AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

Global Trade Analysis Project
https://www.gtap.agecon.purdue.edu/

This paper is from the
GTAP Annual Conference on Global Economic Analysis
https://www.gtap.agecon.purdue.edu/events/conferences/default.asp

Technological Leadership and Sectoral Employment Growth: A Spatial Econometric Analysis for U.S. Counties.

Valerien O. Pede
Social Sciences Division, International Rice Research Institute
Los Banos, Philipines, v.pede@cgiar.org

Raymond J.G.M. Florax
Department of Agricultural Economics, Purdue University
West Lafayette, IN 47907, USA, rflorax@purdue.edu
Department of Spatial Economics, Vrije Universiteit
De Boelelaan 1105, 1081 HV
Amsterdam, The Netherlands

Henri L.F. de Groot
Department of Spatial Economics, Vrije Universiteit
De Boelelaan 1105, 1081 HV
Amsterdam, The Netherlands, hgroot@feweb.vu.nl

Abstract:
This paper investigates the determinants of the technological catch up process and examines to what extent geographical and/or technological proximity to the technology leader impact regional employment growth. The employment growth impacts of technological and geographical proximity to the technology leader are examined at a reasonably low level of spatial aggregation, with sufficient attention to sectoral differences and the role of space. The theoretical framework builds on Glaeser et al. (1992), in which employment growth depends on technological progress. Technological progress is endogenously determined and depends on agglomeration economies, specifically specialization, competition and diversity. We extended the Glaeser et al. (1992) theoretical framework by first considering that technological progress also depends on the characteristics of the agglomeration economies in proximate regions. Next, we considered that technological progress depends on a hierarchical process of catch-up to the technology leader, following previous work by Benhabib and Spiegel (1994). The methodology is applied to data of U.S. counties in the lower 48 states, and we consider two-digit industries following the NAICS classification. Results indicate that human capital plays a crucial role in promoting sectoral employment growth. The effect of technological distance varies, depending on which sector is considered. Technological distance to the leader shows a positive and significant effect on employment growth in the sectors Construction & Manufacturing, Information & Utilities, and Services. No effect of technological distance was noticed for Finance & Management, Transportation & Trade, and Natural Resources. The effect of geographical distance to the technology leader on employment growth also varies across sectors. A negative effect is observed for Construction & Manufacturing and Finance & Management. The effect of geographical distance is positive for Natural Resources and Transportation & Trade. No significant effect of geographical distance was observed for Information and Utilities and Services.

Keywords: regional employment growth, technology leadership, space, spatial econometrics
JEL Classification: R11, R12, C21, O32, O47

1. Introduction

Investigating the process of economic growth across countries of the world has long been a research tradition in economics. However, in the most recent literature there has been a tendency to focus on lower levels of spatial aggregation, such as counties in the U.S. and NUTS 2 regions in the European Union (E.U.).[1] Typically, many of these studies used spatial econometric techniques and focused on capturing the geographical dimension of growth and convergence (Abreu et al., 2005a,b). In addition, a seminal contribution by Bernard and Jones (1996) initiated a discussion as to which sectors are driving the overall productivity convergence result (Sørensen, 2001; Bernard and Jones, 2001).

In the U.S., many studies used states and Metropolitan Statistical Areas (MSA), and to some extent counties, as their spatial unit of observation. Meanwhile sectorally disaggregate studies of economic growth at these levels of spatial aggregation are scarce; exceptions include Bernard and Jones (1996) and Barro and Sala-i-Martin (1991). The relevance of technological distance to the technology leader has been shown to determine economic growth through catch-up processes in cross-country studies (Nelson and Phelps, 1966; Benhabib and Spiegel, 1994). Moreover, several cross-country studies have shown evidence for positive effects of human capital on growth (Mankiw et al., 1992; Islam, 1995; Temple, 1999b), although some studies have also reported a negative correlation with human capital (see, for instance, Benhabib and Spiegel, 1994; Middendorf, 2005; Arcand and d'Hombres, 2007) or no association at all

[1] The appropriate level of spatial aggregation to study the determinants of economic growth constitutes an unresolved issue in the literature. Lower levels of spatial aggregation such as sub-national regions are likely to exhibit a higher mobility pattern of labor, capital and knowledge flows. Therefore, theories developed for cross-country analysis of economic growth cannot simply be applied to lower levels of spatial aggregation. Magrini (2004) provides a discussion of problems associated with the application of cross-country neoclassical growth theories in regional growth analysis.

(Pritchett, 1996).[2] Meanwhile, little is known about the determinants of technological leadership and their implications for regional economic performance, in particular for sectoral employment growth.[3] The existing literature has mainly focused on investigating the effects of agglomeration economies on sectoral employment growth or productivity growth (Glaeser et al., 1992; Bishop and Gripaios, 2009; Shearmur and Polèse, 2005; Frenken et al., 2007; Blien et al., 2006). However, the impacts of the technological and geographical distances of regions to technology leaders remain an important issue in explaining employment growth that has not been fully addressed in the existing literature.

This paper therefore focuses on the issues of space, human capital and technological leadership as determinants of sectoral employment growth, at a spatially and sectorally disaggregated level. The main goal is to uncover the driving forces governing sectoral employment growth. Specifically, we investigate the determinants of technological leadership and analyze their implications for sectoral employment growth. The impact of technological leadership on growth is investigated from the perspective of geographical proximity to the technology leader, as well as technological proximity to the technology leader. Geographical distance refers to the physical proximity of a region to the technology leader. Technological distance describes the difference in technology levels between two regions, irrespective of their physical distance from one another. Each measure of distance potentially plays a role in explaining regional employment growth (Peretto and Smulders 2002; Lynskey, 2001). However, the precise impact of geographical and/or technological proximity to the technology leader

[2] The ultimate link between human capital and growth remains controversial. Results obtained depend on the definition of human capital, the methodology used, the time period of the study and estimations methods (see Savvides and Stengos, 2009, for a review).

[3] In the remainder of this chapter we follow the employment growth model of Glaeser et al. (1992). One should note that they use employment growth as a proxy for productivity growth.

remains unclear, in particular at lower levels of spatial aggregation such as counties in United States.

In this paper we model a growth process in which spatial dependence between regions and spatial externalities related to technology diffusion are accounted for. Economic data at the county level over the period 1990–2008 are considered. In order to account for sectoral differences, the proposed growth model is applied to two-digit NAICS industries.

2. Sectoral Productivity Growth, Human Capital and Technological Leadership

The economic literature has devoted substantial attention to the study of economic growth and total factor productivity in a cross-country setting. Most studies focus on aggregate data for national economies, although a few studies utilize disaggregate levels of spatial aggregation. For instance, Dollar and Wolff (1993) examine the productivity growth in individual industries and the process of convergence of overall productivity growth for a set of developed countries. They observe that in 1963, the U.S. led in labor productivity for all manufacturing industries, but over the period 1963–1986, labor productivity of the other countries converged to the U.S. level in virtually every industry at different rates.

Other studies concentrate on sectoral convergence within specific regions or countries. For instance, sectoral convergence at the regional level in Europe has been addressed in a number of studies (Le Gallo and Dall'erba, 2006; Ertur et al., 2006; Paci and Pigliarou, 1997). Paci and Pigliarou (1997) stress the importance of the continuous process of sectoral reallocation of resources that accompanies economic growth. They argue that aggregate convergence is largely a matter of structural change with a transitory shift from agriculture to manufacturing. In the same vein, Paci and Pigliarou (1999) criticize the neglect of the role played by sectoral mix and structural change on aggregate growth, claiming that sectoral analysis definitively matters in determining aggregate growth across European regions. Cuadrado-Roura et al. (1999) study productivity convergence in Spain and likewise emphasize the importance of a sectorally disaggregated analysis. They argue that aggregate convergence is the result of gradual homogenization of regional productivity structures, and they stress the need for convergence analyses to be appropriately focused on sectors. More recently, Le Gallo and Dall'erba (2006) adopt a spatial approach to study productivity convergence between European regions. They find variability between core and peripheral regions in terms of labor productivity and convergence, and show that convergence speeds differ among sectors.

In the U.S., fewer studies have been conducted to examine sectoral convergence. In an early attempt, Barro and Sala-i-Martin (1991), investigate convergence across U.S. states within eight non-agricultural industries using gross state products provided by the Bureau of Economic Analysis (BEA) for the period 1963–1986. They find convergence occurring at a similar rate in all industries except manufacturing, which converges at a faster rate. Similarly, Bernard and Jones (1996) employ cross-sectional and time series techniques to investigate convergence across U.S. states and industries in terms of gross state product. Using a longer data series than Barro and Sala-i-Martin (1991), these authors find that both cross-sectional and time series techniques provide evidence of convergence in manufacturing and mining sectors, but there is no evidence of convergence in construction and wholesale/retail sectors, while results are mixed for the sectors transportation and services. Bernard and Jones (1996) point to differences in the data to reconcile the substantial difference of their results in comparison to those previously obtained by Barro and Sala-i-Martin (1991). Magura (1999) focused on eight sectors in eight Midwestern states from the same dataset as Bernard and Jones (1996). He employed both cross-section and time series techniques and found evidence of convergence at the aggregate level. However, he found evidence of convergence in manufacturing but not in the non-manufacturing sectors and service sectors, unlike Bernard and Jones (1996). Growth convergence within specific sectors has also been studied. For instance, McCunn and Huffman (2000) used data from the period 1950–1982 and found evidence of convergence in U.S. total factor productivity growth in agriculture. More recently Liu et al. (2008) used cointegration techniques on panel data for the 48 U.S. states over the period 1960–1999, and found evidence of convergence in the agricultural sector.

All these studies stress the relevance of a sectoral analysis of productivity growth. However, given the differences across sectors laid out in these studies, we are interested in exploring to what extent technological leadership and agglomeration forces play a role in regional economic performance. The unequal distribution of productivity levels is to a considerable extent due to disparities in technology levels and capital intensity. At the country level, the aggregate level of technology, often measured in total factor productivity, was shown to vary considerably (Dollar and Wolff, 1993). While some regions or countries are leading in technology, others are lagging behind. For instance, considering total factor productivity of countries of the world, the U.S. is often viewed as the technology leader, and its lead has been maintained for several decades. Focusing on labor productivity rather than total factor productivity, Dollar and Wolff (1993) study a sample of 13 industrialized countries and find that the U.S. has maintained the lead in labor productivity for all manufacturing sectors over the entire period 1963–1986. Technological leadership can be seen as dominance or advance in terms of technological sophistication or high efficiency in the use of inputs. The technology leader exhibits the highest productivity level and other regions may catch-up to its productivity level. The catch-up process involves gravitation towards both technological sophistication and likely also the capital intensity of the leader. For instance, Dollar and Wolff (1993) observe a homogenization of technological sophistication and capital intensity in their sample of countries, with the latter being much stronger.

Catch-up to the productivity level of the technology leader is likely to be determined by the technology and human capital available to the follower. Focusing on the manufacturing industry in Spanish NUTS II regions, López-Bazo et al. (2007) observe that human capital and innovation are positively and significantly related to productivity growth. They emphasize the importance of investment in Research and Development (R&D) for the formation of human capital stock and generating returns to innovation, which both contribute positively to productivity growth. Technology and human capital are also related. Nelson and Phelps (1966) postulate that the rate of adoption of a new technology depends on the ability of regions to implement new ideas and the gap between the theoretical level of technology and the level of technology in practice. In other words, regions adopt technologies based on their level of human capital and their actual technological gap with the leader.

Human capital enhances the ability of a region to develop its own technology but also to implement technologies developed elsewhere, thereby contributing to improving productivity growth. Benhabib and Spiegel (1994) corroborated this assertion. They maintain that the ability of a country or region to catch-up to the productivity level of the leader depends on its stock of human capital. They extend Nelson and Phelps' idea by introducing the notions of domestic innovation and catch-up. Domestic innovation represents endogenous technological progress or the ability of a region to innovate domestically, while the catch-up effect pertains to the diffusion of technology from the leader.

The spillover of human capital and the diffusion of technology across regions confer a spatial dimension to the economic growth process. Indeed, the human capital produced in a specific region may have an impact in other regions, and vice versa. Also, with the diffusion capability of technologies, externalities are expected to spill over across regions (López-Bazo et al., 2006). Spatial effects through human capital and technology diffusion, taking the form of spatial dependence and spatial heterogeneity in economic growth processes, have largely been supported in the literature (Temple, 1999b; Conley and Ligon, 2002; Ertur and Koch, 2006, 2007).

It should be noted that even although the determinants of catch-up have been investigated in cross-country analyses, the direct implications of technological leadership for productivity growth still remain unclear. The impacts of geographical and technological distances to the technology leader on sectoral productivity growth remain particular aspects that have not been clarified. The current paper is placed within this context and proposes to uncover the role of geographical and technological distances to the technology leader on sectoral employment growth.

On the basis of the prediction of the neoclassical growth theory, it can be expected that economies that are more similar to a technology leader in a technological sense may grow slower, whereas those that are more dissimilar will grow faster. Also, regions located geographically close to the technology leader may benefit more due to the ease of knowledge transfers, while those located further away may benefit less of the technology advances of the technology leader depending on the opportunity costs associated with acquiring the technology leader’s capabilities.

Table 1 shows the expected growth pace of regions depending on their geographical and technological proximity to the leader. We hypothesize that regions with low initial productivity and located close to the leader will exhibit the highest growth pace, while those with high productivity and located further away from the leader will exhibit the slowest growth pace. In between, the high productivity regions located far away from the leader will grow relatively slower than the high productivity regions located close to the leader, *ceteris paribus*. Similarly, the low productivity regions located far away from the leader will grow relatively slower than the low productivity regions located close to the leader, *ceteris paribus*.

Table 1: Technological Leadership and Expected Growth Rate.

	Geographical distance to the leader	
Technological distance to the leader	short	Long
High productivity (short)	–	– –
Low productivity (long)	++	+

Note: + fast, ++ fastest, – slow, – – slowest.

3. Econometric Model

In this section we introduce the theoretical and econometric model, and discuss the estimation procedure. Data used in this paper and their sources are also described in this section.

3.1 Operational Specification

The econometric model builds on Glaeser et al. (1992), and extends their approach by accounting for regional in addition to local and national technological progress as well as for catch-up to the technology leader. We start by considering a simple firm production function in which output depends on technology and labor. The model reads as:

$$y_{it}^{s} = A_{it}^{s} f\left(l_{it}^{s}\right), \tag{1}$$

where y_{it}^{s} represents output, l_{it}^{s} is labor input, and A_{it}^{s} is the level of technology, all at time *t* for a representative firm in region *i* and in a specific sector s. Considering firms are competitive, profits are given as:

$$\pi_{it} = A_{it}^{s} f\left(l_{it}^{s}\right) - w_t l_{it}^{s}, \tag{2}$$

with w_t representing the spatially uniform wage rate at time *t*, and taking the price of the final product as numeraire.

Taking the first-order condition for profit maximization yields:

$$A_{it}^{s} f'\left(l_{it}^{s}\right) = w_t, \tag{3}$$

and taking the difference in logarithms of the terms in equation (3) between the initial period (*t*) and the end period (*t* +1) leads to:

$$\log\left(\frac{A_{it+1}^{s}}{A_{it}^{s}}\right) = \log\left(\frac{w_{t+1}^{s}}{w_t^{s}}\right) - \log\left(\frac{f'\left(l_{it+1}^{s}\right)}{f'\left(l_{it}^{s}\right)}\right). \tag{4}$$

Assuming that $f(l_t) = l^{1-\alpha}$ with $0 < \alpha < 1$, the following equation is obtained:

$$\alpha \log\left(\frac{l_{it+1}^{s}}{l_{it}^{s}}\right) = \log\left(\frac{A_{it+1}^{s}}{A_{it}^{s}}\right) - \log\left(\frac{w_{t+1}^{s}}{w_t^{s}}\right). \tag{5}$$

In the case where the labor market is functioning perfectly, wage levels are the same across space and they grow at a constant rate. Therefore the model implies that employment growth is explained by technological progress. Following Glaeser et al. (1992) we consider the overall technology level to have a local and a national component. The overall level of technology available to a representative firm in region *i* can be written as:

$$A_{it}^{s} = A_{local,it}^{s} \cdot A_{national,it}^{s}, \tag{6}$$

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*. At the end period *t* +1, the level of technology is given as:

$$A_{it+1}^{s} = A_{local,it+1}^{s} \cdot A_{national,it+1}^{s}, \tag{7}$$

and taking the ratio between (7) and (6) yields:

$$\frac{A_{it+1}^{s}}{A_{it}^{s}} = \frac{A_{local,it+1}^{s}}{A_{local,it}^{s}} \cdot \frac{A_{national,it+1}^{s}}{A_{national,it}^{s}}. \tag{8}$$

Taking logs between the initial and the end period provides the expression for overall technological progress as:

$$\log\left(\frac{A_{it+1}^{s}}{A_{it}^{s}}\right) = \log\left(\frac{A_{local,\ it+1}^{s}}{A_{local,it}^{s}}\right) + \log\left(\frac{A_{national,\ it+1}^{s}}{A_{national,it}^{s}}\right). \tag{9}$$

Equation (2.9) suggests that the overall progress in technology depends on local technological progress, and the change in nationwide technology.

Following Glaeser et al. (1992) we assume that the growth of national technology is uniform across regions, and local technological progress is related to three types of externalities: specialization, competition and diversity. Consequently, we can specify local technological progress as:

$$\log\left(\frac{A^{s}_{local,\ it+1}}{A^{s}_{local,it}}\right) = g\left(SP_{it}, CP_{it}, DV_{it}\right), \qquad (10)$$

where SP_{it} represents specialization, CP_{it} competition, and DV_{it} diversity, all at time *t* in region *i*.

Following the Glaeser et al. analysis, we also include a number of control variables in the model: the log of earnings,[4] the log of employment in the initial period, and a regional dummy variable indicating a southern region. The initial wage is included in order to account for differences in initial (regional) productivity levels. The initial employment is used to account for a general process of convergence. It is expected that high initial employment will reduce employment growth because of either measurement error or unspecified economic factors correlated with initial employment. The regional dummy variable is used to control for spatial heterogeneity, because fast-growing counties tend to be located in the South, whereas slow-growing counties are located on the East and West coast and in some areas of the Midwest.[5] We also control for the growth of national employment in the pooled sector model to correct for output demand shifts (Terkla and Doeringer, 1991; Blanchard and Katz, 1992).

We extend the Glaeser et al. model in two different ways. In the first extension, we propose that regional employment growth does not only depend on local and national technology progress, but 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 neighboring regions are taken into account (see Bishop and Gripaios, 2009, for a similar line of reasoning). Mathematically, this implies that in addition to local variation in

---

[4] Glaeser et al. (1992) used wages but due to data limitations, we consider earnings, specifically earnings per worker.
[5] The dummy variable South (= 1) is defined as South East and South West counties.

specialization, competition and diversity, we also account for these characteristics in neighboring regions. Local technological progress can therefore be written as:

$$\log\left(\frac{A^{s}_{local,\ it+1}}{A^{s}_{local,it}}\right) = g\left(SP_{it}, CP_{it}, DV_{it}, w_{i\cdot} \cdot SP_{t}, w_{i\cdot} \cdot CP_{t}, w_{i\cdot} \cdot DV_{t}\right), \tag{11}$$

where $w_{i.}$ represents the *i*-th row of an exogenously defined spatial weights matrix *W*, and all other variables are defined as before. This specification thus replaces the original specification given in equation (10). The notion underlying this specification refers to a contagious process, which is purely based on distance, of spatial spillovers in the drivers of technological change. Local technological progress depends on local characteristics of specialization, competition and diversity as well as on the same type of characteristics of proximate neighbors.

In the second variant, we emphasize an alternative view on technology creation and diffusion. We hypothesize that local technological progress depends on local characteristics in terms of specialization, competition and diversity, but in addition we allow for a hierarchical process of catch-up to the technology leader. Following earlier work on technology catch-up by Benhabib and Spiegel (1994), the technology leader should ideally be characterized as the region with the highest productivity level (in a specific sector). Unfortunately, regionally disaggregated productivity data are not available at the level of industries. We therefore use a specialization-like measure to define the technology leader as the region with the highest employment share in a specific sector as compared to total employment in the local economy. This is obviously all but 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. High specialization of a region in a sector could well be because the region uses the technology more efficiently. Indeed, when industries of the same type are concentrated in a region, agglomeration economies are likely to occur and will promote the economic performance of the region. In particular economies of scales are likely to occur in such an environment characterized by the concentration of similar industries. Possible sources of these economies of scales are: information spillovers, local non-traded inputs, and local skilled labor pool. The specialization of certain region in a particular industry could therefore represent an incentive for innovation. Evidence of the positive relationship between specialization and innovation output has been supported in the literature (see for example Paci and Usai, 2000a,b; Greunz, 2004). For instance Paci and Usai (2000b) noticed that regions that are specialized in a particular industry tend to have higher innovative activities. More recently, Fritsch and Slavtchev (2007) used the Regional Innovation System (RIS) that captures technical efficiency (defined as the generation of maximum output from a given amount of resources) to test the impact of specialization on regional innovative performance. Their conclusion shows that regional specialization, to a certain degree is conducive to performance in terms of efficiency. Based on these findings, we consider that the degree of specialization captures to some extent technical performance, and can therefore be used to define technological leadership within specific sectors. However, it should be noted that this measure of technological leadership is not perfect. In some industries, high level specialization may not necessarily be evidence of technological leadership. Large sectors may not necessarily exhibit high productivity levels. It should also be acknowledged that the high specialization in some regions may simply be due to revealed comparative advantage.

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 therefore hypothesize that local technological progress, as an alternative to the specifications in equations (10) and (11), can be specified as:

$$\log\left(\frac{A^{s}_{local,\, it+1}}{A^{s}_{local,it}}\right) = g\left(SP_{it}, CP_{it}, DV_{it}, H_{it}, GD_{i,max}, TD_{it}\right), \tag{12}$$

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

$$GD_{i,\max} = \frac{1}{d_{i,\max}}, \tag{13}$$

with $d_{i,\max}$ being the physical distance to the region identified as the technology leader. 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:

$$TD_{it} = \left(\frac{l^{s}_{it}}{L_{it}}\right)_{\max} - \left(\frac{l^{s}_{it}}{L_{it}}\right), \tag{14}$$

where l^{s}_{it} 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*. This definition of technological progress follows partly from the idea of Benhabib and Spiegel (1994) who stipulate that technological progress depends on the human capital of the follower and its technical gap to the leader. They actually define technological progress in the form of an interaction between human capital and the technological gap. We followed this specification of Benhabib and Spiegel (1994), but in addition we introduce an inverse geographical distance function in the interaction term. Taking the log of this interaction term gives a separately identifiable effect for human capital, geographical distance and the technological gap.

Based on the externalities theories developed by Porter (1990), Marshall (1890) and Jacobs (1969), we expect a positive effect of competition, specialization and diversity on employment growth. The positive effect of human capital on growth has commonly been identified in the literature (see Savvides and Stengos, 2009, for a review), even although several studies have also found a negative impact of human capital on growth (Pritchett, 1996). With respect to employment growth, we would expect that more human capital would contribute to higher employment growth. As far as the technological gap is concerned we would expect a positive effect because regions which are technologically further away from the leader will tend to grow faster due to the advantage of backwardness (Gerschenkron, 1952; Abramovitz, 1986). With regard to the geographical distance variable, regions located geographically far from the leader would be expected to grow less due to increasing costs that may be associated with technology transfers. Due to the use of an inverse distance specification in equation (13), the expected sign is positive.

3.2 Estimation Procedure

We start with a simple Ordinary Least Square (OLS) estimation of the Glaeser et al. model with all 20 sectors pooled together. Subsequently, we group these 20 sectors into six more or less homogenous sectors and re-run the analysis. Finally, we estimate the models for each of the six grouped sectors individually. We strictly follow the operational specification of the Glaeser et al. model for the pooled sectors (20 and 6, respectively), and for the individual sectors we estimate the Glaeser et al. model as well as the two extended versions described in the preceding subsection. Table 2 shows the constituents of these aggregate industries. The six aggregates industries are labeled as follow: Natural Resources, Construction & Manufacturing, Transportation & Trade, Information & Utilities, Finance & Management, and Services.

Table 2: Grouping for Aggregate Industries.

Codes	Two–digit Industries	Categories
11	Agriculture forestry, Fishing and Hunting	Natural Resources
21	Mining	
23	Construction	Construction & Manufacturing
31–33	Manufacturing	
42	Wholesale Trade	Transportation & Trade
44–45	Retail Trade	
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 except Public Admin.	

Spatial regressions are only estimated for the model with technological leadership effects,[6] and we determine the appropriate specification for the spatial process based on the spatial diagnostic tests of the OLS model following the procedure outlined in Anselin et al. (1996). This specification strategy boils down to using the Lagrange Multiplier (LM) tests and

[6] Due to the 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 rather cumbersome.

their robust forms to decide whether a spatial lag or a spatial error process is appropriate (Florax et al., 2003).

The specification of the spatial autoregressive error model is relevant when the dependence works throug[7]h the error process (see Anselin, 1988). The spatial dependence in the spatial error model can be caused by omitted spatially correlated variables. It may also be caused by a situation where boundaries of regions coincide with different behavioral units. The spatial error model can be written as:

$$y = X\beta + \varepsilon,\ \ \varepsilon = \lambda W\varepsilon + u, \tag{15}$$

where y is an $N \times 1$ vector of observations on the dependent variable, X is an $N \times K$ matrix of explanatory variables, 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 $\Omega = \sigma^2 (I - \lambda W)^{-1} (I - \lambda W')^{-1}$. Even though the error term u is assumed to be homoskedastic, the structure of the variance-covariance matrix suggests the presence of (spatial) heteroskedasticity. OLS estimation of the spatial error model is unbiased and consistent but inefficient. The spatial error model may be appropriately estimated using Maximum Likelihood Estimation (MLE) or General Method of Moments (GMM) techniques (Anselin, 2006).

The spatial lag model is relevant when the variable under investigation depends on its spatial lag (Anselin, 1988). It can be written as:

$$y = \rho W y + X\beta + u, \tag{16}$$

7

where ρ is a scalar parameter, and all other variables are defined as before. OLS estimation of the spatial lag model is biased and inconsistent. Appropriate estimation results are obtained by using Maximum Likelihood (MLE), or Instrumental Variables (IV) techniques (Anselin, 1988).

The choice of the appropriate spatial process model for each growth model is based on the Lagrange Multiplier (LM-lag and LM-error) tests associated with the error and lag models. Initially the spatial process model is chosen based on the significance of either the LM-lag or LM-error tests. When both the LM-lag and LM-error tests are significant the model choice is based on the significance of the robust versions of the LM-lag and LM-error tests. In the case where the robust LM-lag as well as the robust LM-error tests is significant, the model with the highest robust LM test is retained (Anselin et al., 1996; Florax et al., 2003).

3.3 Data

The data used in this chapter are for 3,074 counties in the lower 48 U.S. states. Employment data were supplied by Economic Modeling Specialists Inc. (EMSI),[8] and they are disaggregated to two-digit NAICS industries, covering the period 1990–2008. For the estimations in this chapter, we consider complete employment data. Unlike covered employment data, which only comprise payroll jobs covered by unemployment insurance, complete employment data comprise payroll jobs plus non-covered jobs such as proprietors, partners, and others. The complete employment data count both full and part-time jobs. The EMSI employment data combines covered employment provided by the Quarterly Census of Employment and Wage (QCEW) with total employment data from the Regional Economic Information System (REIS).

[8] EMSI is a privately held company based in Idaho. More information about EMSI can be obtained from the company's website at http://www.economicmodeling.com/company/.

Firm establishment data are also from EMSI, but they cover a shorter time span, 1998–2008. The EMSI data have been created from several federal data sources: the Bureau of Economic Analysis (BEA), the Census Bureau (CB), and the Bureau of Labor Statistics (BLS). Earnings data are also obtained through EMSI and they are available from 2001–2008. The earnings data have been computed as a total of two components: wages and salaries, and supplements to wages and salaries.

Human capital data are from the Census Bureau for the decennial years 1990 and 2000. 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. All right hand side variables in the model have been computed for the year 1990, except competition because the establishment data were only available for the year 1998.

4. Spatial Externalities and Regional Economic Growth

Spatial externalities are dynamic and their transmission is facilitated by interactions, long-term relationships and/or spatial proximity. The relative importance of spatial externalities for economic growth is supported by three alternative theoretical approaches in the literature.

First, the Marshall-Arrow-Romer (MAR) approach stipulates that economies with high levels of specialization will grow faster because specialization favors within-sector knowledge spillovers. In other words, firms within the same industry will experience more knowledge spillovers and grow faster. McCann (2001) describes the sources of these externalities in the following terms: (1) the knowledge accumulated by one firm may be used by other firms; (2) within a context of industrial concentration, tacit information is more accessible to firms than if they were spatially dispersed; (3) industrial concentration creates a pool of local skilled labor that could constitute significant labor cost reduction for firms.

Second, Porter's approach stipulates that local competition fosters growth. A competitive environment increases the mutual visibility between firms and pressures them to imitate or innovate.

Third, the Jacobs externality approach hypothesizes that industrial variety in cities is conducive to growth because it allows an intensified exchange of ideas. The diversity of firms stimulates competition and forces them to innovate. Firms located in a diversified environment could benefit from economies of scale and experience higher productivity.

In addition to these externality-based approaches, the size and density effects on growth have also attracted attention (Combes, 2000; Combes et al. 2004; Blien et al. 2006; Bishop and Gripaios, 2009). Bishop and Gripaios (2009) urge researchers to account for these urbanization externalities in empirical studies, because of the varying size and density of spatial units.

There has been a vast literature on the influence of externalities on regional economic performance (see Rosenthal and Strange, 2004 for a review), including two meta-analyses (Melo et al., 2009; De Groot et al., 2007). While productivity growth represents a more realistic measure of economic performance, a large number of studies has considered employment growth as a proxy mainly because sectoral output data are usually not available, in particular for disaggregated sectors. This choice of focusing on employment growth is usually supported by the assumption that productivity growth is proportional to employment change. Arguably, this assumption may not be fully adequate. For instance, Cingano and Schivardi (2003) argue that congestion externalities such as higher rents and pollution are likely to influence mobility choice, and will potentially break or even reverse the causality chain going from agglomeration economies to productivity and employment growth. They consider using Total Factor Productivity (TFP) growth data with a high degree of both geographical and sectoral disaggregation will be closer to the theoretical notion of dynamic externalities. Dekle (2002) also considers TFP growth to investigate the effects of dynamic externalities, pointing out that unless the regional capital stock is constant, omitted variable bias may plague the regression estimates.

The effects of the above-described externalities on economic performance have been evaluated in the literature across many settings (Rosenthal and Strange, 2004). The seminal empirical studies on this issue were based on data for U.S. regions. Indeed, focusing on the six largest two-digit industries in U.S. cities, Glaeser et al. (1992) observed that local competition and diversity, but not specialization, foster employment growth. Different effects are also observed depending on the type of industry considered. For instance, Henderson et al. (1995) found positive effects for both diversity and specialization in high-tech industries, but only for specialization in mature industries. Using a 14-year panel for U.S. county level employment in five two-digit capital goods industries, Henderson (1997) also finds strong evidence of MAR externalities (specialization) and smaller effects of Jacob externalities (diversity).

Apart from the empirical studies for U.S. regions, there have also been several studies in other countries, particularly in Europe. Combes (2000) considers 52 industry sectors and 42 service sectors for 341 local areas in France and observes different effects. While specialization, competition and diversity negatively affect employment growth in industry sectors, diversity has a positive externality effect in service sectors. Usai and Paci (2003) find that diversity has a positive effect on growth while specialization negatively affects growth in Italian regions. The empirical work by De Lucio et al. (2002) on Spanish regions shows that specialization has a negative effect on growth while diversity and competition have no effect. Blien et al. (2006)

study the dynamic of local employment growth in Germany and observe positive effects of both diversity and specialization. Van Oort (2007) investigates the effects of agglomeration economies on growth at the urban level in the Netherlands, accounting for spatial dependence between regions and using spatial econometrics techniques. He observes that Jacobs-related sectoral variety is the dominant spatial condition for agglomeration externalities in the Netherlands. However, his results do not improve in robustness when spatial dependence is accounted for. Using spatial econometrics techniques for U.K. regions at the two-digit level, Bishop and Gripaios (2009) show that specialization has a negative impact on employment growth, while the effect of diversity is heterogeneous across sectors and competition encourages growth. Frenken et al. (2007) focus on the NUTS 3 regions in the Netherlands and decompose diversity into related (within sectors) and unrelated (between sectors) components. They notice that Jacob externalities enhance employment growth, while unrelated diversity has a negative effect. A similar approach is used by Van Stel et al. (2004) for 40 Dutch regions. They find that local competition fosters growth in manufacturing and construction, while diversity has a positive impact on growth in service sectors, and no effect of specialization is observed. Using data on 47 Japanese prefectures at the one-digit level, Dekle (2002) finds evidence of significant externalities for finance, services, wholesale and retail trade sectors and no externalities for the manufacturing industry. Shearmur and Polèse (2005) find no evidence of Jacob externalities for employment growth in Canadian regions.

It can be noticed from the above review that there is no consensus on the impacts of agglomeration economies on economic performance. Mixed results are obtained not only for MAR externalities, but also for Porter and Jacobs externalities. A meta-analysis by De Groot et al. (2007) pointed out that the effects of these agglomeration economies on economic performance vary depending on the proxies used for agglomeration effects, the inclusion/omission of key variables of interest, the time dimension of the studies, the specific regions or countries considered, and more importantly the estimation techniques used. Their meta-analysis supports evidence for significantly positive effects of diversity and competition on growth, but they found no evidence for MAR externalities. Similarly, the recent meta-analysis by Melo et al. (2009) indicates that estimates of the effects of urban agglomeration on productivity depend on country-specific effects, industrial coverage, the specification of the agglomeration economies, the consideration of both endogeneity in labor force quality and heterogeneity in time-variant labor quality.

The timing of agglomeration economies and the spatial extent over which they occur have also been the subject of scrutiny. With regard to timing, Henderson (1997) observes that the largest MAR externalities effects are from several years ago, but they seem to die out after six years, while urbanization effects persisted to the end of the time horizon of their dataset. As far as spatial extent is concerned, Henderson (2003) shows that externality effects remain within the own county and there is no influence from plants located in other counties in the metropolitan area. Similarly, Cingano and Schivardi (2003) notice that the effects of neighboring specialization on TFP growth are not significant. Focusing on data of the Dutch province of South-Holland, Van Soest et al. (2006) also shows that the effects of agglomeration economies on employment growth are positive, but they dissipate rapidly with increasing distance. In this study, only the spatial extent of the variables capturing agglomeration economies are considered by including spatially lagged versions of the externality variables. The incorporation of temporal dynamics in agglomeration economies is left for future study.

5. Measures of Agglomeration Economies

Several operational measures for agglomeration economies have been proposed in the literature (Glaeser et al., 1992; Ellison and Glaeser, 1997; Black and Henderson, 1999; Duranton and Puga, 2000; Blair, 1995; Amiti, 1998; Krugman, 1991; Mulligan and Schmidt, 2005; Duranton and Overman, 2005; Marcon and Puech, 2003). In this section, we discuss the measures of specialization, diversity, and competition as well as the density measure introduced in the preceding section.

Traditionally, specialization in an industry within a region is measured as the fraction of the region's employment that this industry captures, relative to the share of the entire industry in national employment (Glaeser et al., 1992; Henderson, 1997; Cingano and Schivardi, 2003; Suedekum and Blien, 2005). The specialization index compares the relative size of a sector in a region to its relative size in the nation. It is expressed as:

$$S_{i,s} = \frac{E_{i,s}/E_i}{E_s/E}, \tag{17}$$

where $E_{i,s}$ is employment in region *i* in industry *s*, E_i is employment in region *i*, E_s is total employment in the nation in industry *s*, and E is the total employment in the nation. The specialization index indicates how specialized a region is in a specific industry, relative to a situation where employment is randomly distributed across the nation. A value of the specialization index higher than unity indicates that employment in the sector is more concentrated in the region than it is in the nation. Other measures of specialization include the Krugman Specialization Index (Krugman, 1991) and the Index of Regional Specialization (Blair, 1995).

A number of different metrics to measure diversity has also been proposed in the literature. For instance Glaeser et al. (1992) simply measure diversity as the fraction of a city's employment in the largest five industries other than the industry in question. The Gini coefficient for the distribution of employment by sectors has also been used in some studies to capture the Jacobs externalities (see, for instance, Van Oort, 2007). A popular measure of diversity used to capture the Jacobs externalities is the Hirschman-Herfindahl Index (*HHI*). It is expressed as:

$$HHI_i = \sum_s \left[\frac{E_{i,s}}{E_s} - \frac{E_i}{E} \right]^2, \qquad (18)$$

where all variables are defined as in equation (2.17). The Hirschman-Herfindahl Index of spatial concentration captures the degree to which a particular industry's spatial distribution reflects that of the national urban hierarchy (McCann, 2001). A high value of the Hirschman-Herfindahl Index indicates sectoral concentration in a limited numbers of regions.

The Relative Diversity Index (*RDI*) represents another measure of diversity. It is expressed as:

$$RDI_i = \frac{1}{\sum_s \left| \frac{E_{i,s}}{E_i} - \frac{E_s}{E} \right|}, \qquad (19)$$

where all variables are defined as in equation (2.17). A high value of the relative diversity index signals that the regional employment distribution resembles that of the national economy. The Relative Diversity Index (*RDI*) is simply the inverse of the Krugman Specialization Index.

Entropy measures of diversity have also been suggested in the literature (Duranton and Puga, 2000; Bishop and Gripaios, 2009; Frenken et al., 2007).[9] The Total Entropy (*TE*) measure is defined as:

$$TE = \sum_{k=1}^{n} E_k \ln\left(\frac{1}{E_k}\right), \tag{20}$$

where E_k is the share of the *k*-th industry in a region's total employment, and *n* represents the number of industries. Total entropy varies from zero, the case where all employment is concentrated in one industry, to $\ln(n)$, the case where employment is spread evenly across all sectors.

There are also several alternative measures of competition. Glaeser et al. (1992) define competition of 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. It is expressed as:

$$\mathrm{C}_i = \frac{F_{i,s}/E_{i,s}}{F_s/E_s}, \tag{21}$$

where $F_{i,s}$ is the number of establishments in region i in industry *s*, $E_{i,s}$ is employment in region i in industry *s*, F_s is the number of establishments in the nation in industry *s*, and E_s is total employment in the nation in industry *s*. Bishop and Gripaios (2009) propose a measure of competition based on size band data defined as the proportion of establishments in the sector with ten or fewer employees relative to the proportion in this category in Great Britain as a whole. Combes et al. (2004) consider two indicators of local competition: a dichotomous

[9] The entropy measure of diversity has the attractive property of being decomposable into related and unrelated diversity. Unrelated entropy is defined similarly to total entropy in equation (2.22), and related entropy is obtained by taking the difference between total and unrelated entropy (Frenken et al., 2004).

variable on the presence/absence of competition, and a local competition index measured as the negative of the logarithm of the Herfindahl index.

Measures of density are also commonly considered when investigating the role of agglomeration economies for growth (Bishop and Gripaios, 2009; Ciccone, 2002; Pagano and Shivardi, 2003). Bishop and Gripaios (2009) define density as population per square kilometer. Density is also measured in terms of output or employment per square kilometer (Ciccone, 2002; Suedekum and Blien, 2005). However, Dekle (2002) argued that output per square kilometer is more preferable to employment per square kilometer because it better captures the intensity of labor, and human and physical capital.

The literature on the measures of agglomeration economies remains vague when it comes to deciding which operational measures are more appropriate. There are no criteria *per se* to decide on the choice between various measures. Lucio et al. (2002) argue that the measures proposed by Glaeser et al. (1992) are simply ad hoc, and they suggest an endogenous derivation of indexes.[10] Given that our model builds on Glaeser et al. (1992), we will consider their measures of specialization and competition as defined in equations (17) and (21), respectively. These measures are simple and they have been employed in numerous applications (Henderson, 1997; Cingano and Schivardi, 2003; Suedekum and Blien, 2005; Van Oort, 2005). With regard to diversity, we consider a different measure than Glaeser et al. (1992). We use the Relative Diversity Index defined in equation (19), because this diversity measure is simple and more relevant to our analysis than the diversity measure proposed in Glaeser et al. (1992).

[10] It remains unclear, however, how that can be accomplished.

6. Empirical Results

Prior to estimating the sectoral growth models we have to determine a number of details regarding the operational specification of the model. 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, and earnings per worker for 2001.[11]

The geographical distance from each county to the technology leader is computed following the spherical law of cosines.[12] The initial employment level, the initial earnings per worker, the inverse geographical distance, human capital and technological distance are all in logarithmic form. However, the operational measures for the externalities (specialization, competition and diversity) are not transformed to logarithmic values.

In order 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 is defined *a priori* and exogenously on the basis of arc distances between the geographical midpoints of the counties considered. It is a Boolean proximity matrix where elements are coded unity if the distance between counties is less than 92.05 miles, with subsequent standardization enforcing row sums to be equal to one. The spatial weight matrix has dimension 3,074, with 1.23% of the weights being nonzero, an average weight of 0.026, the minimum and maximum number of links between countries being 1 and 88, respectively, with an average of 38.

---

[11] Data on the number of establishments data 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.

[12] The geographical distance between two counties *a* and *b* is expressed as:

$$d = R \cdot \text{acos}[\sin(\text{lat } a) \cdot \sin(\text{lat } b) + \cos(\text{lat } a) \cdot \cos(\text{lat } b) \cdot \cos(\text{long } b - \text{long } a)],$$

where R is the radius of the earth, which is fixed at 3,959 miles, and longitude (abbreviated long) and latitude (abbreviated lat) are expressed in radians.

Table 3 presents the two-digit industries of the NAICS classification with some descriptive statistics. From all 20 industries, retail trade has the highest employment share relative to the U.S. in 1990, followed by manufacturing. With regard to growth, a number of these industries show negative average growth over the period 1990–2008. The largest decline in growth over the period 1990–2008 is observed for the mining sector. The management of companies and enterprises sector shows the highest average growth over the same period. These differences emphasize the need to control for the overall employment growth in the country as a whole, which implies that the analysis focuses on deviations from the long-run trend.

Table 2: Two-digit NAICS Industries.

Codes	Two-digit industries	Percentage of U.S. Employment 1990 (%)	Average Annual Growth Rate 1990–2008 (%)
11	Agriculture forestry, Fishing and Hunting	3.33	–0.67
21	Mining	0.65	–2.21
22	Utilities	0.50	0.33
23	Construction	7.36	0.31
31–33	Manufacturing	10.91	–0.44
42	Wholesale Trade	4.52	–0.75
44–45	Retail Trade	12.58	–0.54
48–49	Transportation and Warehouse	3.63	0.04
51	Information	2.65	0.50
52	Finance and Insurance	5.74	–0.40
53	Real Estate and Rental and Leasing	5.24	–1.47
54	Professional and Technical Services	7.69	–1.12
55	Management of Companies and Enterprises	0.91	2.72
56	Administrative, Support and Waste Management and Remediation	5.48	0.05
61	Educational Services	2.32	0.31
62	Health Care and Social Assistance	9.75	2.16
71	Art Entertainment and Recreation	2.46	–0.98
72	Accommodation and Food Services	7.02	1.66
81	Other Services except Public Administration	6.65	–1.32
92	Public Administration	0.59	1.06

In the sections below, we will present and discuss results for the pooled models and for each of the six aggregated sectors presented earlier in Table 2.

6.1 Pooled Models

We start the estimation by a replication of the Glaeser et al. (1992) model. We estimate the employment growth model with pooled data for all 20 sectors, and present the estimation results in Table 4. We use the ordinary least squares estimator. Columns (1), (2) and (3) show the results, successively including measures for specialization, competition and diversity. The last column, labeled (4), includes all three measures of spatial externalities simultaneously.

All of the control variables have the predicted signs and they are statistically significantly different from zero. Consequently, 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. The latter result may partly be caused by the data used for our model. Since we cannot measure earnings per worker at the beginning of the time period under consideration, this variable may partly pick up initial productivity differences. Finally, the counties of the South exhibit faster employment growth than counties elsewhere in the U.S. All these results are consistent with the findings of Glaeser et al. (1992).

With regard to spatial externalities, the competition and diversity variables are positive and statistically significant, which provides evidence for Porter and Jacobs externalities. Specialization is statistically significant as well, but this estimated parameter shows a negative correlation with employment growth. These results are similar to the results obtained by Glaeser et al. (1992) and Bishop and Gripaios (2009). The latter authors argue that the observed negative effect of specialization cannot systematically be interpreted as definitive evidence against MAR externalities. Their justification is that specialization may be beneficial but primarily results in improvements in productivity, which displaces labor due to demand constraints on expanding output.

Table 3: Pooled Regression, Two-digit NAICS Industries.

	Dependent variable: Employment growth			
	(1)	(2)	(3)	(4)
Constant	–1.180***	–1.201***	–0.890***	–0.890***
	(0.085)	(0.085)	(0.088)	(0.088)
Employment in 1990	–0.012***	–0.013***	–0.020***	–0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
U.S. Employment growth	0.970***	0.976***	0.922***	0.920***
	(0.014)	(0.014)	(0.014)	(0.014)
Earnings per worker	0.125***	0.125***	0.09***	0.090***
	(0.009)	(0.009)	(0.009)	(0.009)
Specialization	–0.005***			–0.002***
	(0.001)			(0.001)
Competition		0.022***		0.022***
		(0.010)		(0.010)
Diversity			0.051***	0.049***
			(0.004)	(0.004)
South dummy	0.010*	0.009*	0.021***	0.021***
	(0.005)	(0.005)	(0.005)	(0.005)

Note: Standard errors of the parameter estimates are in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively. The number of observations is 61,480.

In addition to the results for the grouped sectors identified above, we present the estimation results for the version based on pooled data for the six aggregated sectors. These results are presented in Table 5, which is organized similarly as Table 4 except that column (5) presents the model extended with technological catch-up effects. In all these models, the control variables show the expected sign except for the dummy variable for southern regions now showing a statistically significant negative sign in column (5). With regard to the spatial externality measures, a negative and statistically significant effect can be observed for diversity, while competition has a positive statistically significant impact on employment growth. These results differ from the previous results in Table 4 on the effect of diversity.

With regard to the effect of technological leadership, we obtained a negative and significant effect of human capital on growth, which appears counterintuitive as we would expect human capital to promote employment growth. A negative and significant effect is observed for geographical distance to the leader. This result also appears counterintuitive. Given that we consider an inverse distance function in our model, a greater distance from the technology leader implies that the inverse distance is smaller and we would therefore expect it to be associated with slower growth. The technological gap with the technology leader has a positive and significant impact on growth, implying that regions with an initially larger technical gap with the leader will growth faster. From all three variables capturing the effects of technological leadership, only technological distance shows the expected sign.

The estimates obtained from the pooled regressions can be seen as overall effects on employment. However, they cannot necessarily be generalized to all sectors. It is likely that the effects on employment growth of geographical and technological distances to the technology leader and of the county’s human capital stock are different across sectors.

Table 4: Pooled Regression, Six Aggregate Sectors.

	Dependent variable: Employment growth				
	(1)	(2)	(3)	(4)	(5)
Constant	–0.415***	–0.419***	–0.441***	–0.433***	0.342***
	(0.038)	(0.037)	(0.037)	(0.038)	(0.125)
Employment in 1990	–0.007***	–0.006***	–0.002	–0.001	–0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
U.S. Employment growth	0.951***	0.953***	0.961***	0.962***	0.976***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Earnings per worker	0.043***	0.042***	0.044***	0.041***	0.045***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Specialization	0.001			–0.004***	–0.004***
	(0.006)			(0.001)	(0.001)
Competition		0.007***		0.008***	0.008***
		(0.001)		(0.001)	(0.001)
Diversity			–0.007***	–0.007***	–0.004***
			(0.001)	(0.001)	(0.001)
Human capital					–0.204***
					(0.027)
Geographical distance					–0.009***
					(0.004)
Technological distance					0.018***
					(0.007)
South dummy	–0.004	–0.006	–0.007	–0.010	–0.046***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)

Note: Standard errors of parameters estimates are in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively. The number of observations is 18,444.

6.2 Sectoral Details

We now apply the same estimation procedure that we used for the six aggregate sectors, to each of the sectors individually. Estimation results for the different sectors are presented in Tables 6 through 11. In these tables, column (1) shows OLS estimates for the basic Glaeser et al. model, column (2) is the same model extended with the spatially lagged versions of the variables for agglomeration economies, column (3) further extends the model with human capital, geographical distance and technological distance, and column (4) shows maximum likelihood estimates of the same model as in column (3), but now extended to include the appropriate spatial process (lag or error).

In the traditional Glaeser et al. model, a negative statistically significant effect of specialization and a positive statistically significant effect of diversity are observed for all sectors, except for the natural resources sector. These results are consistent with those obtained for the pooled regressions of the 20 NAICS sectors. The estimation results for the natural resources sector show a positive effect of specialization, which is plausible given that this sector is considered not footloose, and the level of specialization is therefore largely determined by the productivity of land and the availability of natural resources. With respect to competition, a positive and significant effect is observed for all sectors except for Information & Utilities. A similar effect of competition occurred in the pooled regressions. The effect of competition on employment in the Construction & Manufacturing sector is statistically not significant. This could be the case because the employment growth in that industry is affected more by national and international competition rather than by local competition.

With respect to the control variables, the results for individual sectors are occasionally different from those for the pooled models. The expected negative effect of initial employment is only observed for the sector Information & Utilities. However, initial earning per worker has a positive effect on employment growth in all sectors except for Natural Resources and Finance & Management. Also, the dummy variable indicating the presence in the south is positive and significant for all sectors except for the sector Natural Resources. The latter result is rather surprising, because given the high concentration of agriculture in the South, a positive effect would be expected.

In the Glaeser et al. model extended with the spatial lag of externality variables, results of the individual sectors are different from those obtained for the pooled version, with six aggregate sectors. In addition, the impacts of the spatial lag of these externality measures appear to be different across sectors. In some sectors the effects of the spatially lagged externality measures are not statistically significant, in others they are positive or negative. 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.

For all six sectors, OLS estimation of the (extended) Glaeser et al. models show a positive and significant Moran's *I*, indicating the presence of spatial autocorrelation. The spatial diagnostic Lagrange Multiplier tests of the model extended with technological leadership effects indicate that a spatial autoregressive error process is appropriate for Information & Utilities, Construction & Manufacturing and Natural Resources, while a spatial lag process is appropriate for Finance & Management, Transportation & Trade, and Services. We therefore report the corresponding spatial models, estimated using the appropriate maximum likelihood estimators, in column (5) of each table. One should note that the estimated coefficients of the spatial lag model are not directly comparable to the non-spatial results, because they do not include the spatial spillover effects implied by the spatial multiplier process. The estimated coefficients should be multiplied by the factor $1/(1-\rho)$ in order to arrive at asymptotically valid marginal effects including spatial spillovers (see LeSage and Pace, 2009, for details).

Even although the pooled model of the six aggregate industries indicated a negative role for the stock of human capital, it is interesting to note that in the sectoral models human capital has a consistently significant and positive effect on employment growth. This may be suggesting that the positive role of human capital is only observed when differentiating between sectors.

The observed positive impact of human capital corresponds to previous findings of Shapiro (2006) and Poelhekke (2009). Shapiro (2006) used U.S. metropolitan data from 1940–1990 and showed that a higher concentration of college-educated residents is associated with increased employment growth. Similarly, Poelhekke (2009) used German metropolitan data from 1975–2003 and showed that the share of college graduates has a positive impact on employment growth.

Unlike the role of human capital, which is consistent across the different sectors, the impacts of geographical and technological distances vary by sector. A positive and significant effect of geographical distance, which conforms to expectations, is observed for the sectors Natural Resources and Transportation & Trade, while a significantly negative impact is obtained for Construction & Manufacturing, and Finance & Management. The effect of geographical distance to the leader is not statistically different from zero for the sectors Services, and Information & Utilities. One can only speculate as to why the results appear like this. First, the location and degree of specialization in the sectors Natural Resources and Transportation & Trade is mainly dominated by geography and the availability of natural resources and infrastructure. 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. Second, the economic geography of the sectors Construction & Manufacturing and Finance & Management is such in the U.S. that the level of aggregation may be too high to observe an easily interpretable effect. Finally, the sectors Services, and Information & Utilities can maybe be explained by the development in information and communication technologies, which allows innovations to be transferred more easily and cheaper across regions. The time period 1990–2008 actually coincides with the rise of information and communication technology, which could have eroded the effect of geographical distance from the technology leader. Obviously, the differentiation in the effects of geographical distance warrants further investigation.

With respect to the impact of technological distance on employment growth we observe a positive and statistically significant effect in Services, Information & Utilities, and Construction & Manufacturing. The effect of technological distance is statistically not significantly different from zero in the sectors Natural Resources, Finance & Management and Transportation & Trade. A positive effect of the technology gap variable suggests that backwardness represents an advantage for faster growth. Counties with a large initial difference in technological sophistication as compared to the

Table 5: Regression Results for the Sector Natural Resources.

	Dependent variable: Employment growth			
	(1)	(2)	(3)	(4)
Constant	–0.384***	–0.318***	–0.684***	–0.726***
	(0.070)	(0.073)	(0.218)	(0.243)
Employment in 1990	0.046***	0.047***	0.042***	0.041***
	(0.005)	(0.005)	(0.005)	(0.006)
Earnings per worker	–0.025***	–0.025***	–0.026***	–0.024***
	(0.006)	(0.006)	(0.006)	(0.006)
Specialization	0.002**	–0.004**	–0.001	–0.002
	(0.001)	(0.001)	(0.002)	(0.002)
Competition	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Diversity	–0.001	–0.001	–0.004**	–0.003**
	(0.002)	(0.002)	(0.002)	(0.002)
Lag specialization		0.007**		
		(0.003)		
Lag competition		0.001		
		(0.002)		
Lag diversity		–0.022***		
		(0.006)		
Human capital			0.178***	0.193***
			(0.041)	(0.045)
Geographical distance			0.061***	0.062***
			(0.009)	(0.012)
Technological distance			–0.011	–0.013
			(0.011)	(0.025)
South dummy	–0.034***	–0.034***	–0.022***	–0.017
	(0.009)	(0.009)	(0.012)	(0.015)
Spatial error parameter				0.32***
				(0.04)
Moran's *I*	0.05***	0.04***	0.04***	
LM-Error	112.40***	66.30***	63.93***	
Robust LM-Error	4.22**	3.51*	1.22	
LM-Lag	135.43***	81.28***	63.63***	
Robust LM-Lag	27.26***	18.49***	0.93	
LM-SARMA	139.66***	84.80***	64.86***	

Note: Standard errors of parameter estimates are in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively. The number of observations is 3,074.

Table 6: Regression Results for the Sector Construction & Manufacturing.

	Dependent variable: Employment growth			
	(1)	(2)	(3)	(4)
Constant	–0.671***	–0.655***	–4.10***	–4.328***
	(0.176)	(0.178)	(0.382)	(0.438)
Employment in 1990	0.033***	0.031***	0.020***	0.011***
	(0.008)	(0.009)	(0.008)	(0.009)
Earnings per worker	0.036**	0.036**	0.014	0.012***
	(0.019)	(0.019)	(0.019)	(0.019)
Specialization	–0.266**	–0.263**	0.116*	0.031**
	(0.028)	(0.031)	(0.065)	(0.006)
Competition	0.161***	0.167***	0.192***	0.201***
	(0.024)	(0.026)	(0.024)	(0.024)
Diversity	0.013***	0.012***	0.005	0.004***
	(0.004)	(0.004)	(0.004)	(0.004)
Lag specialization		0.002		
		(0.007)		
Lag competition		–0.035		
		(0.073)		
Lag diversity		0.010		
		(0.009)		
Human capital			0.766***	0.853***
			(0.085)	(0.094)
Geographical distance			–0.092***	–0.080***
			(0.017)	(0.027)
Technological distance			0.597***	0.455***
			(0.109)	(0.108)
South dummy	0.029***	0.033***	0.152***	0.156***
	(0.019)	(0.024)	(0.024)	(0.032)
Spatial error parameter				0.410***
				(0.048)
Moran's *I*	0.09***	0.04***	0.07***	
LM-Error	282.63***	283.50***	191.36***	
Robust LM-Error	13.75**	3.60**	16.94***	
LM-Lag	269.58**	279.94***	175.52***	
Robust LM-Lag	0.70	0.30	1.10	
LM-SARMA	283.34***	283.54***	192.46***	

Note: Standard errors of parameter estimates are in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively. The number of observations is 3,074.

Table 7: Regression Results for the Sector Transportation & Trade.

	Dependent variable: Employment growth			
	(1)	(2)	(3)	(4)
Constant	–1.497***	–1.672***	–3.506***	–3.806***
	(0.344)	(0.372)	(0.461)	(0.455)
Employment in 1990	0.088***	0.072***	0.084***	0.065***
	(0.008)	(0.009)	(0.008)	(0.008)
Earnings per worker	0.028	0.041	0.006	0.029
	(0.036)	(0.036)	(0.036)	(0.035)
Specialization	–0.204***	–0.168***	–0.354***	–0.298***
	(0.048)	(0.050)	(0.115)	(0.114)
Competition	0.230***	0.230***	0.309***	0.316***
	(0.042)	(0.043)	(0.043)	(0.043)
Diversity	0.028***	0.026***	0.022***	0.020***
	(0.003)	(0.003)	(0.003)	(0.003)
Lag specialization		–0.019		
		(0.112)		
Lag competition		0.053		
		(0.105)		
Lag diversity		0.041***		
		(0.010)		
Human capital			0.592***	0.630***
			(0.077)	(0.077)
Geographical distance			0.068***	0.053***
			(0.013)	(0.013)
Technological distance			–0.192	–0.173
			(0.133)	(0.132)
South dummy	0.059***	0.071***	0.098***	0.096***
	(0.016)	(0.018)	(0.022)	(0.021)
Spatial lag parameter				0.30***
				(0.04)
Moran's *I*	0.04***	0.03***	0.04***	
LM-Error	56.98***	41.97***	68.43***	
Robust LM-Error	0.26	0.19	0.16	
LM-Lag	83.10***	43.69***	87.43***	
Robust LM-Lag	26.39***	1.91	19.15***	
LM-SARMA	83.37***	43.88***	87.59***	

Note: Standard errors of parameter estimates are in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively. The number of observations is 3,074.

Table 8: Regression Results for the Sector Information & Utilities.

	Dependent variable: Employment growth			
	(1)	(2)	(3)	(4)
Constant	–0.383***	–0.351***	–0.628	–1.105***
	(0.097)	(0.117)	(0.544)	(0.569)
Employment in 1990	–0.056***	–0.063***	–0.059***	–0.066***
	(0.009)	(0.010)	(0.010)	(0.010)
Earnings per worker	0.101***	0.100***	0.103***	0.101***
	(0.009)	(0.009)	(0.009)	(0.009)
Specialization	–0.279***	–0.275***	–0.198***	–0.198***
	(0.026)	(0.027)	(0.035)	(0.035)
Competition	–0.026**	–0.014	–0.027**	–0.021*
	(0.013)	(0.014)	(0.013)	(0.013)
Diversity	0.022***	0.022***	0.019***	0.018***
	(0.005)	(0.005)	(0.005)	(0.005)
Lag specialization		0.141		
		(0.092)		
Lag competition		–0.051***		
		(0.029)		
Lag diversity		0.001		
		(0.010)		
Human capital			0.327***	0.465***
			(0.106)	(0.114)
Geographical distance			0.005	0.017
			(0.017)	(0.021)
Technological distance			1.021***	0.991***
			(0.300)	(0.299)
South dummy	0.002***	0.010***	0.057**	0.067***
	(0.023)	(0.018)	(0.030)	(0.036)
Spatial error parameter				0.24***
				(0.05)
Moran's *I*	0.02***	0.02***	0.02***	
LM-Error	23.33***	20.32***	30.47***	
Robust LM-Error	5.13**	0.02	14.98***	
LM-Lag	19.11***	21.28***	20.97***	
Robust LM-Lag	0.91	0.97	5.48***	
LM-SARMA	24.25***	21.30***	35.95***	

Note: Standard errors of parameter estimates are in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively. The number of observations is 3,074.

Table 9: Regression Results for the Sector Finance & Management.

	Dependent variable: Employment growth			
	(1)	(2)	(3)	(4)
Constant	–0.575***	–0.604***	–2.558***	–2.526***
	(0.129)	(0.167)	(0.469)	(0.472)
Employment in 1990	0.105***	0.096***	0.096***	0.091***
	(0.009)	(0.010)	(0.009)	(0.009)
Earnings per worker	–0.072***	–0.073***	–0.074***	–0.072***
	(0.015)	(0.015)	(0.015)	(0.015)
Specialization	–0.166***	–0.114***	–0.128	–0.121
	(0.045)	(0.049)	(0.109)	(0.109)
Competition	0.196**	0.212**	0.190**	0.197**
	(0.054)	(0.058)	(0.055)	(0.055)
Diversity	0.018***	0.016***	0.014***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
Lag specialization		–0.250***		
		(0.091)		
Lag competition		0.158		
		(0.146)		
Lag diversity		0.032***		
		(0.010)		
Human capital			0.389***	0.405***
			(0.095)	(0.095)
Geographical distance			–0.074***	–0.066***
			(0.022)	(0.022)
Technological distance			0.084	0.089
			(0.160)	(0.160)
South dummy	0.009***	0.017	0.055**	0.062**
	(0.020)	(0.020)	(0.026)	(0.026)
Spatial lag parameter				0.09**
				(0.05)
Moran's *I*	0.01***	0.01***	0.01***	
LM-Error	4.69**	3.21*	6.69***	
Robust LM-Error	0.90	0.94	0.08	
LM-Lag	8.66***	4.5**	7.58***	
Robust LM-Lag	4.87**	2.27	0.98	
LM-SARMA	9.57***	5.49**	7.67**	

Note: Standard errors of parameter estimates are in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively. The number of observations is 3,074.

Table 10: Regression Results for the Sector Services.

	Dependent variable: Employment growth			
	(1)	(2)	(3)	(4)
Constant	–3.927***	–3.333***	–4.195***	–4.343***
	(0.197)	(0.236)	(0.387)	(0.380)
Employment in 1990	0.031***	0.024***	0.025***	0.008
	(0.007)	(0.007)	(0.007)	(0.007)
Earnings per worker	0.383***	0.372***	0.382***	0.374***
	(0.024)	(0.024)	(0.024)	(0.024)
Specialization	–0.056	–0.111	0.567***	0.508***
	(0.050)	(0.051)	(0.139)	(0.136)
Competition	0.010	0.151*	0.004	0.011
	(0.083)	(0.087)	(0.086)	(0.085)
Diversity	0.013***	0.010***	0.011***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Lag specialization		0.492***		
		(0.131)		
Lag competition		–1.088***		
		(0.213)		
Lag diversity		0.028***		
		(0.010)		
Human capital			0.053	0.170***
			(0.074)	(0.072)
Geographical distance			–0.013	0.001
			(0.015)	(0.015)
Technological distance			0.686***	0.638***
			(0.142)	(0.139)
South dummy	0.128***	0.103	0.133**	0.115***
	(0.015)	(0.018)	(0.019)	(0.019)
Spatial lag parameter				0.36***
				(0.03)
Moran's *I*	0.06***	0.05***	0.06***	
LM-Error	164.03***	97.28***	155.96***	
Robust LM-Error	18.72***	4.84***	8.77***	
LM-Lag	169.74***	98.56***	179.99***	
Robust LM-Lag	24.43***	5.72***	32.80***	
LM-SARMA	188.46***	103.40***	188.76***	

Note: Standard errors of parameter estimates are in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively. The number of observations is 3,074.

technology leader tend to grow faster. This is clearly relevant, as expected, in the manufacturing and the service sectors. The insignificant effect of technological distance for employment growth in the other sectors may be due to the fact that technological progress in these sectors is primarily driven by national rather than local or regional technological progress.

7. Conclusion

This chapter focused on the issues of space, human capital and technological leadership as determinants of sectoral employment growth, at a spatially and sectorally disaggregate level. The goal was to uncover how geographical and technological distances to the technology leader determine sectoral employment growth. This was investigated by using an econometric specification inspired by previous work of Glaeser et al. (1992).

We extended the Glaeser et al. model in two important ways. First, we hypothesize that technological progress does not only depend on local characteristics in terms of specialization, competition and diversity, but also on the same characteristics of proximate neighbors. This specification is supported by the notion of a contagious process of technology diffusion across space. Second, we consider that technological progress depends on the characteristics of specialization, competition and diversity, but in addition we include a hierarchical process of catch-up to the technology leader following previous work by Benhabib and Spiegel (1994). These extensions of the original Glaeser et al. model are investigated using data for two-digit NAICS industries in U.S. counties during the period 1990–2008.

A pooled regression of all 20 NAICS sectors following the traditional Glaeser et al. model supports previous findings. Local competition and diversity promote employment growth while specialization has a negative effect on growth. The counties in the South of the U.S. generally have a higher employment growth, initial employment is negatively correlated with employment growth and, higher earnings per worker promote employment growth. The pooled regression of six aggregated sectors also produces similar results, except for the negative effect of diversity. The externality variables and their spatial lag also have different impacts on employment growth, and their effect varies across sectors. However, the evidence of Jacobs externalities tends to be consistent across sectors. Continued future research seems warranted to obtain further insight into the role and impact of externalities, especially in view of sectoral disaggregation and the spatial scale at which externalities are important.

With regard to the role of local and regional technology, the available human capital stock of a county consistently shows a positive and statistically significant effect on employment growth in all sectors. The overall conclusions regarding the effect of geographical and technological distance to the technology leader are not as consistent across the different sectors. Technological distance to the leader shows a positive and statistically significant effect on employment growth in the Services, Information & Utilities, and Construction & Manufacturing sectors. Hence, for these sectors there is ample evidence that "backwardness" creates additional growth potential. In other sectors we find either an adverse or a statistically insignificant effect. The effect of geographical distance to the technology leader on employment growth also varies across sectors. The expected effect of lower employment growth associated with a greater geographical distance to the technology leader is identified only in the Natural Resources and the Transportation & Trade sectors, which is quite remarkable. In other sectors we again find either an adverse or a statistically insignificant effect. It is very well possible that the non-footloose characteristic of these sectors goes a long way in explaining the negative effect on employment growth. A suitably less aggregate analysis on the basis of precisely defined characteristics of different sectors could potentially reveal a more consistent picture in this case as well.