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published in

Economic Notes
2021

DOI (link to publisher)

[10.1111/ecno.12178](https://doi.org/10.1111/ecno.12178)

document version

Publisher's PDF, also known as Version of record

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citation for published version (APA)

Pede, V. O., Florax, R. J. G. M., de Groot, H. L. F., & Barboza, G. (2021). Technological leadership and sectorial employment growth: A spatial econometric analysis for U.S. counties. *Economic Notes*, 50(1), 1-19. [e12178]. <https://doi.org/10.1111/ecno.12178>

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Technological leadership and sectorial employment growth: A spatial econometric analysis for U.S. counties

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Abstract

This paper studies the determinants of technological catch-up considering spatial and sectoral aggregation of industries. We investigate how geographical and technological proximity to the technology leader impact regional employment growth. We model technological progress by means of a hierarchical process of catch-up to the technology leader. We also incorporate measures for knowledge spillover effects to test the roles of competition, specialisation, and diversity at the industry level. Empirical results using data at the county level for different economic sectors (2-dig NAICS) for the United States indicate that human capital plays a crucial role in promoting sectoral employment growth. The association between technological/geographical distance to the technology leader and employment growth varies across sectors.

KEYWORDS

regional employment growth, spatial econometrics, technological leadership

JEL CLASSIFICATION

R11; R12; C21; O32; O47

1 | INTRODUCTION

The quest to explain and understand the sources of economic growth, and the persistent differences across economic units has made significant progress in the past decades; yet several issues still remain elusive. There is a long research tradition investigating the process of economic growth across countries. In this stream of research, one of the most relevant and useful topics is uncovering the role that technological change and technological catch-up processes play in achieving higher levels of economic growth. As the literature advances, the research focus has moved progressively to smaller units of aggregation, such as cities, counties, economic sectors, and firms (see Audrestch & Keilbach, 2007, 2008; Colombelli & Quatraro, 2018; Del Giudice, Scuotto, Garcia-Perez, & Petruzzelli, 2019; Ellison, Glaeser, & Kerr, 2010; Glaeser, Kallal, & Scheinkman, 1992; Sedláček & Sterk, 2017; Pede, 2013; Pede, Florax, & de Groot, 2008; Pede, Florax, & Lambert, 2014, among others). In this context, it has become pivotal to understand the role that ideas generation and the derived effects of knowledge spillover effects (KSE) between firms within and across industries play in the growth process (Audrestch & Keilbach, 2007, 2008; Santoro, Thrassou, Bresciani, & Del Giudice, 2019). Based on the evidence, the extant research indicates that there are significant differences relating to the level of data aggregation that must be considered in the transmission of ideas across economic units. Furthermore, the research, Audrestch and Keilbach (2007, 2008) and Audrestch and Belitski (2013) points out that at lower levels of data aggregation, issues relating to agglomeration and location economies become relevant as they may serve as mechanisms conducive to the proliferation of dynamic externalities of knowledge spillovers between firms within and across industries. Kerr and Robert-Nicoud (2020) provide an excellent analysis in relation to Technological Clusters and argue that tech clusters are geographically driven by high velocity labour markets that allow for significant spillover effects to take place. Because understanding the spatial distribution of industries can potentially provide useful information in explaining observed sectorial employment growth differences and the transmission mechanisms of knowledge spillovers, we set forth to explore these issues in this paper using data at the county level in the United States. Several studies have provided evidence using regional and city level data, yet to the best of our knowledge, there is little to no evidence using county level data (see Kerr & Robert-Nicoud, 2020).

Despite abundant evidence using aggregate level data, it is surprising how little is known about the determinants of technological leadership and derived catch-up processes, and their implications for the observed regional economic performance differences¹ in terms of sectorial employment growth. In this stream of research, the extant literature has focused mainly on studying, understanding and uncovering the effects of agglomeration and location economies on sectorial employment growth or productivity growth (see Bishop & Gripaios, 2010; Blien, Suedekum, & Wolf, 2006; Frenken, Van Oort, & Verburg, 2007; Glaeser et al., 1992; Shearmur & Polèse, 2005; and among others).

Thus, because of its relevance, we hypothesise that spatial considerations—geographical and technological distance—potentially have relevant implications for KSE within and across firms in the same and diverse industries to materialise in increased employment levels. Using sectorial data, we propose to incorporate geographical and technological distance of counties in relation to the technology leader to understand sectorial employment growth differences across six aggregated U.S. economic sectors. In doing so, we propose to bridge the existing gap in the literature as it relates to the potential tight spillover length of smaller and denser clusters (see Kerr & Robert-Nicoud, 2020, for further details).

The rest of the paper is organised as follows. At the outset, we provide a brief yet thorough review of the most salient literature on the issues relating to technological leadership and human capital. In addition, we provide a review of the literature on the topics of KSE and employment growth. We proceed to model a growth process—following Glaeser et al. (1992)—in which spatial dependence between counties and spatial externalities related to

¹See Magrini (2004) for a comprehensive discussion of the problems associated with the application of cross-country neoclassical growth theories in regional growth analysis.

technology diffusion and KSE are accounted for. The main contribution of this paper is to test existing hypotheses on—specialisation, competition and diversity—at the county level to determine whether these hypotheses hold at the lower level of data disaggregation when accounting for spatial dimensions and the role of geographical and technological distances to the technology leader on sectorial employment growth.

2 | LITERATURE REVIEW

One of the most relevant findings in the extant literature indicates that technological leadership can be seen either as economic dominance in terms of high productivity or overall efficiency in inputs use. In this context, a regional leader exhibits the overall highest productivity (efficiency) level, and consequently, other regions aim at catching up to the leader's efficiency levels. In a simple way, this catching-up process involves gravitation of the followers towards the productivity or efficiency level of the leader (Dollar & Wolff, 1993).² To explain this catching up process, there are three well-known theories relating to the presence of KSE and how they may serve as the mechanisms for the catching up to occur. These theories are the Marshall-Arrow-Romer (MAR) theory of specialisation; Porter's theory of competition (Porter, 1990); and Jacobs theory of Diversity (Jacobs, 1969). In the MAR and Porter contexts, knowledge spillovers would be transmitted within the same industry as a result of regional specialisation albeit via different mechanisms; while in Jacobs' the diffusion occurs across industries and as a result of the concentration of diverse industries with high levels of competition in the same geographical proximity.

In this context, seminal work by Audretsch and Feldman (2004) note that knowledge spillovers are undoubtedly an important mechanism for growth (see Bloom et al., 2020, for more recent details), yet their manifestation maybe region and even industry-specific; and demonstrate a decaying effect if technologies are faced with tight spillover lengths (Kerr & Robert-Nicoud, 2020). As such, knowledge is more likely to transfer more directly when little barriers exist and at the same time, knowledge filters are not in place (see Audretsch & Belitski, 2013; Guerrero & Urbano, 2014).

According to Ferraris, Santoro, and Scuotto (2018) and Audrestch and Keilbach (2008), knowledge and its related spillover effects appear to be spatially distributed and consequently limited on their potential reach. Kerr and Robert-Nicoud (2020) argue that “Tech clusters facilitate powerful scaling for the best designs when they combine modular product structures with high-velocity labour markets.” Thus, notice that to address the issues of spatial distribution of KSE and their implications for economic growth, some studies centre their attention on capturing and decomposing the geographical dimensions and interrelations of growth and convergence in the framework of its spatial nature (see for instance Abreu, De Groot, & Florax, 2005a, 2005b; Audrestch & Feldman, 2004; Fujita, Krugman, & Venables, 2001). To illustrate the importance of the spatial disaggregation, the theory states that at lower levels of spatial aggregation, subnational regions are highly likely to be conditioned by patterns of higher mobility as it relates to labour (Kerr & Robert-Nicoud, 2020), capital and knowledge flows, vis-à-vis with what can be observed at the national level.³ These spatial considerations can potentially have relevant effects in terms of the diffusion, generation, and adoption of knowledge spillovers, as proposed by the MAR, Porter, and Jacobs theories. The conditionality imposed by spatial elements may enhance or restrict the within and across industries growth effects (see Feldman & Audretsch, 1999; Magrini, 2004, for more details), beyond the pure agglomeration and location economies described in the literature (see Krugman, 1991).

²Saito, Gopinath, and Wu (2011) argue that in a closed economy, setting high productivity firms are more likely to agglomerate, but that trade liberalisation processes may also cause low productivity firms to gain from agglomeration as a result of increased regional economic development. However, Sjöberg and Sjöholm (2002) argue that the effects of trade liberalisation process on the spatial concentration of economic activities are not straightforward.

³In the United States, some studies used states and Metropolitan Statistical Areas (MSA), and to some extent, counties as their spatial unit of observation. Feldman and Audretsch (1999) use city level data and find robust support to the Jacobs diversity thesis.

Studies in the field of Knowledge Spillover Entrepreneurship, such as Audretsch and Belitski (2013) indicate that a higher concentration of new knowledge in specific regions is conducive to the overall generation of more opportunities for entrepreneurship activity to develop. Along the same line of argumentation, earlier work by Florida (2004) points that the existence of regions, which are rich in the generation of ideas, could be considered Creative cities. Consequently, developments in the field of Knowledge Spillover Entrepreneurship point out to the importance that opportunities play in the development of new business ventures (Audrestch & Keilbach, 2007). A recent study by Del Giudice et al (2019) provides an excellent review of the literature in this field.

Furthermore, the relationship and relative importance of the externalities generated through knowledge spillovers is going to be determined by the capabilities of a follower to catch-up to the productivity or efficiency level of the technology leader; that is, the overall presence of knowledge filters and the absorption capacity of the follower. These are, in turn, likely to be determined by the technology and human capital currently available to the follower and the capability to acquire off the shelf technology (Jones, 2002). In other words, regions are more likely to successfully adopt technologies based on their current level of human capital and their actual technological gap with the leader. Thereby, human capital serves as a vehicle to increase productivity growth through the development of knowledge and the appropriation of knowledge spillovers (see Ferraris et al., 2018; Santoro et al., 2019, for instance). In this sense, early work by Benhabib and Spiegel (1994) maintained that the ability of a country, or region, to catch up to the productivity level of the leader depends positively on its stock of human capital.

The discussion on the knowledge spillover of human capital and the diffusion of technology across regions makes evident the presence of a spatial dimension to the economic growth process beyond the well-documented agglomeration gains noted in the existent literature. However, notice that this spatial dimension has been significantly overlooked in the extant literature (see Kerr & Robert-Nicoud, 2020, for an excellent discussion). In fact, under both MAR and Porter (within industry specialisation), and Jacobs' (across industries diversity) approaches, there are only marginal and implicit references to spatial dimensions considerations to the knowledge spillovers effects. Indeed, we bring forth the argumentation that these considerations are relevant as the human capital produced or available in a specific region may have an impact in other regions through the capabilities of technology development, absorption, transfer, and implementation, and vice versa (see Feldman & Audretsch, 1999, for more detail). It is in this way that we argue that spatial effects working their way through human capital and technology diffusion manifest in the form of spatial dependence and spatial heterogeneity in economic growth processes.

3 | ECONOMETRIC MODEL

3.1 | Operational specification

The econometric model builds directly on Glaeser et al. (1992). We extend their approach by explicitly accounting for regional, local, and national technological progress, as well as for catch-up to the technology leader. We start with a parsimonious firm production function in which output depends on technology and labour. The first-order condition for profit maximisation yields:

$$A_{it}^s f'(l_{it}^s) = w_t, \quad (1)$$

where l_{it}^s is labour, and A_{it}^s is the level of technology, at time t for a representative firm in region i and in a specific sector s . Assuming that $f(l_t) = l^{1-\alpha}$ with $0 < \alpha < 1$, and taking the difference in logarithms in Equation (1) between the initial period (t) and the end period ($t + 1$) leads to:

$$\alpha \log \left(\frac{l_{it+1}^s}{l_{it}^s} \right) = \log \left(\frac{A_{it+1}^s}{A_{it}^s} \right) - \log \left(\frac{w_{it+1}^s}{w_{it}^s} \right). \quad (2)$$

Following Glaeser et al. (1992), the overall technology level has a local and a national component. Consequently, the overall level of technology available to a representative firm in region i at time t can be written as:

$$A_{it}^s = A_{local,it}^s \cdot A_{national,it}^s, \quad (3)$$

where $A_{local,it}^s$ is the local level of technology in sector s in region i , and $A_{national,it}^s$ is the national level of technology in sector s . As done in (2) above, we directly derive the expression for overall technological progress as:

$$\log \left(\frac{A_{it+1}^s}{A_{it}^s} \right) = \log \left(\frac{A_{local,it+1}^s}{A_{local,it}^s} \right) + \log \left(\frac{A_{national,it+1}^s}{A_{national,it}^s} \right). \quad (4)$$

Following Glaeser et al. (1992), we then assume that the growth of national technology is uniform across regions, and local technological progress is related to three types of externalities related to knowledge spillovers as described earlier, namely: specialisation, competition, and diversity. Consequently, we can specify local technological progress along the lines of:

$$\log \left(\frac{A_{local,it+1}^s}{A_{local,it}^s} \right) = g(SP_{it}, CP_{it}, DV_{it}), \quad (5)$$

where SP_{it} represents specialisation, CP_{it} competition, and DV_{it} diversity, all at time t in region i . In line with Glaeser et al. (1992), we include a number of control variables in the model: the log of earnings per worker,⁴ the log of employment in the initial period, and a regional dummy variable taking value 1 for southern regions comprising South East and South West counties, and value 0 for all the other counties.⁵

We extend the Glaeser et al. (1992) model in two different ways. First, we propose that regional employment growth is not exclusively dependent on local and national technology progress; but more importantly also on technological progress in the region. Given the arbitrary nature of the spatial delineation of the spatial units as well as their heterogeneity in size, spatial technological spillovers across neighbouring regions are taken into account (see Bishop & Grippaios, 2010). Mathematically, this implies that in addition to local variation in specialisation, competition, and diversity, their spatial lag was also included. Therefore, we modify the local technological knowledge spillovers progress and rewrite it as:

$$\log \left(\frac{A_{local,it+1}^s}{A_{local,it}^s} \right) = g(SP_{it}, CP_{it}, DV_{it}, w_i \cdot SP_{it}, w_i \cdot CP_{it}, w_i \cdot DV_{it}), \quad (6)$$

where w_i represents the i th row of an exogenously defined spatial weights matrix W ,⁶ and all other variables are defined as before.

The second variant to the model originally proposed by Glaeser et al. (1992), allows us to emphasise an alternative view on technology creation and diffusion. Here, we hypothesise that local technological progress

⁴Glaeser et al. (1992) used wages, but due to data limitations, we consider earnings per worker as a proxy.

⁵The South East and South West comprise the following states: Alabama, Arkansas, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, West Virginia, Louisiana, Oklahoma, Texas, Maryland, and Delaware.

⁶The weight matrix represents the topology of the system of US counties. It is defined exogenously on the basis of distances between the geographical midpoints of the counties considered. In principle, the weight matrix is standardised.

depends, as before, on local characteristics in terms of specialisation, competition, and diversity, but now we also allow for an explicit hierarchical process of catch-up to the technology leader. Following Benhabib and Spiegel (1994), the technology leader should ideally be characterised as the region with the highest productivity or efficiency level (in a specific sector). Ideally, in the context of a firm, one could say that a firm is technically efficient if it achieves the maximum possible output given an amount of resources. *Pari pasu*, from a regional perspective, a region is technically efficient if it produces the maximum innovative output from a given amount of innovative input (see Fritsch & Slavtchev, 2010). Unfortunately, regionally disaggregated productivity data are not available at the level of industries. Given this limitation, we must come up with an approximation and we use an alternative degree of specialisation-like measure to define the technological efficiency. In our specification, we make the working assumption that the most technologically efficient region is the region with the highest employment share in a specific sector as compared to total employment in the local economy. This obviously is not ideal, especially for sectors where employment is primarily determined by the size of the economic base, and goods and services are tradable only to a limited extent.⁷

In addition to the hierarchical catch-up process governed by distance to the technology leader, we assume that contagious diffusion processes play a role as well and the extent to which state-of-the-art technology of the leader can effectively be used in a local economy depends on the local level of human capital. The contagion aspect is taken into account by incorporating the assumption that the geographical distance to the technology leader leads to a distance-decay effect in terms of local employment growth. We formalise this by hypothesising that local technological progress can be specified as:

$$\log \left(\frac{A_{local,it+1}^s}{A_{local,it}^s} \right) = g(SP_{it}, CP_{it}, DV_{it}, w_{i \cdot} \cdot SP_{it}, w_{i \cdot} \cdot CP_{it}, w_{i \cdot} \cdot DV_{it}, H_{it}, GD_{i,max}, TD_{it}), \quad (7)$$

where the subscript t refers to the initial time period, $GD_{i,max}$ is the inverse geographical distance to the technology leader:

$$GD_{i,max} = \frac{1}{d_{i,max}}, \quad (8)$$

with $d_{i,max}$ being the physical distance to the region identified as the technology leader. Now, the human capital available in region i , at the initial time period t , is expressed as H_{it} , and TD_{it} is the technological distance to the technology leader defined as:

$$TD_{it} = \left(\frac{l_{it}^s}{L_{it}} \right)_{\max} - \left(\frac{l_{it}^s}{L_{it}} \right), \quad (9)$$

where l_{it}^s represents employment in region i , in sector s , at the initial time period t , and L_{it} is total employment in region i at time t . The location quotient is only valid under relatively strong assumptions (in line with assumptions that are required to use a revealed comparative advantage measure in international trade as a measure for comparative advantage).⁸

⁷While such an assumption will hopefully be improved upon in future research as more detailed regionally disaggregated productivity data become available, we still find adequate and consistent support in the existent body of literature. A few possible exceptions are mentioned in footnote 8 below.

⁸As mentioned, we acknowledge that this measure does not address in strict terms technological leadership, but rather more of specialisation. The choice of this simplistic measurement is due to the non-availability of data and as such the price that we have to pay for performing the analysis at this refined level of spatial aggregation.

TABLE 1a Composition of aggregated sectors

2 digit NAICS industries	Aggregated sectors
11 - Agriculture forestry, Fishing and Hunting	Natural resources
21 - Mining	
23 - Construction	Construction & Manufacturing
31-33 - Manufacturing	
42 - Wholesale trade	Transportation & Trade
45 - Retail	
48-49 - Transportation and Warehouse	
51 - Information	Information & Utilities
22 - Utilities	
52 - Finance and Insurance	Finance & Management
53 - Real Estate and Rental and Leasing	
55 - Management of companies and enterprises	
54 - Professional and technical services	Services
56 - Administrative and Support services	
61 - Educational services	
62 - Health care and Social Assistance	
71 - Art Entertainment and Recreation	
72 - Accommodation and Food Services	
81 - Other Services	

3.2 | Estimation procedure

Our estimation procedure follows the convention as we start our estimations with a simple ordinary least square (OLS) estimation of the Glaeser et al. (1992) model with all 20 NAICS sectors pooled. Subsequently, we group these 20 NAICS sectors into six—more or less—homogenous sectors (aggregated sectors), and re-estimate all models. We strictly follow the operational specification of the Glaeser et al. (1992) model for the pooled NAICS sectors, and for the aggregated sectors, we estimate the Glaeser et al. (1992) model as well as the two extended versions described in the preceding section. The alternative sets of estimations allow the possibility of a full decomposition of results by pooled sectors and aggregated sectors, while accounting for the added spatial dimensions. Notice that because of our interest in the sectorial decomposition of employment growth, we perform the spatial estimations only for the six aggregated sectors.

Table 1a shows the composition of the aggregated industries. The six aggregate industries are labelled as: “Natural Resources,” “Construction and Manufacturing,” “Transportation and Trade,” “Information and Utilities,” “Finance and Management,” and “Services.”

As noted, we conducted spatial regressions only for the models that include technological leadership effects,⁹ and we determine the appropriate specification for the spatial process based on the spatial diagnostic tests of the model estimated by OLS, following the procedure outlined in Anselin, Bera, Florax, and Yoon (1996). This specification strategy consists of using the Lagrange Multiplier (LM) tests and their robust forms to decide whether a spatial lag, a spatial error process or their combination is appropriate (Florax, Folmer, & Rey, 2003). It is worth

⁹Due to a large number of observations for the pooled models with 6 and 20 sectors (N = 18,444 and 61,480, respectively), the use of spatial estimators is operationally cumbersome.

TABLE 1b Descriptive statistics on specialisation, competition, and diversity

2 digit NAICS industries	Competition		Specialisation		Diversity	
	Average	SD	Average	SD	Average	SD
11 - Agriculture forestry, Fishing and Hunting	2.45	7.03	4.07	5.02	0.04	0.06
21 - Mining	4.96	85.70	3.48	8.96	0.02	0.05
22 - Utilities	11.07	145.26	1.60	3.40	0.01	0.02
23 - Construction	–	–	0.91	0.65	0.02	0.02
31–33 - Manufacturing	2.35	7.73	1.13	0.82	0.11	0.08
42 - Wholesale trade	–	–	0.80	0.56	0.02	0.02
45 - Retail	1.89	5.54	0.99	0.30	0.03	0.02
48–49 - Transportation and Warehouse	2.48	1.76	0.96	0.68	0.02	0.02
51 - Information	14.93	221.97	0.58	0.48	0.01	0.01
52 - Finance and Insurance	2.90	17.67	0.64	0.34	0.02	0.01
53 - Real Estate and Rental and Leasing	3.11	13.33	0.53	0.52	0.01	0.01
54 - Professional and technical services	6.13	74.46	0.41	0.44	0.03	0.01
55 - Management of companies and enterprises	6.90	56.82	0.50	1.27	0.01	0.01
56 - Administrative and Support Services	6.36	35.26	0.41	0.49	0.03	0.01
61 - Educational services	32.70	268.60	0.55	1.18	0.01	0.01
62 - Health care and Social Assistance	2.74	14.00	0.88	0.51	0.03	0.03
71 - Art Entertainment and Recreation	3.29	8.27	0.81	1.17	0.01	0.01
72 - Accommodation and Food Services	3.47	35.57	0.94	0.63	0.03	0.03
8.1 - Other Services	3.59	23.56	0.78	0.41	0.01	0.01

Note: Averages are computed across all 3074 counties.

noting that the specification of the spatial autoregressive error model is relevant when the dependence works through the error process (see Anselin, 1988). The spatial error model can be written in the general form shown as:

$$y = X\beta + \varepsilon, \varepsilon = \lambda W\varepsilon + u, \quad (10)$$

where y is an $N \times 1$ vector of observations on the dependent variable, X is an $N \times K$ matrix of explanatory variables as defined in (7) earlier, β is a vector of unknown parameters, W is an $N \times N$ weight matrix, which defines the spatial structure of regions, λ is a scalar parameter, u is an $N \times 1$ vector of random error terms with mean 0 and variance σ^2 , and ε is an $N \times 1$ vector of random error terms with mean 0 and variance-covariance matrix $\Omega = \sigma^2(I - \lambda W)^{-1}(I - \lambda W')^{-1}$. The spatial lag model is relevant when the variable under investigation depends on its spatial lag (Anselin, 1988). It can be written as:

$$y = \rho W y + X\beta + u, \quad (11)$$

where ρ is a scalar parameter, and all other variables are defined as before. The choice of the appropriate spatial process model for each growth model is based on the LM tests associated with the error and lag models.

3.3 | Data

The data used in this paper are for 3074 counties in the lower 48 U.S. states. Employment data are from Economic Modelling Specialists Inc. (EMSI), and they are disaggregated to two-digit NAICS industries, covering the period 1990–2008. Firm establishment and earnings data are also from EMSI. Human capital data are from the Census Bureau for the year 1990. In our estimations, we define human capital as the proportion of the population with at least a high school degree. Employment growth is defined as the logarithm of the employment ratio for the years 2008 and 1990.

As done elsewhere, and following the specification developed in Glaeser et al. (1992) we define specialisation ($SP_{i,t}$) in industry within a region as the fraction of the region's employment that this industry captures, relative to the share of the entire industry in national employment (see Cingano & Schivardi, 2003; Feldman & Audretsch, 1999; Henderson, 1997; Suedekum & Blien, 2005, for more details). We consider the Relative Diversity Index (RDI) as a measure of diversity ($DV_{i,t}$). Intuitively a high value of the RDI signals that the regional employment distribution resembles that of the national economy. We follow Glaeser et al. (1992), and define competition ($CP_{i,t}$) within an industry in a region as the number of establishments per worker in this industry in the region relative to the number of establishments per worker in this industry in the country.

A number of details regarding the operational specification of the model are relevant here. First, remember that all right-hand side variables in the final model are defined for the initial year 1990, except for the competition measure, which is defined for 1998 (descriptive statistics on specialisation, competition and diversity are presented in Table 1b), and earnings per worker, which is defined for 2001.¹⁰ Second, the geographical distance from each county to the technology leader is computed following the spherical law of cosines. Third, the initial employment level, the initial earnings per worker, the inverse geographical distance, human capital and technological distance are all in logarithmic form. Finally, the operational measures for the externalities (specialisation, competition, and diversity) are used in a linear fashion. On the descriptive statistics presented in Table 1b, the highest level of specialisation is observed in “Educational Services,” the highest level of competition in “Agriculture Forestry, Fishing and Hunting,” while the manufacturing sector shows the highest level of diversity among all 20 NAICS industries.

To estimate the spatial regressions models, a spatial weight matrix is defined. The spatial weight matrix represents the topology of the system of U.S. counties, and it is exogenously defined based on arc distances between the geographical midpoints of the counties considered. As a result, we obtain a Boolean proximity matrix, where elements are coded as unity if the distance between counties is less than the threshold distance 92.05 miles.¹¹

4 | EMPIRICAL RESULTS

4.1 | Pooled models

We start the estimation as noted earlier by conducting a replication of the Glaeser et al. (1992) model, using regional pooled data for all 20 NAICS sectors, as reported in Table 2. Columns (1), (2), and (3) show the results, successively including measures for specialisation, competition, and diversity. The last column, labelled (4), includes all three measures of spatial externalities simultaneously.

¹⁰Table 1b shows averages and standard deviation on specialisation, competition and diversity. Data on the number of establishments needed to compute the competition variable were only available for the period 1998–2008. The earnings data were only available for the period 2001–2008.

¹¹The threshold distance is selected to ensure that all regions (counties) have at least one neighbour.

TABLE 2 Pooled regression, 20 two-digit NAICS industries

	Dependent variable: Employment growth			
	(1)	(2)	(3)	(4)
Constant	-1.107*** (0.083)	-1.087*** (0.083)	-0.866*** (0.085)	-0.882*** (0.857)
Employment in 1990	-0.008*** (0.001)	-0.006*** (0.001)	-0.017*** (0.001)	-0.021*** (0.001)
U.S. Employment growth	0.965*** (0.014)	0.960*** (0.013)	0.919*** (0.014)	0.925*** (0.014)
Earnings per worker	0.112*** (0.009)	0.110*** (0.009)	0.085*** (0.009)	0.088*** (0.009)
Specialisation	0.003*** (0.001)			0.007*** (0.001)
Competition		0.000 (0.000)		0.000 (0.000)
Diversity			0.047*** (0.004)	0.053*** (0.004)
South dummy	0.010* (0.005)	0.011** (0.005)	0.021*** (0.005)	0.021*** (0.005)
N	61,480	61,480	61,480	61,480
F statistics	281.08***	281.58***	280.35***	281.72***

Note: Standard errors of the parameter estimates are in parentheses. Significance at the 1%, 5%, and 10% level is signalled by ***, **, and *, respectively. All models are estimated, accounting for sector fixed-effects.

The first result to highlight is that all of the control variables have the predicted signs and they are statistically significant at conventional levels, indicating that high initial employment leads to slower growth; employment growth at the county level is higher when national employment grows, and high earnings per worker are associated with faster growth. In the last estimation (Column 4) the Southern counties exhibit faster employment growth than counties elsewhere in the United States. As expected, all these results—for the control variables—confirm the findings of Glaeser et al. (1992).

With regard to spatial externalities of knowledge spillovers, it is worth noting that the diversity and specialisation variables yield positive and statistically significant effects on employment growth. These results are similar to the results obtained by Bishop and Gripaos (2010), but only marginal to those from Glaeser et al. (1992). In our case, specialisation has a positive effect and provides evidence along the lines of MAR theory. Competition appears very minimal and insignificant in opposition to Porter's argumentation.

In addition to the results for the pooled data for all 20 NAICS sectors (Table 2), we present the estimation results for the version based on pooled data for the six aggregated sectors (Table 3). Columns 1–4 are defined as in Table 2, while Column 5 presents the model extended with technological catch-up. As before, the control variables show the expected signs. Now, the spatial externality measures show a negative and statistically significant effect for specialisation in Models 1 and 4, but for the comprehensive model, including human capital, geographical and technological effect, the role of specialisation becomes positive with a slightly higher magnitude. While the results from Models 1–4 provided evidence against the MAR theory, Model 5 (comprehensive and accounting for agglomeration effects) provides support to the thesis that regional specialisation through high concentration leads to

TABLE 3 Pooled regression, six aggregated sectors

	Dependent variable: Employment growth				
	(1)	(2)	(3)	(4)	(5)
Constant	−0.605*** (0.059)	−0.689*** (0.058)	−0.703*** (0.058)	−0.661*** (0.059)	−1.496*** (0.082)
Employment in 1990	−0.066*** (0.003)	−0.061*** (0.003)	−0.090*** (0.003)	−0.077*** (0.003)	−0.055*** (0.003)
U.S. employment growth	0.010*** (0.000)	0.010*** (0.003)	0.010*** (0.000)	0.010*** (0.000)	0.010*** (0.000)
Earnings per worker	0.086*** (0.006)	0.092 (0.006)	0.098*** (0.006)	0.090*** (0.006)	0.041*** (0.006)
Specialisation	−0.005*** (0.000)			−0.002*** (0.000)	0.007*** (0.000)
Competition		0.003*** (0.000)		0.003*** (0.000)	0.003*** (0.000)
Diversity			0.012*** (0.000)	0.010*** (0.000)	0.005*** (0.000)
Human capital					0.315*** (0.016)
Geographical distance					−0.022*** (0.006)
Technological distance					0.570*** (0.025)
South dummy	0.005 (0.059)	0.006 (0.003)	0.013*** (0.003)	0.14*** (0.003)	0.068*** (0.004)
N	18,444	18,444	18,444	18,444	18,444
F statistics	499.43***	637.32***	691.95***	524.61***	647.65***

Note: Standard errors of parameters estimates are in parentheses. Significance at the 1%, 5%, and 10% level is signalled by ***, **, and *, respectively. All models are estimated, accounting for sector fixed-effects.

employment growth. Competition and diversity consistently show positive and statistically significant impact on employment growth in all models, providing support to the Porter's and Jacobs' on competition, and support to Jacobs' in terms of diversity as in Feldman and Audretsch (1999, p. 419) where using city level data they provide considerable support for the diversity thesis. Notice as well that Model 4 in Table 3 (pooled six aggregated sectors) is consistent with Model 4 in Table 2 (pooled 20 NAICS sectors), in all estimated coefficients. The only exception is the Specialisation coefficient that now has the reverse sign. Also, results in Model 4 (Table 3) support the findings on Glaeser et al. (1992).

Now, when we introduce the spatial considerations, with regard to the role of technological leadership, we obtain—unexpectedly—negative and significant association between the geographical distance to the leader and employment growth. Intuitively, the reader needs to remember that we use an inverse distance function and therefore expect it to be positively associated with employment growth. On the other hand, the estimates for the technological distance are positive and significant, indicating as expected that those located further away from the

technology leader will tend to benefit the most from a possible catching-up effect, and consequently experience higher growth in employment. As expected, the coefficient of Human capital is positive and highly significant. That is, higher levels of human capital result in positive externalities that are conducive to higher employment growth. Finally, the estimates obtained from the pooled regressions can be seen as an overall association with employment growth. However, they cannot necessarily be generalised to all sectors. It is likely that the role of geographical and technological distances to the technology leader is different across sectors.

4.2 | Sectorial results

To uncover issues of knowledge spillovers and spatial dependence, we tease the data to further explore the validity of our model and we now apply the same estimation procedure (as reported in Tables 2 and 3), to each of the aggregated sectors defined in Table 1a. Estimation results for each of the aggregated sector are reported in Table 4. We replicate Glaeser et al (1992) model in Table 4—columns (a) showing the OLS estimates for the basic model extended with the spatially lagged versions of the externality variables used to account for agglomeration economies. Columns (b) provide the extension of the Glaeser et al (1992) model accounting for human capital, geographical distance and technological distance. Based on the spatial diagnostic statistics of the model in column (b), the appropriate spatial process is presented in columns (c). Given the likely endogeneity related to the consideration of specialisation-like measure to define the technological distance, estimated coefficients presented in columns b and c of Table 4 are interpreted in terms of association with employment growth rather than causal effects.¹²

The sectorial estimations provide some interesting exploratory results as we find that not all sectors are affected in the same way by the dynamic externalities knowledge spillover process. Also, the results of the six aggregated sectors are different from those obtained for the pooled version (Table 3). Primarily, this means that the standard assumption that the transmission, adoption and incorporation of externalities relating to knowledge spillovers are different and specific to each economic sector holds. For instance, the expected negative association with initial employment holds for almost all aggregated sectors. Second, the expected positive association with earnings per worker is observed in all sectors except a few, where it is either negative or insignificant. The South dummy variable is also positive and significant for almost all sectors.

As we test the MAR; Porter; and Jacobs theories of dynamic externalities of knowledge spillovers, we find robust evidence of a negative association with specialisation across all the aggregated sectors; confirming previous results obtained earlier for the pooled models. County level data provide sufficient evidence against the MAR predictions of regional specialisation leading employment growth. Of particular relevance is the case where a negative sign is indicative of competition in terms of externalities across counties, whereas a positive sign may point to externalities being relevant at a higher spatial scale level than the county alone. We find positive and significant evidence in favour of Porter's and Jacobs' competition argumentation, only for the sectors "Information and Utilities," and "Finances and Management." In these sectors, the intuitive argumentation would indicate that smaller firms would imply faster growth. For the other sectors with negative estimated coefficient ("Services" and "Construction and Manufacturing") the reverse argument implies that large firms—perhaps those in industries marked by economies of scale—would favour faster employment growth. Unexpectedly, evidence of spatial externality of diversity is observed only in the sectors "Natural resources" and "Transportation and Trade." In all these aggregated sectors, the association between employment growth and competition is significant (except the "Natural Resource" sector).

¹²Only estimates in columns c are discussed. Estimates in columns b are shown to indicate the appropriate spatial process presented in columns c.

Dependent variable: Employment growth

[illegible]

TABLE 4 (Continued)

Dependent variable: Employment growth									
	Natural resources			Construction & manufacturing			Transportation & trade		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Technological distance		-0.264* (0.156)	-0.303** (0.142)		-0.558 (0.165)	-0.013 (0.025)		0.123* (0.075)	0.220*** (0.07)
South dummy	0.033 (0.022)	0.077*** (0.026)	0.044 (0.037)	-0.075*** (0.025)	0.099*** (0.027)	-0.017 (0.015)	0.046*** (0.014)	0.149*** (0.016)	0.112*** (0.027)
Spatial error parameter			0.50*** (0.041)			0.32*** (0.04)			0.62*** (0.034)
Diagnostic statistics									
Moran's I		0.07***			0.08***			0.13***	
LM-Error		171.176***			201.528***			557.574***	
Robust LM-Error		11.284***			89.280***			74.321***	
LM-Lag		160.004***			114.898***			486.460***	
Robust LM-Lag		0.112			2.650*			3.206*	
LM-SARMA		171.288***			204.178***			560***	
Constant	-4.652*** (0.419)	-6.761*** (0.576)	-7.635*** (0.613)	-1.138*** (0.328)	-5.143*** (0.461)	-6.029*** (0.511)	0.129 (0.238)	-2.297*** (0.323)	-3.218*** (0.366)
Employment in 1990	-0.137*** (0.011)	-0.134*** (0.011)	-0.148*** (0.011)	-0.041*** (0.009)	-0.038*** (0.009)	-0.049*** (0.009)	-0.005 (0.007)	-0.019*** (0.007)	-0.028*** (0.007)
Earnings per worker	0.540*** (0.045)	0.514*** (0.045)	0.551*** (0.047)	0.172*** (0.036)	0.075** (0.035)	0.086** (0.036)	0.059** (0.026)	0.007 (0.027)	-0.006 (0.026)
Specialisation	-0.209*** (0.015)	-0.284*** (0.29)	-0.278*** (0.029)	-0.674*** (0.035)	-1.069*** (0.066)	-1.060*** (0.066)	-0.343*** (0.032)	-0.171* (0.092)	-0.173* (0.093)
Competition	0.008*** (0.002)	0.006*** (0.002)	0.007*** (0.002)	0.011*** (0.001)	0.010*** (0.001)	0.011*** (0.001)	-0.006 (0.004)	-0.014*** (0.004)	-0.009*** (0.004)

Diversity	0.040*** (0.006)	0.038*** (0.006)	0.035*** (0.006)	0.042*** (0.005)	0.036*** (0.005)	0.034*** (0.005)	0.015*** (0.004)	0.011*** (0.004)	0.012*** (0.003)
Lag specialisation	0.041 (0.051)			0.301*** (0.093)			0.318*** (0.065)		
Lag competition	-0.010** (0.005)			-0.006* (0.003)			-0.111*** (0.015)		
Lag diversity	0.017 (0.014)			0.007 (0.011)			-0.022** (0.009)		
Human capital		0.433*** (0.111)	0.597*** (0.121)		0.979*** (0.084)	1.132*** (0.093)		0.502*** (0.063)	0.745*** (0.071)
Geographical distance		-0.012 (0.017)	0.005 (0.026)		0.014 (0.023)	-0.022 (0.032)		-0.014*** (0.013)	-0.158*** (0.022)
Technological distance		-0.884*** (0.323)	-0.876** (0.319)		-1.011*** (0.15)	-0.987*** (0.148)		0.215* (0.121)	0.301*** (0.119)
South dummy	0.061** (0.026)	0.129*** (0.031)	0.130*** (0.041)	0.064*** (0.021)	0.221*** (0.027)	0.207*** (0.034)	0.169*** (0.017)	0.157*** (0.018)	0.127*** (0.030)
Spatial error parameter			0.40*** (0.046)			0.38*** (0.046)			0.63*** (0.034)
Diagnostic statistics									
Moran's I		0.06***			0.06***			0.15***	
LM-Error		104.913***			136.912***			719.679***	
Robust LM-Error		59.947***			113.330***			247.400***	
LM-Lag		60.226***			50.839***			500.969***	
Robust LM-Lag		15.261***			27.257***			28.690***	
LM-SARMA		120.173***			164.169***			748.369***	

Note: Standard errors of parameter estimates are in parentheses. Significance at the 1%, 5%, and 10% level is signalled by ***, **, and *, respectively. The number of observations is 3074.

It is interesting to note that in the sectorial models, human capital has a consistently significant and positive association with employment growth. The observed positive association with human capital corresponds to previous findings of Shapiro (2006) and Poelhekke (2013). As it was noted earlier in the paper, we argued that given the spatial consideration and the geographical and technological distance to the leader, spatial dimensions must be relevant in explaining employment growth at lower levels of data aggregation. To test the validity of the proposed model specification, we conduct an OLS estimation of the (extended) Glaeser et al. (1992) models for all six aggregated sectors. The spatial estimation shows a positive and significant Moran's I , indicating the presence of spatial autocorrelation. The Lagrange Multiplier tests—error and lag—were all significant and their robust form as well. It is interesting to note that for all six aggregated sectors, the LM-error is always higher in magnitude than the LM-lag, and therefore the model with spatial autoregressive error process is deemed appropriate (column c).¹³

The role of geographical and technological distances from the leader yield mixed results across the six sectors. This is also a major and relevant result from our research. Not all sectors respond in the same direction and magnitude as it relates to geographical and technological dispersion. In this context, a positive and significant association with geographical distance is observed for the sectors “Natural Resources” and “Construction and Manufacturing” while a significantly negative association is obtained for “Transportation and Trade” and “Services.” The association with geographical distance to the leader is not statistically different from zero for the “Finance and Management” and “Information and Utilities” sectors. One can only speculate as to why the results appear like this. First, the location and degree of specialisation in the sectors “Natural Resources” and “Construction and Manufacturing” is mainly dominated by geography and the availability of natural resources and infrastructures. As a result, these sectors are generally not footloose, and it is therefore difficult to overcome locational disadvantages in terms of being located further away from the technology leader. That is, these sectors have a location specific advantage that is spatially dependent and not necessarily related to efficiency gains, but related to agglomeration economies. Second, the economic geography of the sector “Finance and Management” is such that the level of aggregation may be too high to observe an easily interpretable association. Finally, the insignificant association with geographical distance for the sector “Information and Utilities” may be explained by the development in information and communication technologies, which allows innovations to be transferred more easily and cheaper across regions regardless of physical distance. In this regard, Feldman and Audretsch (1999) note that information use is less location-specific than knowledge creation. Obviously, the differentiation in the effects of geographical distance warrants further investigation. This is currently outside the scope of this paper, but a relevant topic for future research.

Finally, with respect to the role of technological distance on employment growth, we observe a positive and statistically significant association in “Transportation and Trade” and “Services sectors.” But the association with technological distance is statistically not significant in the “Construction and Manufacturing” sector. A positive association with the technology gap variable suggests that backwardness—a large initial difference in technological sophistication as compared to the technology leader—represents an advantage for faster growth. The insignificant association with technological distance for employment growth in the “Construction and Manufacturing” sector may be due to the fact that technological progress in this sector is primarily driven by national rather than local or regional technological progress. Furthermore, the magnitudes of the estimated coefficients are different, with “Information and Utility,” and “Finance and Management” holding a larger (about 3–4 times fold) coefficient in comparison to “Transportation and Trade,” and “Services.” In addition, these coefficients are in the opposite direction. In other words, marked differences should be expected in the determinants of employment growth across sectors as the evidence indicates.

¹³Given that the LM-error and LM-lag are significant together with their robust form, one could argue that the appropriate spatial process is the ARAR model, which incorporates an error process and autoregressive lag progress. We have also estimated the ARAR model for all six aggregated industries, but the estimated spatial lag parameter was either negative or insignificant. Therefore, the spatial error process stands.

5 | CONCLUSION

The empirical estimates in this paper allow for some exploratory and tentative conclusions. We demonstrate that spatial dependence considerations are relevant in explaining sectorial employment growth differences when using data disaggregated at the county level. First, our empirical estimates indicate the presence of statistically significant differences across economic sectors in terms of the capabilities for knowledge spillovers to be fully absorbed and translate into higher employment. In general, we find that regional diversity tends to promote its own growth, while the estimates for regional specialisation and competition provide mixed results that are specific at the sectorial level. In this regard, our analysis provides mixed support to the three alternative theories of dynamic externalities, with results being particular at the sectorial level of data aggregation. In addition, this paper finds evidence supporting our hypotheses that space, human capital and technological leadership are relevant determinants of sectorial employment growth, at a spatially and sectorially disaggregated level. However, conclusions regarding the association with geographical and technological distance to the technology leader vary across sectors. Finally, while our paper makes use of data from the United States exclusively, we hypothesise that the lessons learned could be very applicable to other cases where KSE are present and where economies search for mechanisms to expand knowledge. Future research in the field of technological leadership and catching up process will prove essential to continue understanding their effects on employment growth.

DATA AVAILABILITY STATEMENT

Data is available from the authors upon written request.

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How to cite this article: Pede VO, Florax RJGM, de Groot HLF, Barboza G. Technological Leadership and Sectorial Employment Growth: A Spatial Econometric Analysis for U.S. Counties. *Economic Notes*. 2021;50: e12178. <https://doi.org/10.1111/ecno.12178>