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Geography and High-Tech Employment Growth in US Counties‡

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Abstract

This article investigates the role of geography in high-tech employment growth across US 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 selected high-tech subsectors. 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 fastest growth in high-tech industries.

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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 et al., 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. King et al., 2003; Maggioni, 2004; Smilor et al., 2007; Florida et al., 2008). Prominent in these investigations is the role of geographic distance.

Yet, these studies typically focus on a particular sector and/or a particular geographic area. In their meta-analysis of studies on innovation and regional growth, De Groot et al. (2007) found strong evidence of heterogeneity in outcomes across sectors, space and time, suggesting the need for more comprehensive analysis. There is a near absence of studies that examine high-tech growth across the spectrum of sectors, across a wide and varied geography and across time. There also is a paucity of testing the relative importance of competing explanations for high-tech employment growth.

Therefore, in this article we examine the role of geography in high-tech employment growth for US counties in the lower 48 states from 1990 to 2006. Included in the analysis are measures of within-industry clustering (localization), urban agglomeration, human capital and proximity to research universities. A notable contribution is our use of four-digit North American Industrial Classification System (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 where data typically are not available. County-level analysis follows from the necessity of searching for externality effects that may have limited geographic scope (Rosenthal and Strange, 2001). Another novel feature of the study is the extensive use of geographic information systems (GIS) data, which is required for examination of the growth influences that extend beyond county borders. 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 location in the urban hierarchy (Partridge et al., 2008a; 2008b).

We include the geographic proximity measures in reduced-form employment growth regressions. The extensive use of GIS data and detailed industry data allows us to construct exogenous measures that capture a plethora of factors that potentially underlie high-tech growth across the entire geography of the USA. Although we are not able to sort out all the precise channels of influence, we are able to assess the relative roles of within-industry clustering, urban agglomeration and universities.

We divide the sample into metropolitan and nonmetropolitan counties to allow for different growth generating processes. For both subsamples, we examine whether aggregate high-technology employment growth differs from growth in 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 subsectors. We then separately examine the aerospace, computers and software, and engines and turbines high-tech industries as examples of more finely defined sectors to assess whether the degree of industry aggregation affects our conclusions.

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 article.

Among our primary findings, there is little, if any evidence of within-industry cluster growth benefits (or localization economies), either within the county or across nearby counties. On the contrary, the results suggest negative growth effects associated with high-tech clustering. There is evidence of beneficial urbanization 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 for close proximity.

We also find human capital 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 generally does not appear to stimulate high-tech employment growth. Regarding differences across high-tech subsectors, urban agglomeration economies appear to play a much smaller role for metropolitan biotechnology and natural resource high-technology industries. The overall conclusions are not affected by the degree of aggregation of the high-tech sector.

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 is particularly important in nonmetropolitan counties where the high-tech industry is fast growing. Thus, our primary findings also apply for the fastest growing counties that are typically of interest to policymakers. From these results, we offer policy recommendations regarding the need to focus more on basic human capital to promote regional and national competitiveness and less on strategic plans of local and regional governments of 'picking winners'.

2. Relevant literature

Following the seminal paper of Glaeser et al. (1992), a common focus of studies on industry clustering and urban agglomeration has been to search for evidence of knowledge externalities or productive spillovers between firms. A commonly believed mechanism for the transfer of spillovers is face-to-face contact, which suggests there are benefits from close proximity (Audretsch and Feldman, 1996; Crescenzi, 2005). Yet, organizational cooperation and regional migration flows can geographically extend the benefits (Crescenzi et al., 2007; Rodriguez-Pose and Crescenzi, 2008; Weterings and Ponds, 2009).

Productivity enhancing spillovers only translate into employment growth to the extent the demand for goods and services and labor supply are elastic and firms are mobile (Combes et al., 2004; Blien et al., 2006; Duranton, 2011). An additional complication in searching for evidence of within-industry spillovers in growth studies is that general convergence or mean reversion of growth across the USA causes growth to be negatively related to the size of the sector (Delgado et al., 2010). Kim (1995) notes a long-run decline in US industry specialization throughout most of the twentieth century. Duranton (2007) develops a model of industry churning across cities where industries start and thrive at the location of innovation because of spillovers occurring between co-located firms in the same industry, but as cross-industry knowledge spillovers gain in importance in the industry, firms relocate to other locations. Therefore, industry clustering does not necessarily lead to a positive circular feedback of industry specialization on employment growth in the industry (Blien et al., 2006, Duranton, 2011; Wolfgang, 2013).

Spillovers among firms across industries more likely occur in large urban areas that contain a diversity of industries. Glaeser et al. (1992) find more evidence of externalities arising from industry diversity than from industry specialization or clustering. Since this seminal study, an extensive literature has developed with widely varying findings

(Beaudry and Schiffauerova, 2009). In a meta-analysis, De Groot et al. (2007) report more consistent evidence of positive effects for industry diversity than for specialization or within-industry clustering.

Often viewed as a key feature in innovation, knowledge spillovers may be particularly associated with the high-tech sector, though the evidence is mixed here as well. Partridge and Rickman (1999) find little evidence of within-industry high-tech spillovers at the US state level, whereas evidence of spillovers between high-tech firms and their customers and suppliers has been reported in a number of studies (Ketelhohn, 2006; Maine et al., 2010). Evidence for within-industry spillovers in information technology have been reported by Dedrick et al. (2003) and Cheng and Nault (2012), though Hitt and Tambe (2006) conclude that such spillovers in this industry are smaller than commonly believed. Using plant level panel data, Henderson (2003) finds evidence of benefits to high-tech plants from the scale and number of high-tech plants in the area, but does not find evidence of urbanization economies. Yet, in an earlier study, Henderson et al. (1995) report that high-tech industries were more likely to start in industrially diverse cities.

Universities also may serve as a source of knowledge spillovers (Braunerhjelm et al., 2000; Maine et al., 2010). To be sure, universities and industry clusters may serve as substitutes in innovation generation (D'Este et al., in press). Among high-tech firms, Maine et al. (2010) find larger benefits of 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. Anselin et al. (2000) found evidence of university spillovers in the US two-digit Standard Industrial Classification 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.

Besides local knowledge creation, universities have been found to increase local human capital (Winters, 2011a), a factor routinely found to directly increase economic growth (Glaeser et al., 1995; Simon, 1998, Simon and Nardinelli, 2002; Crescenzi and Rodriguez-Pose, 2012). Greater human capital also indirectly increases growth by raising the productivity of other workers through spillovers (Rauch, 1993; Moretti, 2004) and increasing the quality of life and attracting high human capital workers (Winters, 2011b). Existence of high human capital workers, or what Florida (2002) labeled the creative class, has been reported to spur new firm formation and high-tech specialization in metropolitan areas (Lee et al., 2004) and enhance the economic performance in the high-tech sector for US metropolitan regions (Bieri, 2010). Human capital also may be required for knowledge to be diffused and assimilated in nearby areas (Rodriguez-Pose, 1999; Rodriguez-Pose and Crescenzi, 2008; Crescenzi and Rodriguez-Pose, 2012). Fagerberg et al. (2011) conclude that education is crucial for developing technological capability, in which less education reduces the economic benefits of knowledge flows.

Large urban areas may offer a number of other advantages besides knowledge spillovers that lead to strong high-tech employment growth. Urban areas may better translate innovation into growth (Varga, 2000; Sedgley and Elmslie, 2004). In a study of the largest Spanish metropolitan areas, Arauzo-Carod and Viladecans-Marsal (2009) found that higher the technological level of the industry, the more firm establishments preferred to locate in the center of the metropolitan area. Urban areas also offer cultural amenities that attract educated workers (Glaeser et al., 2001). Urban labor markets similarly provide better skill matching and sharing of workers (Costa and Kahn, 2001; Rosenthal and Strange, 2003). Greater competition among firms can either positively affect urban growth through spurring innovation (Porter, 1998) or negatively affect growth because of greater competition for customers and inputs (Rosenthal and Strange, 2003).

3. Empirical model and implementation

The above discussion suggests three broad geographic factors of primary interest that may underlie differences in high-tech employment growth. The first is the size of the high-tech sector. The second is the influence of urban agglomeration. Human capital and universities comprise the third force. We are not able to separately identify all the specific channels through which each of these influence high-tech employment growth. We instead aim to establish whether and in what way geography matters for local US high-tech employment growth.

We examine the 1990–2006 period, which begins and ends at the peak of the business cycle and 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. Including the severe recession of 2007–2009 would conflate its effects with the long-term effects we attempt to identify. The 1990–2006 period also captures the globalization of advanced technology industries that began 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 only gains jobs during the expansionary phase of a business cycle when all areas are growing, but also across business cycles and structural shocks. Nevertheless, we also describe results obtained from splitting the sample in two at the year 2000 to assess whether the post-dot.com bust period differs.

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 high-tech employment may be fundamentally different depending on the rural or urban nature—e.g. more R&D is conducted in urban areas and related assembly is often more rural intensive. Data issues also suggest key statistical differences because rural counties may have an increase of 100% employment in high-tech employment, e.g. 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.[1] We further confirm that a small base does not influence our findings when we estimate equations weighting by county population, in which the weighted results are qualitatively similar. In further sensitivity analysis, we also divide the nonmetropolitan sample into micropolitan versus nonmicropolitan (non-core rural) counties and metropolitan counties into subsamples using a 250,000 overall metropolitan (1990) population threshold. But, the results again do not qualitatively differ from

1 A metropolitan area is defined for counties that surround a city of at least 50,000, typically based on commuting linkages.

the base results, further suggesting that initial industry size is not driving our results. We compress the reporting of our results to a simple metropolitan/nonmetropolitan division for brevity and ease of interpretation.

Our dependent variables are measures of employment growth over the 1990–2006 period using different industry aggregations. 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 into five subsectors: (i) manufacturing high-technology; (ii) services high-technology, (iii) information technology; (iv) biotechnology and (v) natural resource high-technology subsectors.[2] Further analysis focuses on even finer industry delineations. Our definition of high-technology industries is that developed by the US Bureau of Labor Statistics (Hecker, 2005). Table A1 lists the high-technology industries and their classification.

The data for high-technology employment are from the consulting firm Economic Modeling Specialists, Inc. (EMSI) (economicmodeling.com), which have been used in a variety of published studies (Fallah et al., 2011; Nolan et al., 2011;). 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 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 US Bureau of Labor Statistics, County Business Patterns from the US 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 US high-technology employment growth.

A key feature of the empirical model is the general 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:

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

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.[3] **WEMPI** contains the average log employment in industry i for the nearest five counties to capture possible clustering across county borders.[4] AGGLOM is a vector that includes variables measuring incremental distances to different tiers in the urban hierarchy and population variables to reflect urbanization effects.[5] AMENITY represents natural amenities and X has other standard control variables described below.

2 There is some overlap across these high-tech grouping. For example, biotechnology is also one of the high-tech manufacturing sectors. Table A1 shows the specific industries in each category.

3 In the overall total employment model, the interpretation for the lagged total employment variable is urbanization effects.

4 We measure distance using the population-weighted centroid of the county. Note that, instead, measuring the average employment in the nearest 10 counties did not affect the results.

5 It would be helpful to assess the role of R&D expenditures on high-tech employment, but such data are unavailable at the county level.

The regression coefficients are α, φ, γ, λ and δ; 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. Table A2 shows the detailed variable definitions and sources.

Potential benefits of knowledge spillovers, labor market pooling and better access to (within-industry) inputs, suggest a positive coefficient for the lag of industry employment (EMPI). For the broadly defined high-tech sector, spillovers between firms from different subsectors could be interpreted as either diversity or localization effects. Congestion effects arising from increased competition for inputs and demand, mean reversion (Blien et al., 2006; Wolfgang, 2013) and technological catching up (Fagerberg et al., 2011) would cause the coefficient to be negative. A similar interpretation can be given to the coefficient for neighboring county industry specialization (**W**EMPI). Neighboring county specialization also can reflect crowding out or competition effects from nearby firms.

Several variables related to urban agglomeration (AGGLOM) are included. 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. To account for spillovers over distance we include several geographic distance measures reflecting county proximity to metropolitan areas differentiated by their status in the hierarchy. Although some benefits from urban agglomeration such as knowledge externalities may have limited geographic scope, others like labor market pooling can extend to the state level or beyond (Rosenthal and Strange, 2001). In fact, 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-twentieth 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.[6]

Beyond the nearest metropolitan area, we also include the incremental distances to higher tiered metropolitan areas to reflect added benefits (e.g. spillovers) for proximity to larger cities. First, are incremental (or marginal) distances to reach metropolitan areas of at least 250,000 and then at least 500,000 and finally, over 1.5 million population. Figure 1 provides an example for illustration and Partridge et al. (2008a) provide more details of these distance variables.[7] The largest category generally reflects

6 If it is a one-county metropolitan area, this distance term is zero. Population-weighted county centroids are from the US Census Bureau. If it is a multiple county metropolitan area, the distance is from the population weighted center of that county to the population-weighted center of the metropolitan area.

7 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 60 km away, then the nearest metropolitan area is 60 km away and the incremental distance value for the nearest metro area >250,000 is equal to zero. Likewise, assume the nearest metropolitan area has over 1.5 million people and is 100 km away. Then the distance to the nearest metropolitan area is 100 km and the *incremental* distances to the nearest metropolitan areas of at least 250,000, 500,000 and 1.5 million are all zero. As another example, suppose nonmetropolitan county A is 100 km from its nearest metro area of any size (say 100,000 population), 140 km from a metro area >250,000 people (say 350,000 population), 320 km from a metro area >500,000 (which happens to be 2.5 million). Then the incremental distances are 100 km to the nearest metropolitan area, 40 incremental kilometers to a metro area >250,000 (140-100), 180 incremental kilometers to a metro area >500,000 (320-

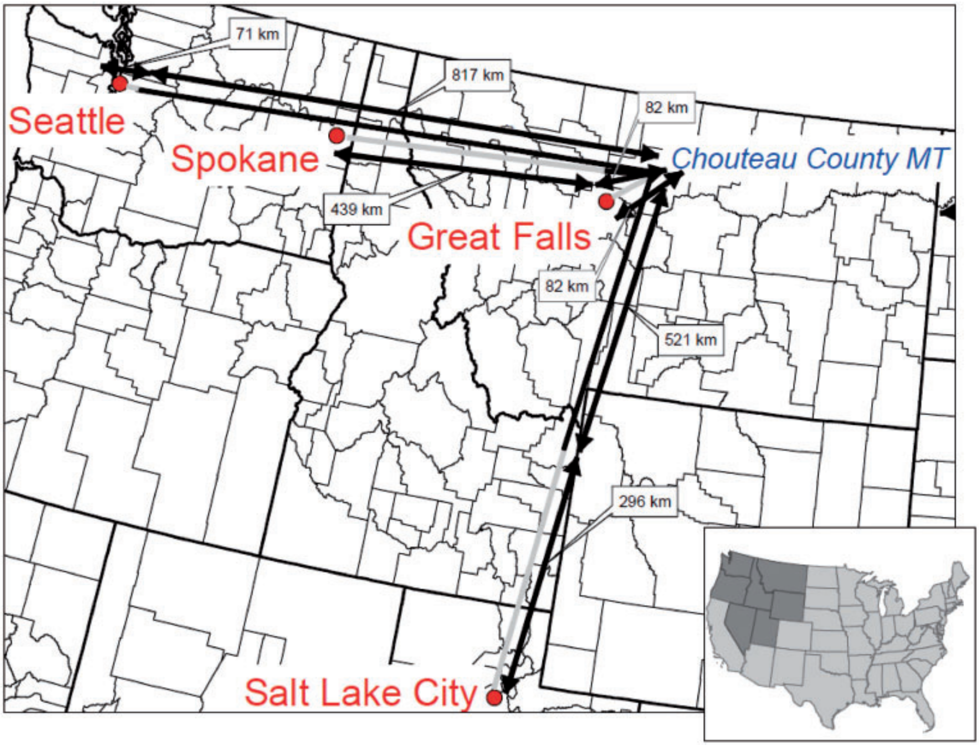


Figure 1. Example of the distance variables. Choteau County Montana is a rural county. Its nearest metropolitan area is Great Falls, MT, The nearest metropolitan area of at least 250,000 of the population is in Spokane, the nearest metropolitan area of at least 500,000 of the population is in Salt Lake City and the nearest metropolitan area of at least 1.5 million people is Seattle. The black portion of the arrows shows the distance to the immediately lower tier and the gray cross-hatched arrows shows the incremental distances we control for in the regression models. For example, Spokane is 521 kms away from Choteau County, which is decomposed into the 82 km that was the distance to Great Falls (the lower tiered city) and 439 km that it is *incrementally* farther than Great Falls. See Partridge et al. (2008a) for further details.

national and top-tier regional cities. There may be measurement error when using straight-line distance rather than travel time(s), but this measurement error would bias the distance coefficients toward zero, suggesting a larger distance effect than we report.[8]

140), and 0 incremental kilometer to a metro area >1.5 million because that metropolitan area is already above the 1.5 million mark.

8 The correct measure is a combination of travel time or access, but what is the correct travel time? For example, commuting times vary by time of day. Likewise, long distance times by railroad, highway or plane also greatly vary, meaning that using one travel time is impossible. Yet, all of these time measures are correlated with distance, which is why we use distance as a proxy for urban access. Nevertheless, we expect that with the developed US 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. Rosenthal and Strange (2008) also considered how human capital effects attenuated with distance. But some key differences with that earlier paper is they considered wages (as a proxy for productivity) across *all* industries and their distance effects were in terms of concentric rings—e.g. 0–8 km, 8–40 km, etc.

The EDUC vector controls for human capital by including the initial 1990 percent of the population aged 25 years or older and has: (i) at least a high school degree but no further education, (ii) some college/university but no degree, (iii) associates degree but no further degree and (iv) at least a bachelor's degree. We expect a greater share with a bachelor's degree to be positively linked to high-technology growth. But for assembly-line positions in high-tech manufacturing, there may be a need for workers with medium skill or education levels (e.g. associate degree). We expect the role of medium skills to play a stronger role in the nonmetropolitan sample. Likewise, to account for knowledge spillovers from research-intensive universities, we include a dummy variable for location within 160 km of a Carnegie Classification research-intensive university and major Land Grant universities. The results are not sensitive to instead specifying the dummy for location within 80 km.

We also include the average share of the population with at least a bachelor's degree in the nearest five counties.[9] Greater human capital in nearby regions may create knowledge 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). Greater neighboring county educational attainment may also be attractive to high-tech firms. Alternatively, it may reduce local employment growth because high-technology firms may rather locate in the neighboring county due to better access to an educated workforce.[10]

Natural AMENITIES are measured using a 1–7 scale developed by the US Department of Agriculture (Table A2). 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 (McGranahan and Wojan, 2007). To the extent high-tech firms are not land intensive, they would be willing to pay the higher land prices in natural amenity rich areas to employ skilled workers at lower nominal wages. The X vector controls for other factors that potentially influence growth including population–age composition shares and race and ethnic population shares described in Table A2. We also account for the average of lagged-initial period median household incomes in nearby counties to account for access to 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. The standard errors are adjusted for clustering of residuals in Bureau of Economic Analysis Economic Areas (addressing issues of spatial autocorrelation and heteroscedasticity).

4. Empirical results

Table 1 reports descriptive statistics for the dependent and independent variables.[11] Panels a, b and c of Figure 2 display maps for total high-tech employment growth and growth in two high-technology subsectors (defined in Appendix 1): high-tech

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

10 We also include controls for the racial composition and age composition of the county to further account for labor force quality considerations such as high-tech firms may prefer younger workers.

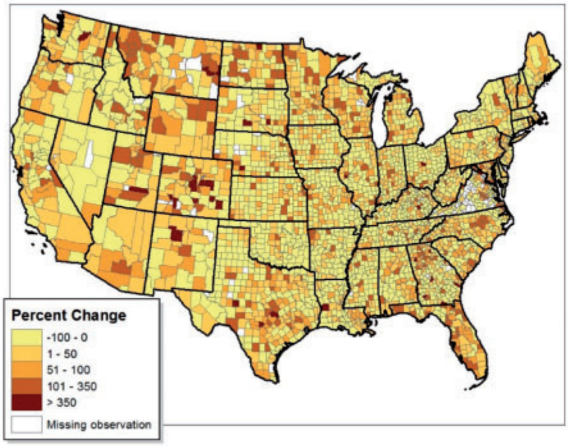
11 The employment growth-dependent variables are reported as percentage change, but we use rates of change in the actual regression models (i.e. divide percentage change by 100).

Table 1. Descriptive Statistics

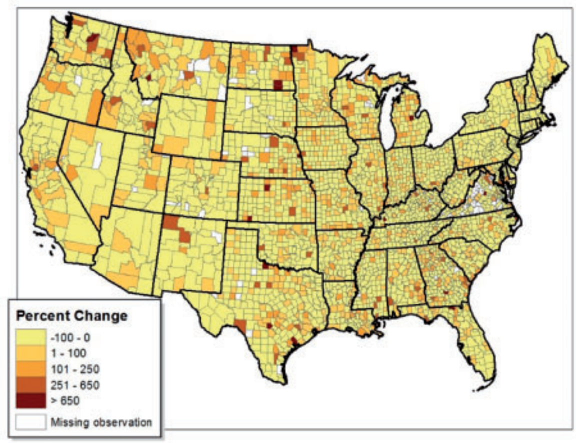
Variables	Metropolitan counties Mean	Metropolitan counties std	Nonmetropolitan counties Mean	Nonmetropolitan counties Std. Dev.
Employment growth variables (1990–2006)				
Percentage change in total employment	38.8	61.4	0.167	0.264
Percentage change in biotech	143.0	585.9	0.279	3.106
Percentage change 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 nnformation 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	90,535	230,064	7965	8344
Biotechnology	634	2395	25	133
Natural resources HT	415	2420	64	157
Total HT	11,190	33,153	716	932
Information HT	5257	17,610	932	275
Manufacturing HT	4183	15,688	289	412
Private service HT	6280	17,708	309	600
Manufacturing	13,596	37,269	1722	2411
Private services	55,398	33,153	3730	4292
Distance variables in kilometers				
Distance to nearest/actual urban center	24.4	19.8	96.7	58.2
Incdist to metropolitan >250 km	36.8	74.5	67.0	106.4
Incdist to metropolitan >500 km	36.573	68.256	42.855	66.134
Incdist to metropolitan >1500 km	91.579	131.827	88.935	111.164
Proximity to research university—160 km	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	191,967	434,755	22,308	20,451
Population of nearest MA	1,082,961	2,236,041	279,335	412,487
Median HH income in the nearby counties	28,302	5271	25,894	4271
Percent of agricultural employment	4.12	4.03	10.82	8.89
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
Nearby counties' bachelor degree and above	15.562	5.330	12.382	3.560
Percentages of other races	1.868	4.046	1.785	4.850

Note: Table A2 shows the variable definitions. Also, descriptive statistics for age shares and race shares are not included in Table 1 for the sake of brevity.

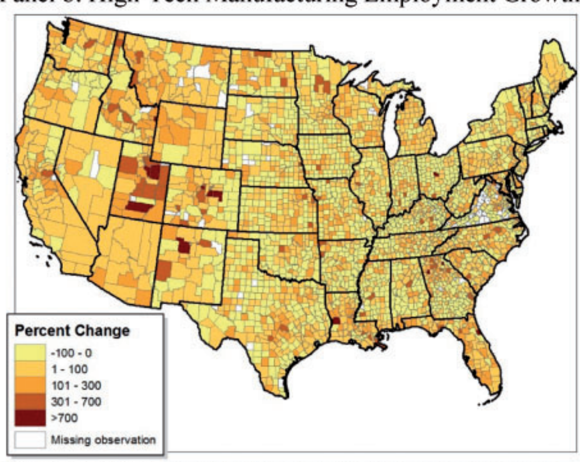
manufacturing and information technology. Panel a shows notable hot spots for total high-technology growth in Colorado, Oregon, Washington, North Dakota and Montana (though California also fares well), whereas the southern Plains and Eastern USA had some of the weaker performances. High-tech manufacturing growth is more evenly distributed across the USA and information technology has some hot spots such as Utah and near Atlanta, Georgia, but there also are some 'cold



Panel a: Total High-Tech Employment Growth



Panel b: High-Tech Manufacturing Employment Growth



Panel c: Information Technology Employment Growth

Figure 2. Employment growth (1990–2006).
Panel a: total high-tech employment growth. Panel b: high-tech manufacturing employment growth. Panel c: information technology employment growth.
Notes: blank is missing observations. Table A1 shows industry 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 log initial employment of nearby counties[a]	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 to research universities160kms	−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)

(continued)

Table 2. Continued

Variable	Total Emp-HT		Total Emp		Manufacturing		Services	
	1	2	3	4	5	6	7	8
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 college graduates in nearby counties[a]		0.001		−0.009		−0.002		−0.02 **
		(0.22)		(−1.2)		(−0.25)		(−2.06)
Other explanatory variables[b]	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^2	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://wwkesw.bea.doc.gov/bea/regional/docs/econlist.cfm. The superscripts on the coefficients indicate the significance level, *refers to 1% significance level, **indicates 5% significance level and ***indicates 10% level. [a]The nearby variables are the average value of the nearest five counties. The weight matrix used is normalized so that rows sum to 1.
[b]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 log initial employment in nearby counties[a]	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 universities—160 km	−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**		.000013*		4.98E-06 *
		(6.85)		(2.31)		(4.51)		(4.11)

(continued)

Table 3. Continued

Variable	Total Emp-HT		Total Emp		Manufacturing		Services	
	1	2	3	4	5	6	7	8
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 college graduates in nearby counties[a]		−0.03*		0.003		0.016		−0.005
		(−2.65)		(1.08)		(1.53)		(−1.15)
Other explanatory variables[b]	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^c	1963	1963	1963	1963	1959	1959	1963	1963
R^2	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://wwkesw.bea.doc.gov/bea/regional/docs/econlist.cfm. The superscripts on the coefficients indicate the significance level:*refers to 1% significance level, **5% significance level and ***10% level. [a]The nearby county variables are the average value of the nearest five counties. The weight matrix used is normalized so that rows sum to 1.
[b]This includes age composition shares, race/ethnic shares and median household income in the BEA region. [c]The number of observations slightly varies across regressions due to missing employment data as a result of BEA disclosure.

spots' interspersed across the country. We next use regression analysis to better understand these spatial patterns.

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.[12] For each industry category, the first column of results reflects a parsimonious model that does not include the demographic variables (educational attainment, total population, age and racial/ethnic population shares). These more parsimonious models help assess whether multicollinearity greatly affects 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).[13]

4.1. High-technology versus aggregate industry categories

A comparison of the parsimonious model results with the base model results in both Tables 2 and 3 reveal that the results are relatively robust. 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 greatly 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 level 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' or 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 industry clusters are an important source for job growth. As the aggregate high-tech sector contains heterogeneous subcomponents, this notion of clustering extends beyond simply representing localization and approximates Porter's (2000) concept of interconnected firms across related sectors to the extent that these key relations are within the high-tech sector. Initial 1990 nearby-county high-technology employment is statistically insignificant in both the base metropolitan and nonmetropolitan models.

Consistent with urbanization or diversity economies (Glaeser et al., 1992; De Groot et al., 2007), the results suggest that 1990–2006 high-technology employment growth is positively related to own-county population in the nonmetropolitan sample and overall

12 A handful of extremely small counties are omitted due to the Bureau of Economic Analysis not disclosing manufacturing employment data for confidentiality reasons.

13 Presumably, any historic self-sorting related to the initial employment level is accounted for by controlling for the initial 1990 high-technology employment level.

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 (comparing column 2 with column 4) shows that the coefficient is considerably larger in the high-technology model, especially in the nonmetropolitan sample. Although industry diversity and urbanization are critical to overall growth, they appear to matter more in the high-technology sector. We leave to future research to determine how much of these growth effects can be attributed to greater industry diversity versus other urbanization agglomeration effects.

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 a strong deterrent to growth in nonmetropolitan settings, in which the negative distance relationship is particularly strong for the high-technology sector compared with overall total employment. 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.

To put these results in perspective, we use the distance regression coefficients that are significant at the 10% level and corresponding distance variable means and standard deviations from Table 1 for the metropolitan and nonmetropolitan samples. In the metropolitan sample, when measured at the mean distance from the center of its own metropolitan area and at the mean distance(s) from successively larger tiered metropolitan areas, expected total high-tech employment growth in the county is 32% less than growth in an otherwise equal county located at the center of a metropolitan area with more than 1.5 million people (in which all distance variables would then equal zero). Correspondingly, a 1 standard deviation increase in all of the metropolitan distance variables would be expected to reduce total county high-tech employment growth by 45%, all else equal. Similarly, for the four distance variables, the corresponding reductions of nonmetropolitan total high-tech employment growth when measured at the mean or after a 1 standard deviation increase in all distances are 28% and 25%, respectively. These calculations show that proximity to larger cities is economically consequential when considering (from Table 1) that the mean total high-tech employment growth rate is 28% (standard deviation =81%) in metropolitan counties and −3% (standard deviation =76%) in nonmetropolitan counties.[14]

The human capital variables have their expected effects in which a larger share of the initial 1990 adult population with a bachelor's 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 that for overall employment growth. A 1

14 We could add squared distance variables to capture any nonlinear effects of distance. However, we do not consider additional distance terms because Partridge et al. (2008b) find that they have virtually no effect on population growth when the response is evaluated at the mean distance, most likely because the use of several incremental distance variables already captures nonlinearities.

standard deviation increase in the metropolitan and nonmetropolitan share of college graduates (from Table 1) is associated with 24% faster metropolitan county total high-tech growth and 14% faster nonmetropolitan county high-tech employment growth over the 1990–2006 period. There is a similar pattern for the population share with some college (but no college degree).[15] 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 high-tech growth within a given state. While the precise channels of causation are difficult to untangle, the results suggest that availability of a good workforce and/or the availability of high human capital entrepreneurs is related to faster job growth. Nonetheless, the results showing an important role of an educated workforce along with the deconcentration of the industry also broadly supports the 'social filters' component of the regional systems of innovation, because it illustrates that concentrations of knowledge workers can facilitate new opportunities and innovations in other sectors that are relatively small (Crescenzi et al., 2008; Fagerberg et al., 2011; Crescenzi and Rodriguez-Pose, 2012).

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 bachelor's degree in the nearest five counties has a statistically insignificant relationship with metropolitan high-technology employment growth and a negative relationship in nonmetropolitan counties. Yet, our positive findings for human capital within the county but insignificant (or negative) effect for nearby counties is consistent with Rosenthal and Strange's (2008) findings for workers across all industries in terms of productivity—i.e. access to *nearby* human capital is important for productivity. Our results further suggest rather limited spatial spillovers in terms of knowledge and human capital. Indeed, the nonmetropolitan result suggests that more educated nearby 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. The statistically insignificant university results also are consistent with the recent findings in Crescenzi et al. (2007) and D'este et al. (in press). 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 results, 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 for

15 A reviewer noted that high school graduates could include those who passed a GED equivalence test. Likewise, the 'some college' category may include those who received specific training as well as those who did not receive a college/university degree. Our regression coefficients report the average response for a particular category. We leave it to future research to examine whether there is heterogeneity in the effects for even finer educational categories.

specific high-technology industry groupings below because high-technology workers in specific occupations such as software development may be more footloose than those who need to be near R&D facilities.

4.2. Sensitivity analysis

We next assess the sensitivity of these base results with different variable definitions and specifications. For results that are not reported in the article, they are available online in an appendix available at www.xxx.com. First, we assess whether our results are sensitive to the use of lagged log own-employment level and the average log own employment in the nearest five counties by substituting the *level* in both cases. However, the own-industry high-technology employment results were not consequentially affected and the nearby county results were qualitatively similar to before.[16]

We then re-estimate the model by dropping all neighboring county (W^*X) variables to assess whether potential endogeneity and high correlation with the corresponding own-county variables were affecting the results (data not shown). But, the primary results were essentially unchanged. Likewise, when we replaced the 1–7 amenity score with a continuous z-score that was used in developing the measure, the main agglomeration results were not materially affected. Regarding the amenity variable results, the metropolitan total high-tech sector amenity coefficient actually became negative and significant at the 10% level (which supports our previous lack of *positive* amenity results for the high-tech sector). The nonmetropolitan amenity coefficient remained insignificant.

4.3. High-technology subsectors

Tables 4 and 5 consider metropolitan and nonmetropolitan subsectors, respectively, within the high-technology sector. We separately consider high-technology growth in manufacturing, services, information, biotechnology and natural resources to assess whether the aggregation of the high-tech sector obscures positive spillovers within more narrowly defined sectors. Biotech and high-tech natural resources 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 by zeros.[17]

16 We also examined the sensitivity of the results to using the total number of university graduates in the nearest five counties rather than the average university graduate population share. The main results were basically unchanged for the lag industry employment and college graduate share variables. Likewise, the nonmetropolitan results for surrounding county college graduates were qualitatively similar. For the metropolitan county sample, the weighted nearby county college graduate variable coefficient switched from insignificant to positive and significant in three cases (overall high-tech, high-tech manufacturing and biotech) and from positive and significant to insignificant for (high-tech services and information technology). Thus, in general, our main finding of inconsistent effects of the effects of nearby college graduates is maintained. The high-tech subsector results are described in Section 4.3.

17 The employment growth variable for biotech and natural resources is constructed as $100 \times (\text{Employment}_{2006} - \text{Employment}_{1990})/\,[(\text{Employment}_{2006} + \text{employment 1990})/2]$. About 2% of the observations had zero employment in both years in the natural resource sector and about 19% in biotech (mostly in the nonmetropolitan sample). For those two industries, we set percent change in employment growth equal to zero if there was zero employment in both years. If emp90 >0 and emp06 =0, then employment growth is −1. Also, if emp90 =0 and emp06 >0, then employment growth =1. While this

Table 4. High-tech employment growth: metropolitan counties

Variable	Manufacturing-HT 1	Services-HT 2	Information-HT 3	Biotech[a]-HT 4	Natural resources[a]-HT 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 log initial employment—neighboring counties[b]	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 km	−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 km	−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 km	0.0002	−0.001 **	−0.106	−0.006 **	0.001
	(0.32)	(−2.13)	(−0.98)	(−2.38)	(0.84)
Proximity to research universities—160 km	−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)

(continued)

Table 4. Continued

Variable	Manufacturing-HT 1	Services-HT 2	Information-HT 3	Biotech[a]-HT 4	Natural resources[a]-HT 5
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 college graduates in nearby counties[b]	0.007	0.008	0.025 **	0.09 ***	0.028
	(0.67)	(0.78)	(2.03)	(1.76)	(1.1)
Other explanatory variables[c]State dummies	Y	Y	Y	Y	Y
	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^d	1033	1038	1038	1040	1040
R^2	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://wwkesw.bea.doc.gov/bea/regional/docs/econlist.cfm. The superscripts on the coefficients indicate the significance level: *refers to 1% significance level, **5% significance level and ***10% level.

[a]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.

[b]Nearby county variables are the average value of the nearest five counties. The weight matrix used is normalized so that rows sum to 1.

[c]This includes age composition shares, race/ethnic shares and median household income in BEA region. [d]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[a]-HT 4	Nat. Res[a]-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 log initial employment in nearby counties[b]	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 km	−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 km	−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 km	−0.0001	−0.0003	−0.001*	−0.0004	−0.0009
	(−0.22)	(−1.04)	(−2.81)	(−0.35)	(−1.10)
Proximity to research university—160 km	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)

(continued)

Table 5. Continued

Variable	Manufacturing-HT 1	Services-HT 2	Information-HT 3	Biotech[a]-HT 4	Nat. Res[a]-HT 5
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 college graduates in nearby counties[b]	−0.017***	−4.244E-04	0.011	0.013	−0.125**
	(−1.71)	(−0.03)	(0.98)	(0.43)	(−2.56)
Other explanatory variables[c]	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[d]	1900	1954	1945	1963	1963
R^2	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://wwkesw.bea.doc.gov/bea/regional/docs/econlist.cfm. The superscripts on the coefficients indicate the significance level: *refers to 1% significance level, **5% significance level and ***10% level.

[a]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.

[b]The nearby county variables are the average value of the nearest five counties. The weight matrix used is normalized so that rows sum to 1.

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

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

The results in Tables 4 and 5 across subsectors are similar to the overall high-technology employment growth results from Tables 2 and 3 (though we stress some differences below). The similarities suggest our results are not sensitive to the aggregation of the high-technology sectors.[18] Across the high-technology subsectors, the biotechnology model is less precisely estimated and has a much smaller R^2 statistic. There also appears to be a lesser role for geographic distance for metropolitan biotech employment growth. To put these distance results in perspective using the four biotechnology distance regression and the corresponding mean distances from Table 1, the expected reduction in metropolitan county biotechnology growth equals −18% and the corresponding nonmetropolitan county response is −34%, compared to an otherwise equal county at the center of a metropolitan area with more than 1.5 million people. These results compare with the average biotechnology metropolitan and nonmetropolitan growth rates of 143% and 28%, respectively (from Table 1).

In both the metropolitan and nonmetropolitan models, there is a strong inverse relation between the 1990 log of initial employment in each of the high-tech subsectors 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.[19] Thus, even when using more homogeneous disaggregated industry categories, the results do not support the classic notion of localization economies or the more recent version of clusters (Porter, 1998).[20] 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 and findings for France by Duranton et al. (2010).

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 significant positive relationship. This again suggests

process adjusts for cases of zeros in the beginning and ending year, it does produce a slightly different scaling than the other industries in Tables 4 and 5.

18 The aggregated industry categories also capture spillovers that are broader such as the need for more educated workers in general or inputs such as specialized patent attorneys or venture capitalists. The disaggregated categories would capture more specific spillovers of the more specialized form such as workers who are trained to only work in (say) software design—not information technology in general.

19 To further investigate nonlinearities for within-industry clustering, we added a square of the initial 1990 log lagged own-employment to the models. There was one case (nonmetro high-tech natural resources) when the square term was *positive* and statistically significant, but in this case, the marginal effect was negative when evaluated at the mean 1990 own-employment level. We also tried the average own-industry employment *share* in the nearby five counties (versus log employment level), but the results were also qualitatively similar to our base results.

20 Porter's cluster grouping of 'related' industries can extend outside of a specific high-tech sector (e.g. Delgado et al., 2010). Yet, because related industries are typically in the supply chain, high-tech sectors typically have other 'related' high-tech industries. Duranton (2011) concludes that cluster measurement errors are small when using finely defined industry classifications. Nonetheless, these related-industry cluster effects are relatively small compared to the negative own-industry effects in Delgado et al. (2010). Using descriptive statistics from their Table 1 and regression results from their Table 3 (model 3.8), a 1 standard deviation increase in the within-industry one-digit location quotient is associated with a 2.92% decrease in that industry's employment growth. Conversely, a 1 standard deviation increase in the location quotient of related cluster employment *outside* of the industry is only associated with 0.33% faster growth and a 1 standard deviation increase in the location quotient of industries related to the cluster (but outside of the cluster) is associated with 0.095% faster growth (together they sum to just under 0.43%). In our case, the 'negative' results are similar whether examining aggregated groupings that capture broader positive spillover effects or narrower grouping that reflect specific spillovers.

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 biotech is somewhat surprising, but is consistent with a more ‘random’ or nonsystematic distribution for its 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 4-year university degree share is somewhat weaker in nonmetropolitan areas, with the direct share statistically insignificant for the high-technology service and the high-technology natural resource subsectors, which may indicate that the broader nonmetropolitan labor market pooling effects for human capital, are at a more aggregated level. 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 location within 160 km of a research intensive or major land-grant university, further suggesting that universities play their primary role as providers of human capital, not through localized knowledge spillovers. That does *not* mean US 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, reliance on a model of state funding suggests 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.[21]

21 We also re-estimated the subsector models using the continuous amenity variable provided by Economic Research Service rather than the ranking. There were not any notable changes in the metropolitan amenity results, though in the nonmetropolitan results, the amenity variable became positive and significant at the 10% level in the information tech model.

We also consider whether the qualitative conclusions are sensitive to using greater disaggregation that may better capture specialized aspects of within-industry spillovers. One consideration is the need to select industries with sufficient numbers of nonzero observations to make general statements, which is more difficult with greater disaggregation. Three disaggregated industries come closest to meeting these criteria: (i) computers and software (NAICS 5415 + 3341); (ii) aerospace (aerospace product and parts manufacturing) and (iii) engines and turbines (engine, turbine and power transmission equipment manufacturing), in which we created the dependent variable consistent with that for the biotechnology and natural resource technology models. Rows 1–3 of Table 6 only present the key agglomeration results, though the general pattern for the other results remain the same as before.

For all three metropolitan models, the own-lagged employment coefficient is negative and statistically significant. For nonmetropolitan areas, the own-employment lag coefficient is negative in all three cases, but is only statistically significant for computers and software. The lack of significance could be due to insufficient variation (more zeros) in the smaller nonmetropolitan counties. Likewise, the nearby county own employment also is statistically insignificant in all cases. Regardless, the results continue to support the notion of few net-positive own-industry localization effects, suggesting that our findings are not an artifact of how we aggregate the high-tech sector.

4.4. Quantile regression results

The high-technology growth process could be nonlinear because 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 that 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 specifically 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 7 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 with at least one significant difference in a 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 level 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 is also 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 with 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

Table 6. Employment growth-disaggregated high-tech industries (*t*-statistics in parentheses)

	Metropolitan Counties		Non-Metropolitan Counties	
	1990 log initial employment	1990 initial employment in nearby counties	1990 log initial employment	1990 initial employment in nearby counties
	1	2	3	4
(1) Computers and software	−1.32*	0.15	−2.22**	0.09
	(−4.44)	(0.47)	(−2.27)	(0.56)
(2) Aerospace product and parts manufacturing	−0.44*	−0.04	−0.36	−0.46
	(−3.78)	(−0.23)	(−1.17)	(−1.45)
(3) Engine, turbine and power transmission equipment manufacturing	−0.36**	−0.29	−0.20	0.21
	(−2.42)	(−0.92)	(−0.99)	(1.21)

The empirical model includes the same variables as the base model. The estimates of the other variables are available on request.

Note: Robust (spatially clustered) *t*-statistics are in parenthesis. The superscripts on the coefficients indicate the significance level: *refers to 1% significance level, **5% significance level and ***10% level.

services and information high-tech industries. Only for biotech sectors in metropolitan counties 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.

4.5. Comparing the 1990s to post 2000

We re-estimate the models after dividing the sample into the periods of 1990–2000 and 2000–2006 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). For the entire high-tech industry and for the individual high-tech industry groupings, the results display strikingly similar patterns across both decades. Foremost, the own-industry employment level 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 somewhat 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 the nonmetropolitan sample after 2000. Overall, while there are modest changes, it is noteworthy how comparable the results are across the decades.

Table 7. Quantile regression results: 90th–10th percentile (*t*-statistics in parentheses)[a]

Variable	Log(initial employment) 1	Distance to nearest metropolitan 2	Proximity to university 3	Neighboring college graduates 4	Associate degree 5	Bachelor's degree 6
Metropolitan						
Hi-tech	−0.25*		−0.30**			
	(4.45)		(1.98)			
Manufacturing hi-tech	−0.41 *			0.05**	0.14***	
	(6.03)			(2.39)	(1.96)	
Services hi-tech	−0.48 *				−0.18**	
	(5.22)				(2.45)	
Information tech	−0.36*			0.07**		
	(5.51)			(2.44)		
Bio-tech	−1.13*		1.72**			
	(4.88)		(2.51)			
Natural resources tech	−1.00*			0.081***		
	(6.63)			(1.84)		
Nonmetropolitan						
Hi-tech	−0.58*	−2.09E-03**				
	(5.75)	(2.4)				
Manufacturing hi-tech	−0.34*				0.21*	0.05***
	(4.09)				(2.99)	(1.89)
Services hi-tech	−0.76*	−2.47E-03**				
	(8.16)	(2.14)				
Information tech	−0.63*	−2.85E-03**				0.05*
	(6.31)	(2.19)				(2.85)
Bio-tech	−0.46**					0.082***
	(2.24)					(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 in which the superscripts *refers to 1% significance level, **5% significance level, and ***10% level. 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.

4.6. Pooled regressions

One concern is that there could be omitted county fixed effects that could be correlated with the explanatory variables—most importantly the lagged own-industry employment level. In particular, omitted county effects may be associated with the initial distribution of the high-tech sector. To assess this issue, we created a pooled sample over the 1990–2006 period for high-tech manufacturing, high-tech services, information technology, biotechnology and high-tech natural resources (creating five observations per county). We then estimate a county fixed effects model using the respective industry's employment growth as the dependent variable. We control for the log initial county industry employment, average surrounding county industry employment and industry dummies to account for different national industrial growth rates. As the initial demographic/geographic variables and the distance variables are fixed for each county, they cannot be included in this model. Yet, they are fixed or change very slowly over time, subsuming their effect into the county fixed effects. Two disadvantages of the pooled model are: (i) the model assumes a common regression coefficient on the own-industry county employment variable and (ii) the model requires omitting many variables of interest.

In the pooled regression results (data not shown), the coefficient on the key own-industry variable equals −0.61 ($t = -9.10$) in the metropolitan sample and −0.44 ($t = -9.86$) in the nonmetropolitan sample, which strongly supports our previous findings about the lack of within-industry agglomeration effects.[22] We find some evidence of positive spillovers over space, as nearby-county own-industry employment was positive and statistically significant at the 1% level. Yet, as we noted earlier, there is some overlap in the high-tech industry definitions, which means some caution should be exercised in interpreting these results.

4.7. Exploring other forms of localization economies

We further experimented to assess whether positive own-industry clustering effects and localization economies were not captured by the lagged own-industry level, which has been our main focus. First, we re-estimated the base model for the high-tech industries in Tables 2–5 over the 2000–2006 period. We then use the 1990 lagged own-industry employment level (not the 2000 level) and we added the lagged dependent variable—i.e. 1990–2000 percent change in the industry's employment. Thus, we can ascertain whether at the margin, a growing sector in the immediate past helps produce positive localization effects or whether it is the scale of the industry that has a positive (or negative) effect, assuming the net effects of localization economies or within-industry clustering are positive. However, in almost all cases (data not shown), the coefficient on both the lagged own-industry employment variable and its lagged growth rate were negative and significant, except for the positive and significant nonmetropolitan 1990 own-industry high-tech manufacturing employment coefficient, the positive and insignificant coefficient on the nonmetropolitan high-tech natural resources lagged own-industry growth variable and the negative and insignificant lagged own-industry employment coefficient for natural resources in both the metropolitan and nonmetropolitan samples. This result suggests that growing high-tech industries do not generally benefit in terms of future employment growth whether in terms of facilitating future cluster links in *related* industries or as a sign of growing agglomeration within that industry (at the margin).

We further investigated whether our results differed if we instead measured growth and the local size of the industry relative to the nation. Specifically, we measured industry growth in the dependent variable by taking local industry *i*'s growth minus national growth in industry *i*. We then measured the relative size of the industry by using the location quotient for the industry (i.e. divide the county share by the national employment share for industry *i*). Nonetheless, the results (data not shown) were highly

22 We also considered using 'five year' panels over the 1990–1995, 1995–2000 and 2000–2006 periods in a fixed effects model. However, we did not have consistent four-digit level high-tech industry data for this entire period.

similar to what we report suggesting that scaling relative to the nation does not affect our conclusions regarding the lack of positive clustering effects.

5. Summary and policy conclusions

We examined the role of geography in high-tech employment growth for US counties from 1990 to 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 numerous factors such as natural amenities and demographic characteristics of the local population. Overall, our findings suggest that geography significantly influenced high-tech employment.

We found little, if 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 Marshall-Arrow-Romer externalities, there is more 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. Urban agglomeration economies appeared to play a smaller role for metropolitan biotechnology and natural resource high-technology industries. We find little support then for the notion that policymakers can pick high-tech winners on the basis of concentration of an industry or on its recent performance in the local economy.

Human capital is also 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. These findings tend to support the social filter models of innovation (Crescenzi and Rodriguez-Pose, 2012). 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 generally 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 benefits may be spreading across the globe, raising productivity everywhere.

The absence of positive clustering effects casts some doubt on the expected efficacy of government attempts to create clusters such as the Obama administration's promotion of regional innovation clusters in its *Strategy for American Innovation*. The administration launched initiatives to help create and foster regional innovation clusters based on regional competitive advantages. The attempt is to increase knowledge and expertise needed for creation of 'cutting-edge' products, under which high-tech products generally could be classified.

Identifying growth-promoting clusters may be more difficult than commonly believed as it involves defining within- and between-industry spillovers and the geographic scope of interactions (Duranton, 2011; Yu and Jackson, 2011). Efficacious cluster policy also requires identifying a market failure, the reason for the failure, how policy can correct the failure and who benefits from the policy, which may require a completely specified model of the regional economy of interest (Duranton, 2011). The results from the current study suggest these benefits do not exist within or across high-tech subsectors. 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 distressed or remote US 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 USA is no longer a leader among advanced countries in terms of university attainment for young adults (OECD, 2011).Consequently, as suggested by Varga (2000), more comprehensive economic development approaches are needed in the USA to spur high-tech growth.

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Appendix

Table A1. High-tech industries: NAICS classifications

High-tech	NAICS 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
	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 products 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

(contimued)

Table A1. Continued

High-tech	NAICS code	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

Table A2. Variable definitions

Dependent variables		
Employment change (%ΔEMPI)	Percentage change in total or major sector employment for the period 1990–2006	US BEA, REIS
HT employment change	Percentage change in HT total or the HT subsector employment for the period 1990–2006	EMSI
Independent variables		
AGGLOM		
Dist to nearest/actual metropolitan area	Distance (in kilometer) 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 >250 km	Incremental distance to the nearest/actual metropolitan area with at least 250,000 population in 1990 in kilometers	Authors' est.
Incdist to metro >500 km	Incremental distance to the nearest/actual metropolitan area with at least 500,000 population in 1990 in kilometers	Authors' est.
Incdist to metro>1500k	Incremental distance to the nearest/actual metropolitan area with at least 1,500,000 population in 1990 in kilometers	Authors' est.
Nearest/actual urban center pop	.	Authors' est.
AMENITY		
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 of pop ≤6 years	Percent population ≤6 years, 1990.	1990 Census, Geolytics
Percent of pop 7–17 years	Percent population 7–17 years, 1990.	1990 Census, Geolytics
Percent of pop 18–24 years	Percent population 18–24 years, 1990.	1990 Census, Geolytics
Percent of pop 55–59 years	Percent population 55–59 years, 1990.	1990 Census, Geolytics
Percent of pop 60–64 years	Percent population 60–64 years, 1990.	1990 Census, Geolytics
Percent of pop ≥65 years	Percent population ≥65 years, 1990.	1990 Census, Geolytics

(continued)

Table A2. Continued

Independent variables		
Education		
Percent of HS graduate	Percent population ≥25 years and are high school graduates, 1990.	1990 Census, Geolytics
Percent of some college, no degree	Percent population ≥25 years and having some college, no degree, 1990.	1991 Census, Geolytics
Percent of associate degree	Percent population ≥25 years having an associate degree, 1990.	1992 Census, Geolytics
Percent college graduate	Percent population ≥25 years that are 4-year college graduates, 1990.	1990 Census, Geolytics
Race	1990 percent of Hispanic, Asian, African Americans and Native Americans	1990 Census, Geolytics
Surrounding variables		
Proximity to research university—160 km	Indicator for being within 160 km of Carnegie I research intensive university or a major 1862 Land Grant university.	Dorfman et al. (2011)
WEMPI		
Neighboring counties initial employment/ sectoral employment	Weighted average of the initial employment in nearest five counties	1990 Census, Authors' est.
Neighboring counties initial HT employment/ HT sectoral employment	Weighted average of the initial HT employment in nearest five counties	EMSI, Authors' est.
Neighboring counties percent of bachelor degree and above	Weighted average of the bachelor degree and above in nearest five 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.