Geography and high-tech employment growth in U.S. counties

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2012

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February 27, 2012

Abstract. This paper investigates the role of geography in high-tech employment growth across U.S. counties. The geographic dimensions examined include industry cluster effects, urbanization effects, proximity to a research university, and proximity in the urban hierarchy. Growth is assessed for overall high-tech employment and for employment in various high-tech sub-sectors. Econometric analyses are conducted separately for samples of metropolitan and nonmetropolitan counties. Among our primary findings, we do not find evidence of positive localization or within-industry cluster growth effects, generally finding negative growth effects. We instead find evidence of positive urbanization effects and growth penalties for greater distances from larger urban areas. Universities also appear to play their primary role in creating human capital rather than knowledge spillovers for nearby firms. Quantile regression analysis confirms the absence of within-industry cluster effects and importance of human capital for counties with fast growth in high-tech industries.

*Earlier versions of this paper were presented at the The Ohio State University Glenn School of Public Affairs; Southern Regional Science Association Meetings in New Orleans; North American Regional Science Association Conference, Miami, FL; and the Western Regional Science Association Conference, Kauai, HI.

1. Introduction

Spurring growth in the high-tech sector has been a pervasive focal point of regional economic development efforts (Malecki, 1981; 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, urban agglomeration, 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.

Geographic distance may affect high-tech firms in many of the ways it does all firms (Jovanović, 2003, Puga, 2010). Such geographic considerations include access to markets for inputs and products (King et al., 2003; Rosenthal and Strange, 2003; Andersson and Hellerstedt, 2009), proximity to human capital (Glaeser et al., 1995; Simon, 1998, Simon and Nardinelli, 2002), positive knowledge spillovers from firms (Crescenzi, 2005), universities (Braunerhjelm et al., 2000) and buyers and sellers (Ketelhohn, 2006; Maine et al., 2010), and negative spillovers from increased competition (Rosenthal and Strange, 2003; Tallman et al., 2004).The influence of geographic distance also has been reported to vary across high-tech sectors (Arauzo-Carod and Viladecans-Marsal, 2009; Anselin et al., 2000). However, no study has systematically examined the role of geography along all dimensions across the spectrum of high-tech industries.

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 within-industry clustering, urban agglomeration, human capital, proximity 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 geographic distance was not 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 changing in importance (Partridge et al., 2008a; 2008b).

A notable contribution of the study is the extensive use of Geographic Information Systems data in constructing the various measures. Geographic proximity measures for counties are calculated to capture within-industry spillovers, human capital spillovers, spillovers emanating from research-intensive industries, and economic effects of remoteness in the urban hierarchy. Another novel feature is our 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 crucial for examining less-populated counties because the data typically are not available. We split the sample into metropolitan and nonmetropolitan counties to allow for different growth generating processes. 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, information technology, biotechnology 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. Section 5 briefly summarizes and concludes the paper.

Among our primary findings, there is not any evidence of within-industry cluster growth benefits, either within the county or across nearby counties. On the contrary, 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 are 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, aside from their contribution to human capital, proximity to research universities generally 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 biotechnology and natural resource high-technology industries.

Quantile regression analysis confirms the absence of within-industry high-tech cluster effects and greater importance of human capital in counties with fast-growing high-tech industries. Distance to the nearest metropolitan area also was particularly important in nonmetropolitan counties where the high-tech industry was fast growing. Thus, our primary findings also apply for the fastest growing counties that are typically of interest to policymakers. From these results, we make some policy recommendations about the need to focus more on basic human capital in order to promote regional and national competitiveness.

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 argued to follow a spatially-balanced growth path (Partridge et al., 2008a). Although many of the factors underlying high-tech employment growth also apply to aggregate employment growth in general, significant differences might be expected, including differences across high-tech subsectors.

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 such as broad considerations of access to markets for inputs and products (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 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 suggests increasing economic disadvantages in remote areas. Using hedonic growth 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 spillovers from co-location also are possible if the firms are competitors (Rosenthal and Strange, 2003; Tallman et al., 2004).Often viewed as a key feature 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 sector 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. Duranton et al. (2010) similarly find little evidence of cluster benefits for France. Glaeser et al

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

(1992) and Partridge and Rickman (1999) 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). Nevertheless, contrary findings for high-tech plants are reported by Henderson (2003).

In addition to knowledge spillovers obtained from co-located firms within the same industry, 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 increase human capital, 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), in which migration flows between areas may be affected by their geographic proximity. Gallie and Legros (2007) suggest that the existence of spillovers depends on the degree of cooperation between public and private researchers and may dominate location in importance. Weterings and Ponds (2009) provide evidence that information contained in non-regional knowledge flows may be more valuable 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

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[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.

(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 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 local U.S. high-tech employment growth during the 1990-2006 period.

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 shocks such as the “dot.com” bubble in the late 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 captures the globalization of advanced technology industries that started with offshore sourcing of the manufacturing of basic components and later moved to outsourcing of higher-level tasks. The length of the period also tests the success and durability of economic development initiatives. A successful strategy is not one that simply gains jobs during the expansionary phase of a business cycle when all areas are growing, but also across business cycles and across structural shocks. Yet, we also describe results obtained from splitting the sample into the 1990s and post 2000.

We use data for counties of the lower 48 U.S. states and the District of Columbia. It is important to delineate the samples by degree of urbanity because rural counties may have an increase of 100% employment in high tech employment for example even though actual industry employment may only be 10 workers, implying that including counties with small bases could lead to noisy results. Hence, we divide the sample into metropolitan and nonmetropolitan county subsamples using the June 2003 metropolitan area definitions.[3] We further confirmed that a small base was not influencing our findings when we estimated equations weighting by county population, in which the weighted results were qualitatively similar. In further sensitivity analysis, we also split the nonmetropolitan sample into micropolitan versus non-micropolitan (non-core rural) counties and metropolitan counties into sub-samples using a 250,000 overall metropolitan (1990) population level as the dividing point. But the results again did not qualitatively differ from the base results. Thus, we compress the reporting of our results 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 five into sub-sectors: (1) manufacturing high-technology; (2) services high-technology, (3) information technology; (4) biotechnology; 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 typically based on commuting linkages.
[4]Biotechnology and natural-resource intensive are subsets of the first three major categories. 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, even at the six-digit level. Thus, we believe we have among the most comprehensive studies of U.S. 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:

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

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 localization and clustering effects of the particular industry due to information spillovers, labor market pooling, better access to inputs, or congestion effects due to competition.[5] **W**EMPI contains the average employment in industry *i* for the nearest 5 counties to capture possible clustering across county borders.[6] **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, which may be spatially clustered. Appendix Table 2 presents the detailed variable definitions and sources.

[5]In the overall total employment model, the interpretation for the lagged total 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 distinguish 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 higher-tiered metropolitan areas to reflect added benefits (e.g., spillovers) from proximity to larger cities. 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 regression coefficients toward zero, suggesting a larger distance effect than we report.[9]

[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, if the 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.

[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.

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 location 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.

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 also may 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 shares described in Appendix Table 1. We also account for the average of median household incomes in nearby counties to account for access to nearby markets. State fixed effects account

[10]Note that measuring this for the nearest 10 counties did not affect the results.

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 reflects 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 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

A comparison of the parsimonious model results to the base model results in both Tables 2 and 3 reveals 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 generally did not significantly change, we focus on the more fully-specified base models (though we note that our within industry clustering results would be even more negative with parsimonious specifications).

Regarding the base high-technology results in column (2), the initial 1990 employment

[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 historic self-sorting related to the initial employment share is then accounted for.

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 the absolute value 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 job growth. The spatial lag of 1990 initial high-technology employment is statistically insignificant in both the base metropolitan and nonmetropolitan models. Taken together, the findings do not support claims that "regional innovation systems" are a dominant feature in high-technology industry growth, at least when limited to their own industry.

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 population in the nonmetropolitan sample and overall metropolitan area population in the metropolitan sample. This suggests 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. While industry diversity and urbanization are critical to overall growth, they appear to matter 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 for metropolitan high-technology growth approximates that for overall metropolitan total employment growth, but is less than that for overall 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). Even after controlling for the possibility that more educated people locate in particular states, near urban areas, and in high amenity locations, there remains a strong role for the college graduate labor supply to influence growth within a given state. While the precise channels of causation are hard to untangle, the results suggest that availability of a good workforce or the availability of high human capital entrepreneurs is related to faster job growth.

While local availability of university-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 actually pull 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 in specific occupation such as software development may be more footloose than those who need 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 growth in manufacturing, services, information, biotechnology, and natural resources. The latter two sectors are more prone to have values of zero in both 1990 and 2006. 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 to reduce any undue influence.[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 lesser role for geographic distance for 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. As already mentioned, this result is not an artifact of population size or initial base size as we obtain qualitatively similar results when weighting by county population or using finer sample categories.[14] Thus, even

[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.
[14]To further investigate nonlinearities for within-industry clustering, we added a square of the initial 1990 lagged own-employment share to the models. There were some cases when the square term was *positive* and statistically significant, but in all cases, the marginal effect was negative when evaluated at the mean 1990 own employment share.

when using more disaggregated industry categories 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 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 high-tech 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 and with the view that biotechnology firms are connected to the broader region and global networks (Waxell and Malmberg, 2007).

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 college degree share in the surrounding five counties that has the primary effect. The association between high-technology employment and the four-year university degree share is somewhat 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 not any nonmetropolitan cases where there is a positive relationship for surrounding county average college graduate share—again suggesting no positive regional knowledge spillover or labor market linkages. In fact, the average college graduate share in neighboring counties is 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 not any 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 both the 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 the beneficial growth 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.

4.3 Quantile Regression Results

The high-technology growth process could be nonlinear in that the factors associated with growth could vary between fast- and slow-high-tech-growing counties. For example, what could differentiate fast-growing from slow-growing locations is a greater reliance on human capital and it is possible fast-growing locations also are much more favorably affected by within-industry clustering, which is obscured in the standard regression analysis because it reflects an average effect. In addition, policymakers may be especially interested in differences for the fastest growing cases to emulate them. Thus, we use quantile regression analysis to examine whether there are significant differences across the distribution of high-tech industry county-level growth. Table 6 reports the cases where there are significant differences in the quantile regression coefficients between the fastest growing counties (the 90th percentile) in terms of the respective high-tech industry relative to the slowest growth counties (the 10th percentile). The results are presented for the geographic variables of interest that had significant differences in more than one high-tech industry.

A striking result is that comparing the 90th percentile to the 10th percentile, there is consistently a greater negative coefficient across sectors for the initial 1990 employment. That is, a lower share of high-tech employment is associated with even faster subsequent growth (regardless of the high-tech sector) at the 90th percentile. This provides yet stronger evidence against the within-industry cluster growth argument because our findings are the strongest for the *fastest* growing cases.

It also is notable that human capital in metropolitan areas and nonmetropolitan counties is of the greatest importance where many of the high-tech sectors are fast-growing (as indicated by the education coefficients being larger at the 90th growth percentile compared to the 10th percentile). Where there is faster high-tech growth in nonmetropolitan counties, there is a greater penalty for high-tech firms in terms of distance from the nearest metropolitan area. This is particularly evident for firms in the services and information high-tech industries. Only for biotech firms in metropolitan areas where the industry is growing fastest is it more important to be close to a research university, though the result is negative for the high-tech industry generally. In sum, the quantile regressions results suggest that many of the key trends identified in our general regression results often are stronger for the fastest growing locations.

4.4 Comparing the 1990s to Post 2000

We re-estimated the models after dividing the sample into the periods of 1990 to 2000 and 2000 to 2006 to assess the robustness across the two decades. The latter period reflects much slower growth with steady outsourcing and increased global competition. [The results are not reported due to brevity.] What is striking is that for the entire high-tech industry and for the individual high-tech industry groupings, the results display very similar patterns across both decades. Foremost, the own-industry employment share coefficient remains negative and statistically significant in every case across both decades. If there was a subsector likely to exhibit changes across the two decades, we expected it to be the information technology sector as it shifted from a significant mainframe environment in 1990 to an entirely different environment based on the internet. Yet, even here, the results were surprisingly stable across the decades.

There are some minor differences across the decades worth noting. First, distance and population of the own metropolitan area became slightly less important after 2000 in the metropolitan samples. Proximity to metropolitan areas also was of smaller importance in the nonmetropolitan results after 2000. Thus, there is slight evidence that urban agglomeration effects became less consequential for high-technology industries. The college graduate share also tended to be slightly less consequential in both the metropolitan and nonmetropolitan samples after 2000. Overall, while there are modest changes, it is noteworthy how comparable the results are across the decades.

5. Summary and Policy Conclusions

We examined the role of geography in high-tech employment growth for U.S. counties from 1990-2006 using both standard and quantile regression analysis. 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. We control for many factors such as natural amenities and demographic characteristics of the local population. Overall, our findings suggest that geography significantly influenced high-tech employment.

We did not find any evidence of within-industry 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 and the quantile regressions suggest this result also is true for the fastest growing locations. As opposed to localization or MAR externalities, there is evidence of beneficial urban agglomeration economies (or Jacobs externalities) 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 smaller role for metropolitan biotechnology 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 and this effect was strongest in the fastest growing counties. Human capital effects were generally localized, except for the information technology and biotechnology subsectors in metropolitan counties, in which human capital in nearby counties was positively associated with their employment growth. Besides their contribution to human capital, proximity to research universities did not appear to stimulate high-tech employment growth. In contrast to the results for overall employment growth, natural amenities did not affect high-tech employment growth.

Where there is faster high-tech growth in nonmetropolitan counties, there is a greater penalty for high-tech firms in terms of distance from the nearest metropolitan area, particularly for firms in the services and information high-tech industries. Only for biotech firms in metropolitan areas where the industry is growing fastest is it more important to be close to a research university. Yet, these results do not indicate that research universities are unimportant as their research may be spreading across the globe, raising productivity everywhere.

The absence of positive clustering effects casts doubt on the expected efficacy of government attempts to create clusters such as 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 within-industry 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. Such findings add even more urgency to efforts to increase regional and national university completion rates as the U.S. is no longer a leader among advanced countries in terms of university attainment for young adults (OECD, 2011). Thus, as suggested by Varga (2000), more comprehensive economic development approaches are needed in the U.S. 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
Incdist to metro>250k	36.8	74.5	67.0	106.4
Incdist to metro>500k	36.573	68.256	42.855	66.134
Incdist 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 univ100mi.	-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 of Own 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 variables are 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.

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)	(-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 are 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 are 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 are 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 6. Quantile Regression Results: 90th-10th Percentile (t-statistics in parentheses)*

Variable	Log(Initial Employment) -1	Distance to Nearest Metro -2	Proximity to University -3	Spatial Lag of College Graduates -4	Associate Degree -5	Bachelors Degree -6
Metropolitan:						
Hi-tech	-0.25 (4.45)		-0.30 (1.98)			
Manufacturing Hi-Tech	-0.41 (6.03)			0.05 (2.39)	0.14 (1.96)	
Services Hi-Tech	-0.48 (5.22)				-0.18 (2.45)	
Information Tech	-0.36 (5.51)			0.07 (2.44)		
Bio-Tech	-1.13 (4.88)		1.72 (2.51)			
Natural Resources Tech	-1.00 (6.63)			0.081 (1.84)		
Nonmetropolitan						
Hi-Tech	-0.58 (5.75)	-2.09E-03 (2.4)				
Manufacturing Hi-Tech	-0.34 (4.09)				0.21 (2.99)	0.05 (1.89)
Services Hi-Tech	-0.76 (8.16)	-2.47E-03 (2.14)				
Information Tech	-0.63 (6.31)	-2.85E-03 (2.19)				0.05 (2.85)
Bio-Tech	-0.46 (2.24)					0.082 (1.92)
Natural Resources Tech	-1.08 (10.34)					

*The reported result is the difference in the regression coefficient at the 90th percentile and the corresponding regression coefficient at the 10th percentile. In parentheses are the t-statistics for the difference in the two quantile regression coefficients. The quantile regression specifications include the same variables as the full specifications in Tables 2-4. We are only reporting the statistically significant results for the key variables for the sake of brevity, though almost all of the other differences between the 90th and 10th percentile are statistically insignificant.

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 equipment manufacturing
	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

Appendix Table 2: Variable Definitions

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
Incdist to metro>250k	Incremental distance to the nearest/actual metropolitan area with at least 250,000 population in 1990 in kms	Authors' est.
Incdist to metro>500k	Incremental distance to the nearest/actual metropolitan area with at least 500,000 population in 1990 in kms	Authors' est.
Incdist 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 have an associate 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 of Hispanic population, 1990.	1990 Census, Geolytics
% of Asian	Percent of Asian population, 1990.	1990 Census, Geolytics
% of African American	Percent of African American population, 1990.	1990 Census, Geolytics
% of native American	Percent of Native American population, 1990.	1990 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, 1989.	1990 Census, Authors' est.