of some college, no degree	Percent population 25 years and over that have some college, no degree, 1990.	1991 Census, Geolytics
% of associate degree	Percent population 25 years and over that haveassociate degree, 1990.	1992 Census, Geolytics
% college graduate	Percent population 25 years and over that are 4-year college graduates, 1990.	1990 Census, Geolytics
% of Hispanic	Percent ofHispanic population, 1990.	1991 Census, Geolytics
% of Asian	Percent ofAsian population, 1990.	1992 Census, Geolytics
% of African American	Percent ofAfrican American population, 1990.	1993 Census, Geolytics
% of native American	Percent ofNative American population, 1990.	1994 Census, Geolytics
Surrounding Variables		
Proximity to research university-100 mile	Indicator for being within 100 miles of Carnegie I research intensive university or a major 1862 Land Grant university.	Dorfman et al. (2011)
Spatial lag of the initial employment/sectoral employment	Weighted average of the initial employment in nearest 5 counties	1990 Census, Authors' est.
Spatial lag of the initial HT employment/HT sectoral employment	Weighted average of the initial HT employment in nearest 5 counties	EMSI, Authors' est.
spatial lag of percent of bachelor degree and above	Weighted average of the bachelor degree and above in nearest 5 counties	1990 Census, Authors' est.
Median HH surrounding counties	Weighted average median household income in surrounding counties within a BEA region[a], 1989.	1990 Census, Authors' est.

Appendix Table 2: Variable Definitions