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THE CHANGING SPATIAL DISTRIBUTION OF ECONOMIC ACTIVITY ACROSS U.S. COUNTIES

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The Changing Spatial Distribution of Economic Activity across U.S. Counties

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Abstract

This paper studies the recent trends in the spatial distribution of economic activity in the United States. Using county-level employment data for 13 sectors — which cover the entire economy — we apply semi-parametric techniques to estimate how agglomeration and congestion effects have changed between 1972 and 1992. Non-service sectors are found to be spreading out and moving away from centers of high economic activity to areas 20 to 60 kilometers away; service sectors, on the contrary, are increasingly concentrating in areas of high economic activity by attracting jobs from the surrounding 20 kilometers. (*JEL* R11, R12)

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1 Introduction

Peaks of high activity with lots of 'empty' space in between are a striking feature of the economic landscape. Starting with Marshall (1890) this phenomenon has been explained by the interaction of agglomeration and congestion forces. Positive externalities — knowledge spillovers, thick labor markets, and forward and backward linkages — lead to agglomeration; negative externalities — rising commuting costs and increasing land rents — cause congestion and put a cap on the size of clusters.[1]

Agglomeration and congestion forces may change over time, thus affecting the economy's spatial distribution. Using U.S. county-level data, we analyze changes in the spatial distribution of different sectors between 1972 and 1992. More particularly, we estimate an employment growth equation, where the explanatory variables are initial employment at different distances. Though related to previous work on changes in geographical concentration (Kim, 1995, Dumais, Ellison and Glaeser, 1997), this paper diverges from the existing literature in a number of ways.

First, while most empirical studies have focused on manufacturing, we consider thirteen sectors, ranging from agriculture and manufacturing to services and government. We find that services behave differently from the rest of the economy. Manufacturing and most other sectors are moving out of centers of high economic activity, whereas services are moving in from the surrounding hinterlands. This tendency is consistent with the decline in transportation costs over the past decades (Smith, 1989). Until recently manufacturing was concentrated in urban areas to be close to the market. Cheaper transportation is now weakening these agglomeration forces, giving manufacturing firms the chance to move out of congested areas (Glaeser, Scheinkman and Schleifer, 1995). Services, by contrast, have traditionally been non-tradeable, forcing them to spread out. As transportation costs drop, services are becoming more tradeable, allowing them to take advantage of agglomeration economies.

Second, whereas Kim (1995) focuses on census regions and Dumais *et al.* (1997)

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[1] This argument underlies much of the work in urban economics (Mills, 1967, Henderson, 1974) and economic geography (Krugman, 1991a, Fujita, Krugman and Venables, 1999).

consider U.S. states, we look at counties. This finer level of disaggregation is preferable because static estimates of externalities suggest they have limited geographical reach. Ellison and Glaeser (1997), for instance, find that spillovers are stronger within counties than within states. Micro-founded studies come to similar conclusions (Jaffe, Trajtenberg and Henderson, 1993, Wallsten, 1999).

Third, no artificial geographical bounds are placed on agglomeration effects. A county's employment growth is not only affected by the county under consideration, but also by all nearby counties. This is hardly a novel idea: nearly half a century ago Harris (1954) pioneered the notion of market potential — a weighted average of purchasing power where the weights decay with distance — to explain the location of manufacturing in the United States. In spite of that, most empirical studies only consider local effects. An exception is Hanson (1998) who uses state level data to see how agglomeration effects decline through space.

Estimating a simple decay function will not do for our purposes though. Since the dependent variable is the growth of employment, rather than the level, the effect of distance may be more complex. For instance, we find that services are concentrating in urban centers by absorbing services of nearby areas. In our estimated equation this shows up as growth in services being positively affected by employment in the own county; negatively affected by employment in close-by counties; and not affected by employment in more far-off counties. This is a third-degree polynomial, rather than a simple decay function. Assuming any specific functional form *a priori* is thus unwarranted; instead, we use a semi-parametric approach which limits itself to imposing some smoothness properties.

2 Theoretical framework

In a simple constant returns to scale world without spatial externalities, perfect mobility of capital and labor tends to bring about an even distribution of economic activity across space, since the use of land leads to decreasing returns to the mobile factors of production. Some clustering does occur though once particular geographical features are taken into account. Farmers, for instance, locate where land is more fertile, and mining companies locate next to mineral deposits.

Further clustering arises when spatial externalities are introduced (Marshall, 1890, Mills, 1967, Henderson, 1974, Rodríguez Clare, 1996, Fafchamps, 1997, Fujita, Krugman and Venables, 1999). In the presence of agglomeration economies returns to labor and capital increase with the level of economic activity. These positive feedback mechanisms reinforce the initial patterns of specialization. Originally, better sunlight for outdoor filming prompted movie producers to leave New York for Southern California; since then much of the industry has located in the L.A. area, including companies such as Disney, which do not depend on bright sunlight.

Location cannot always be traced back to specific geographical features though. Historical accident and expectations, rather than initial inherent advantage, may determine where industries locate (Matsuyama, 1991, Krugman, 1991b). Even so, the role of randomness is short-lived. Once historical accident has led to a particular pattern of specialization, it becomes self-sustaining (Fujita, Krugman and Venables, 1999).

We are interested in understanding how the location of economic activity across U.S. counties has evolved between 1972 and 1992. Starting off in equilibrium, the economy's spatial distribution can change for two reasons. First, location may be affected by changing geographical features or by new random events. For instance, previously fertile land turns into a desert. We will assume that such changes are too slow to be important over a period of twenty years. Second, the impact on location of inherent geographical features and of past random events may change. For instance, the L.A. sunshine leads to less clustering if agglomeration economies weaken; or the negative productivity effect of hot climes is reduced by the introduction of air conditioning.

To understand the economy's changing spatial distribution, we would therefore ideally regress employment growth on inherent geographical features and on past random events. However, data on many geographical features — let alone data on past random events — are not available, so that they cannot be used as explanatory variables. Initial employment is a good proxy though, since the initial distribution of employment across counties reflects these underlying variables. The basic estimating equation therefore regresses employment growth on initial employment. The coefficient on initial employment represents changes in the way the underlying geographical characteristics affect the spatial distribution. For instance, the coefficient will be negative if agglomeration economies become weaker; in that case positive feedback mechanisms lose strength, and economic activity becomes more dispersed.

2.1 A model with localized externalities

The economy is divided into a large number of counties, specialized in different kinds of activities. Technologies are C.R.S. and the output of a representative firm in county i and sector s is:

$$q^{is} = q^{s}(l^{is}, k^{is}, h^{is}; \theta_{is}) \tag{1}$$

where l is labor, k is capital, and h is land. The parameter θ_{is} represents the determinants of location: geographical features — such as climate and proximity to waterways — and past random events. Agglomeration economies reinforce the effect of these locational determinants, though congestion eventually limits the size of spatial clusters (Henderson, 1974).

Without going into modeling details, a county with more attractive geographical features has more labor and capital. Appropriate normalization ensures that a higher θ_{is} corresponds to more attractive geographical features, so that a county's sectoral labor force L^{is} is a positive function of θ_{is}:

$$L^{is} = G^{s}(\theta_{is}) \tag{2}$$

where $\frac{\partial L^{is}}{\partial \theta_{is}} > 0$. This formulation is sufficiently general to accommodate a wide variety of positive and negative feedbacks; the stronger agglomeration economies — or the weaker congestion effects — the greater the impact of a change in θ_{is} on L^{is}. If production is Cobb-Douglas and θ_{is} is a Hicks-neutral productivity factor, expression (2) can be simplified to:[2]

$$L^{is} = \theta_{is}^{\gamma^s} \tag{3}$$

The exponent γ^s measures the strength of spatial externalities; the stronger agglomeration economies — or the weaker congestion effects — the larger γ^s.

If θ_{is} is time-invariant, county-level sectoral employment growth between 1972 and 1992 can be written as:

$$\log L_{1992}^{is} - \log L_{1972}^{is} = (\gamma_{1992}^s - \gamma_{1972}^s)\ \log \theta_{is} \tag{4}$$

Assuming time-invariance of θ_{is} is fine if a period of twenty years is too short for substantial changes in geographical features to take place or for new random events to occur which affect location.

Estimating (4) is impossible because not all elements making up θ_{is} are observable. Initial sectoral employment forms a good proxy for θ_{is} though. To see this, invert (3) for 1972, which yields $\theta_{is} = (L_{1972}^{is})^{1/\gamma_{1972}^s}$. Substituting this expression into (4) gives an estimable equation:

$$\log L_{1992}^{is} - \log L_{1972}^{is} = \alpha^s\ \log L_{1972}^{is} \tag{5}$$

where $\alpha^s = \frac{\gamma_{1992}^s - \gamma_{1972}^s}{\gamma_{1992}^s}$. A negative α^s reflects weakening agglomeration economies, leading to employment becoming more spread out; a positive α^s corresponds to strengthening agglomeration economies, with employment becoming more concentrated.

Although θ_{is} is unobservable, we do have data on some geographical variables that affect productivity. Controlling for those improves estimation of (5). We also include an intercept to control for aggregate trends in sectoral employment (driven, for instance, by changes in technology or preference). The estimable equation then becomes:

$$\log L_{1992}^{is} - \log L_{1972}^{is} = \alpha_o^s + \alpha_l^s\ \log L_{1972}^{is} + \alpha_h^s H^i \tag{6}$$

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[2] Assume $q^{is} = \theta_{is}(L^{is})^{\beta_0}(K^{is})^{\delta_0}(l^{is})^{\beta_1}(k^{is})^{\delta_1}(h^{is})^{(1-\beta_1-\delta_1)}$ is the representative firm's production function. Agglomeration economies come from $(L^{is})^{\beta_0}(K^{is})^{\delta_0}$; the greater β_0 and δ_0, the stronger the agglomeration effects. Congestion comes from the fixed supply of land; the greater the importance of land (the smaller β_1 and δ_1), the stronger congestion. Aggregating up to the county level and equating returns to capital and labor across counties gives a complex expression, the essence of which is captured by (3), where $\gamma_s = \frac{1}{1-(\beta_0+\beta_1)-(\delta_0+\delta_1)}$. Therefore, the greater γ_s, the stronger agglomeration economies or the weaker congestion effects.

where H^i is the vector of observed geographical features. As an example, suppose proximity to waterways contributes more to productivity in 1992 than in 1972; we would then expect a positive coefficient on the proximity to waterways variable. In the empirical section equation (6) will be referred to as **Model 1**.

Though the estimable equation looks familiar from the empirical growth literature, our interpretation is quite different. The standard convergence view would interpret the coefficient on L_{1972}^{is} as the speed at which the economy approaches steady state. Given the high mobility of capital and labor between U.S. counties, transitional dynamics are likely to be short though. We therefore take the view that the economy is in steady state at all times; changes in the spatial distribution between 1972 and 1992 are interpreted as the economy moving from one steady state to another.

2.2 Including spatial spillovers

Spatial externalities do not stop at county borders; agglomeration economies and congestion effects spill over into neighboring locations (Harris, 1954, Fujita and Ogawa, 1982). A rural county in Southern California still benefits from its proximity to Los Angeles, whereas a rural county in the middle of nowhere does not. When firms move out of urban centers to avoid increasing congestion, they are likely to prefer close-by, less congested areas over far-off locations.

To take into account the effect of neighboring locations, we replace $\alpha_l^s \log L_{1972}^{is}$ in equation (6) by:

$$\int_0^\infty \alpha_l^s(m_i)\ \log L_{1972}^{is}(m_i)dm_i \tag{7}$$

where $L^{is}(m_i)$ denotes sectoral employment in counties situated m_i kilometers from county i. In other words, employment growth in county i depends on a geometric average of initial employment in the surrounding area.

If the dependent variable were the level of employment, it would be natural to model $\alpha_l^s(.)$ as a simple decay function. However, given that the dependent variable is the growth of employment, we have no strong prior about the shape of $\alpha_l^s(.)$. For instance, suppose weakening agglomeration economies encourage firms to spread out. Economic clusters lose employment, whereas areas close to those clusters gain employment; this would show up as $\alpha_l^s(.)$ starting off with a negative sign, then turning positive at relatively short distances, before decaying to zero at longer distances.

It is therefore important not to put any *a priori* restriction on the shape of $\alpha_l^s(.)$. For estimation purposes we replace expression (7) with a discrete approximation and obtain the following estimable regression:

$$\log L_{1992}^{is} - \log L_{1972}^{is} = \alpha_o^s + \sum_{m=0}^{D} \alpha_l^s(m_i) \ \log L_{1972}^{is}(m_i) + \alpha_h^s H^i \tag{8}$$

where each value of index m represents a distance interval from county i — say, from 0 to 5 km, from 5 to 10 km, etc. — and D is the number of intervals considered. There is no natural distance beyond which agglomeration and congestion effects die out; however, as will be shown, the effect of counties more than 100 kilometers away is negligible. In the empirical section equation (8) will be referred to as **Model 2**.

To improve efficiency, we impose a certain smoothness on function $\alpha_l^s(.)$ by adopting a roughness penalty approach. This method, pioneered by Good and Gaskins (1971) and Silverman (1982), prevents the slope of $\alpha_l^s(.)$ from changing too rapidly by adding a penalty function to the standard least square criterion:

$$\sum_{m=1}^{D-1} \lambda^2[(\alpha_l^s(m+1) - \alpha_l^s(m)) - (\alpha_l^s(m) - \alpha_l^s(m-1))]^2 \tag{9}$$

The parameter λ determines the severity of the penalty for a given difference in 'neighboring' coefficients; a greater λ implies a higher degree of smoothing. When the estimating function is a likelihood function instead of least squares, Silverman (1982, 1984) has shown that the above yields a kernel estimator of $\alpha_l^s(.)$.

The roughness penalty approach consists in adding $D-2$ artificial observations at the end of the sample. If T is the number of true observations, the artificial observations go from $n = T+1$ to $n = T+D-2$. For artificial observation n the dependent variable and all regressors are 0, except for $L^{is}(n-T-1) = \lambda$, $L_{1972}^{is}(n-T) = -2\lambda$, and $L_{1972}^{is}(n-T+1) = \lambda$. Applying the standard OLS formula to the modified sample yields the roughness penalty estimator. Standard errors are obtained by bootstrapping.

2.3 Including aggregate employment spillovers

Some spatial effects — such as market potential and land prices — come from aggregate, rather than sectoral, employment externalities. To include such aggregate employment effects, take equation (8) and replace the regressor L^{is}_{1972} with $(L^{i}_{1972})^{\alpha-\beta}(L^{is}_{1972})^{\beta}$, where L^{i}_{1972} is total employment. We are thus considering total and sectoral employment to be imperfectly substitutable in their agglomeration and congestion effects. Re-writing $(L^{i}_{1972})^{\alpha-\beta}(L^{is}_{1972})^{\beta}$ as $(L^{i}_{1972})^{\alpha}(\frac{L^{is}_{1972}}{L^{i}_{1972}})^{\beta}$, and substituting into L^{is}_{1972} in equation (8) yields the following expression:

$$\log L^{is}_{1992} - \log L^{is}_{1972} = \alpha^s_o + \sum_{m=0}^{D} \alpha^s_l(m_i) \log L^{i}_{1972}(m_i) + \sum_{m=0}^{D} \beta^s(m_i) \log \frac{L^{is}_{1972}(m_i)}{L^{i}_{1972}(m_i)} + \alpha^s_h H^i \tag{10}$$

The empirical section will refer to this equation as **Model 3**.

3 The Data

County-level sectoral employment data come from the Regional Economic Information System (REIS) compiled by the U.S. Bureau of Economic Analysis (BEA). We use employment data for 1972 and 1992 in thirteen sectors, covering the entire economy: farming; agricultural services; mining; construction; manufacturing; transportation and utilities; wholesale; retail; FIRE (finance, insurance and real estate); other services; federal government; military; and state and local government. After dropping Alaska and Hawaii from the analysis,[3] we are left with 3092 counties. Sectoral employment data are missing for some counties, either because they are unavailable or because they are not disclosed.[4]

Between 1972 and 1992 employment in the contiguous United States grew on average 2% a year *(Table 1)*. Growth was fastest in agricultural services and in 'other services'. Farming, manufacturing and the military, on the contrary, experienced a reduction

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[3] Alaska and Hawaii are quite different from the contiguous U.S. both in terms of distance to the mainland and in terms of geography (Hawaii is made up of islands; Alaska is close to the polar circle). Our assumption of perfect capital and labor mobility with the rest of the country may therefore not be appropriate.

[4] For some counties sectoral employment is not revealed in order not to violate employer confidentiality. For other counties sectoral employment is simply reported as 'less than 10'; in those cases we set employment equal to 5.

in absolute employment levels. A similar picture emerges when considering employment shares; farming and manufacturing shrunk dramatically, with 'other services' filling the gap.

Data on county area, latitude, and longitude come from the U.S. Geological Survey (USGS). Counties are assumed to be centered at their county seat. The average county size is 2491 square kilometers, corresponding to an average diameter of approximately 50 kilometers (30 miles).[5] Counties vary considerably in size, however: the coefficient of variation of county area is 1.36. Western counties in particular tend to be larger than their eastern counterparts. Distance d_{ij} between counties i and j is calculated 'as the crow flies' using the following formula:

$$d_{ij} = \frac{10000}{90} \arccos[\sin lat_i \sin lat_j + \cos lat_i \cos lat_j \cos(long_j - long_i)] \qquad (11)$$

where lat is the latitude and $long$ is the longitude of the county seat in degrees. This is a reasonable approximation of transportation distance, given the density of the U.S. road and rail network.

Distance d_{ij} is used to construct the employment variables $L^{is}(m_i)$. We divide distance from county i into 5 km intervals: 0-5 km, 5-10 km, 10-15 km, etc. We go to a maximum of 100 kilometers, since estimation results suggest that spatial effects die out beyond that distance.[6] For each distance interval (or 'donut') we sum the sectoral employment of all counties, of which the county seats are located in that particular 'donut'. This procedure, performed with the help of a Fortran program, yields a vector of 20 employment variables $L^{is}(m_i)$, in addition to the own county employment. In case there is no county seat in a given 'donut', $L^{is}(m_i)$ is set to zero. This normalization is equivalent to setting to zero the externalities that affect 'island' counties, that is, counties with no neighbors.

By construction, county seats located in large counties are less likely to be close

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[5] This approximation obviously underestimates the actual diameter, since counties are not perfect circles. It is nevertheless useful as a ballpark figure.

[6] This ignores the possibility of optimal spacing between cities (Isard, 1956), an issue that would require another methodology.

to other county seats. To correct for this phenomenon, county area is included as a separate regressor.[7] We also control for being on an 'edge' — such as an ocean, lake or border — since this may affect location. For instance, if ocean shipping becomes cheaper, counties on the coasts benefit; if tariffs come down, counties on the U.S. border gain. We construct separate 'edge' dummies for: the Atlantic ocean; the Pacific ocean; the Great Lakes; the gulf of Mexico; the Mexican border; and the Canadian border. Information of proximity to borders and water was compiled from detailed maps provided by the American Automobile Association (AAA).

Changes in location have also been affected by general trends, such as the tendency for jobs to move to the West and the South (Blanchard and Katz, 1992, Mills and Hamilton, 1994, Glaeser, Scheinkman and Schleifer, 1995, Hanson, 1998). Latitude and longitude are therefore included as regressors. Finally, given that economic activity in the U.S. is concentrated on the Atlantic and the Pacific seaboards, we consider the possibility that the coasts are subject to different employment trends. We therefore add dummies for counties located in states on the East coast or the West coast.

4 Empirical Results

To facilitate interpretation, the dependent variable is of the form $\frac{\log L^{is}_{1992} - \log L^{is}_{1972}}{20}$, so that all coefficients can be interpreted in terms of annual growth rates. One practical issue that arises in calculating the dependent variable is what to do with zero observations. Omitting counties with zero initial employment and no employment growth would bias results in favor of convergence: after all, if convergence forces were at play, counties with no initial employment should grow fastest. To avoid this bias, we replace all 0 employment by 1. This is akin to assuming that at least one person in each county performs one of the 13 broadly defined functions corresponding to each sector. It implies that counties with no employment in both census years show up with zero employment growth, which

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[7] Instead of assuming that economic activity is concentrated at the county seat, we could also adopt the view that economic activity is evenly spread across each county. In that case we would regress on employment density (as in Ciccone and Hall, 1996), rather than on employment level. Experimenting with this alternative did not improve our results though.

is the correct interpretation.

4.1 A model with localized spatial externalities (Model 1)

Our starting point is **Model 1**, which regresses annual sectoral employment growth on initial sectoral employment, without taking into account spatial and aggregate spillovers. Regression results are shown in *Table 2*. Whereas non-service sectors became more spread out between 1972 and 1992, service sectors became geographically more concentrated. This is reflected in the sign of the coefficients on initial employment: negative in non-service sectors, and positive in service sectors. Note that the economy as a whole behaves like the service sectors; this is not surprising, given the fast growth of services.

The coefficients on initial employment are not hard to interpret. Take, for instance, the coefficient of -0.006 on initial manufacturing employment. This means that a 1% increase in initial manufacturing employment would have led to a 0.006% annual decrease in manufacturing employment growth. Put differently, if county A started out with twice the manufacturing employment of county B, its manufacturing employment growth would have been a total of 8% lower between 1972 and 1992.

In contrast to both the convergence approach (Mankiw, Romer and Weil, 1992, Barro and Sala i Martin, 1995) and the mean reversion view (Quah, 1993), we interpret changes in the economy's spatial distribution as movements from one steady state to another. We believe our interpretation is more appropriate in the given context. Take, for instance, the positive coefficient on initial total employment (the first column in *Table 2*). According to the convergence view, this would imply that eventually all U.S. employment will concentrate in a single county, a hardly credible prediction; according to our view, it simply means that U.S. employment became more concentrated between 1972 and 1992.

The positive coefficient on initial total employment is also hard to reconcile with the mean reversion framework, which assumes that random shocks move counties temporarily away from the U.S. average. Mean reversion therefore predicts lower growth for counties with high initial employment, implying a negative coefficient on initial employment. This contradicts our findings for total employment and for the service sectors. But even for those sectors with negative coefficients, mean reversion cannot be the entire explanation. Mean reversion alone leaves the distribution of employment unchanged. *Table 3,* however, suggests a narrowing of the distribution: for the most important sectors with negative coefficients — manufacturing, farming and wholesale — σ-convergence holds, implying employment becoming more equally spread across counties. Lastly, the t values of the coefficients on initial employment are higher than would be expected in a stochastic mean reversion setup.

Our results therefore lead to contradictions with the two main hypothesis used in the empirical growth literature. They are, however, easy to interpret within our framework. A negative coefficient on initial employment indicates employment spreading out; a positive coefficient means employment concentrating. Since we view these effects as coming from changes in agglomeration and congestion forces, there is no reason to believe that these trends will persist in the future. Manufacturing, for instance, was highly decentralized prior to the industrial revolution, at which point it started to concentrate in cities. We are now witnessing the opposite: manufacturing is spreading out again, possibly because of lower transportation costs or because of pollution concerns.

The control variables in *Table 2* give further details about changes in the economy's spatial distribution. The positive coefficients on 'county area' say that larger counties experienced faster employment growth. This indicates local crowding out through, for instance, land prices. The effect is strong and significant for all sectors, except for manufacturing and for wholesale. The negative coefficient on 'latitude' and the positive coefficient on 'longitude' for most sectors show jobs moving South and West, a well documented finding (Blanchard and Katz, 1992, Glaeser, Scheinkman and Schleifer, 1995, Hanson, 1998). Farming jobs, instead, moved North and West. The latitude and longitude effects are largely mitigated for counties located on or near the Eastern seaboard. Counties in the states of California, Oregon, and Washington also experienced faster employment growth, but contrary to Eastern counties, the effect is not stronger along the coast. The Gulf of Mexico had an equally beneficial effect on growth, especially in services. However, we find no evidence of the Canadian and Mexican borders affecting job migration.

4.2 A model with spatial spillovers (Model 2)

The next set of regressions (**Model 2**) examines the effect of neighboring counties. *Figure 1* and *Figure 2* show the employment regressors at different distances, and *Table 4* gives the estimation results for the other regressors. The effect of geographical features largely confirms the results of **Model 1**. As for the impact of neighboring counties, we can again distinguish between non-service and service sectors.

In most non-service sectors, employment spreaded out to nearby areas. Look, for instance, at the graph 'wholesale on wholesale' in *Figure 1*. Assume county A is a wholesale cluster. The negative coefficients at short distances indicate that in a radius of 20 kilometers around A wholesale employment relatively declined; the positive coefficients at intermediate distances suggest that in a radius of 20 to 60 kilometers around A wholesale employment relatively increased. In other words, wholesale employment moved out of areas with high wholesale employment to nearby areas with less wholesale employment.

The opposite happened to the service sectors and to the economy as a whole. Services became geographically more concentrated by absorbing service employment of surrounding areas. Take, for instance, the retail sector (the graph 'retail on retail' in *Figure 2*). Now assume county A is an important retail center. The coefficients suggest that in a radius of 5 kilometers around A retail employment increased, whereas in a radius of 5 to 20 kilometers around A retail employment declined. Existing clusters are therefore pulling jobs away from their respective hinterlands.

4.3 A model with aggregate employment spillovers (Model 3)

To investigate how much of the results are due to sectoral effects and how much to aggregate effects, we turn to **Model 3**. Results for regressors other than initial employment are omitted from the paper; they are not sufficiently different from those presented in *Table 2* and *Table 4* to warrant presentation. Results regarding initial employment at different distances are presented in *Figures 3*, *4* and *5*. Again two distinct patterns emerge from the data: one affecting service sectors and the other affecting the rest of the economy. Some sectors which cannot be clearly defined as forming part of services or not, such as transportation and utilities, look like a combination of the two dominant patterns.

The pattern for non-service sectors — such as farming, manufacturing and construction — shows employment moving away from specialized clusters and away from centers of high aggregate employment. Look, for instance, at construction in *Figure 3*: the coefficients at short distances in 'construction on construction' (the sectoral effect) and 'construction on total' (the aggregate effect) are negative. In addition, for quite a few sectors — such as construction and manufacturing — we observe positive coefficients at distances of 20 to 60 kilometers. Jobs have thus been moving out of high density locations to the surrounding areas. This description is reminiscent of the so-called suburbanization of America (Cheshire, 1999). Our results are also consistent with the observed decline in transportation costs. To see this, note that moving out of high employment centers represents a cost: lower agglomeration economies; and a benefit: reduced congestion. As transportation becomes cheaper, the geographical reach of agglomeration economies increases, thus reducing the cost of locating in the hinterland.

Most service sectors show quite a different pattern. Although services have been moving out of specialized clusters, they have become increasingly concentrated in urban centers. Look, for instance, at 'FIRE' in *Figure 4*. On the one hand, services have been leaving locations with a high share of service employment (negative coefficients in 'FIRE on FIRE'); on the other hand, services have been concentrating in areas of high aggregate employment by attracting service employment of the hinterlands (positive coefficients, followed by negative coefficients, in 'FIRE on total'). Though contrary to what happened in the rest of the economy, these results are not inconsistent with the decline in transportation costs. Due to prohibitively high transportation costs, services were traditionally non-tradeable, giving little opportunity for agglomeration economies to kick in. Cheaper transportation has made services increasingly tradeable, encouraging firms to concentrate and to take advantage of agglomeration economies.

Note that we have not said anything about the small positive effects of aggregate employment at distances of 20 to 60 kilometers in many of the service sectors (see, for instance, 'FIRE on total'). This may be consistent with economic geography theories which predict a hierarchy of towns and cities some distance apart from each other (Isard, 1956).

5 Conclusion

In this paper we studied the evolution of sectoral employment patterns in U.S. counties over the period 1972-1992. To explain changes in the economy's geographical distribution, we focused on changes in spatial externalities, rather than on transitional dynamics or mean-reversion processes. Since spatial externalities do not stop at county borders, we allowed for employment growth to be affected by all surrounding counties in a radius of 100 km. Spatial effects were modeled in a semi-parametric fashion to allow for multiple inflection points.

Apart from already well known results, such as the employment shift toward the South and the West of the U.S., our findings indicate a slight increase in the concentration of county-level employment over the period considered. This tendency is most notable in the service sectors, which increasingly located in centers of high employment by absorbing service jobs from counties less than 20 kilometers away. In contrast, 'dirty' industries such as farming, manufacturing, and wholesale tended to move away from high activity areas. We also find that counties located near the Atlantic and Pacific oceans and the Gulf of Mexico experienced faster employment growth, while proximity to Canada and Mexico had no noticeable impact.

This work illustrates how a geographical analysis of growth can benefit from an explicit and careful treatment of spatial externalities. It can be extended towards a more structural approach by seeking to uncover the relationship between employment, on the one hand, and intrinsic and inherited productivity differentials across counties, on the other hand. This is the object of future research.

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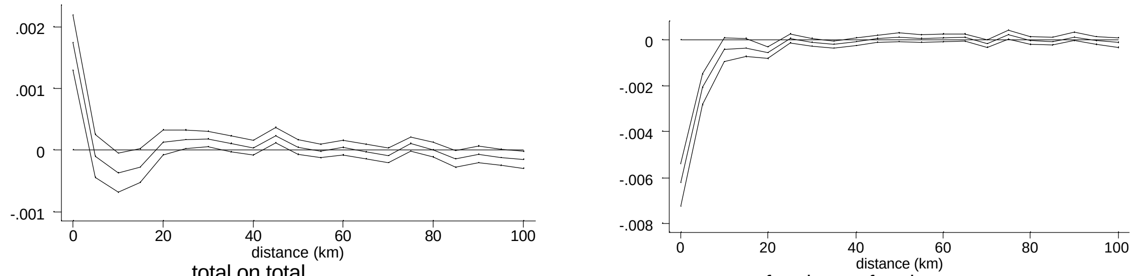
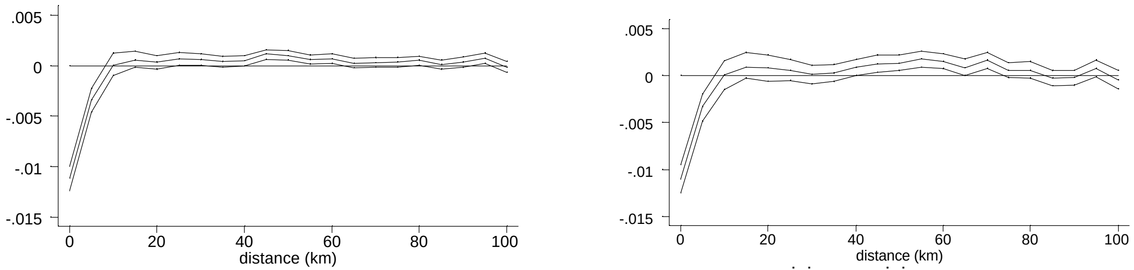


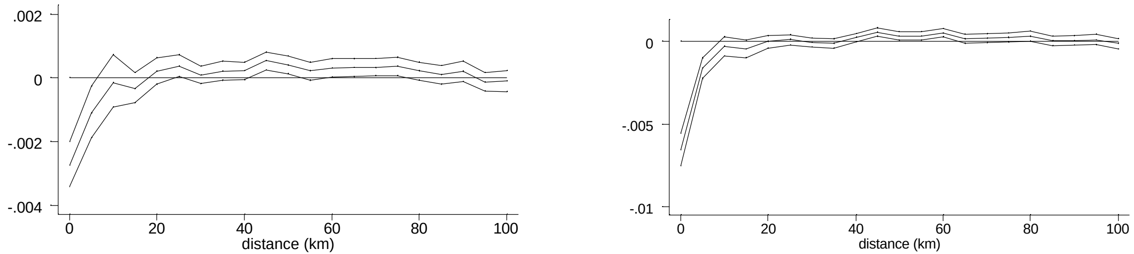
total on total

farming on farming



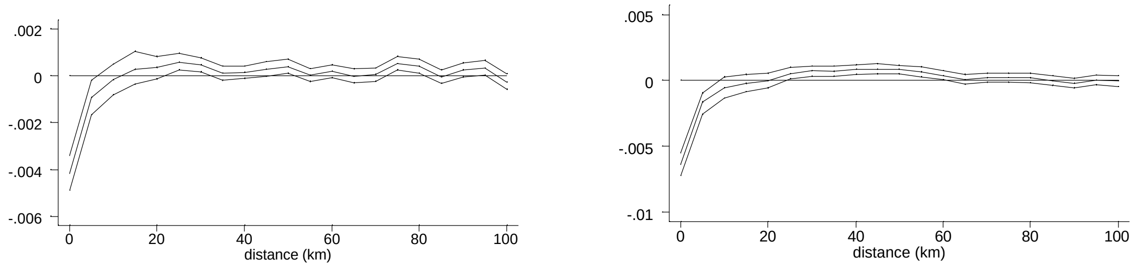
ag serv on ag serv

mining on mining



construction on construction

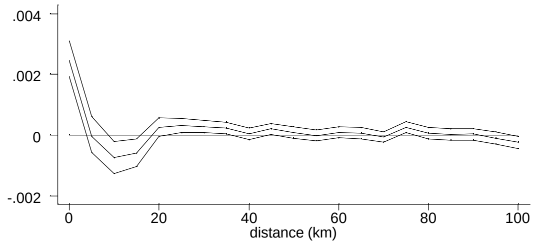
manufacturing on manufacturing



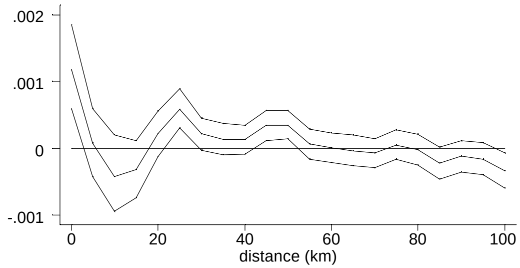
transp/util on transp/util

wholesale on wholesale

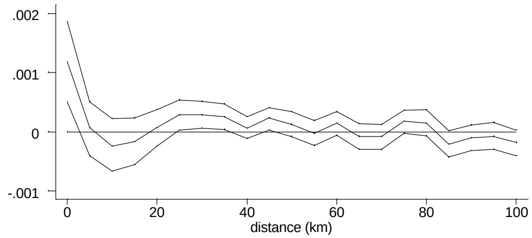
Figure 1: Effect of sectoral employment (logs) at different distances on sectoral employment growth (cont'd in Figure 2)



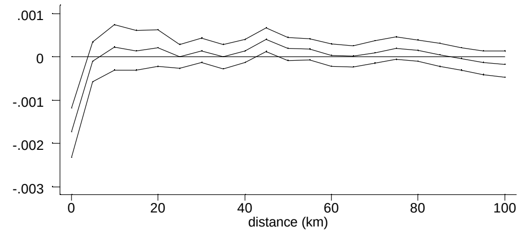
retail on retail



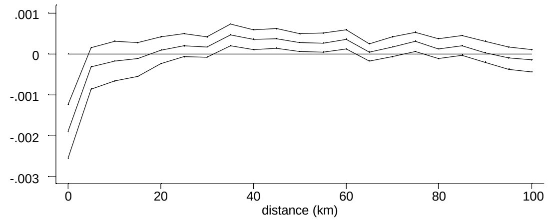
FIRE on FIRE



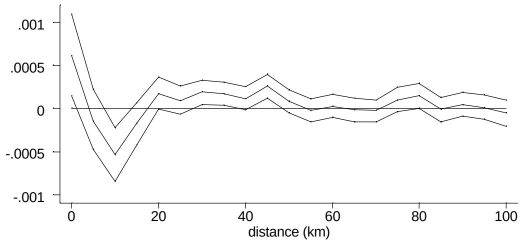
other serv on other serv



fed civ on fed civ

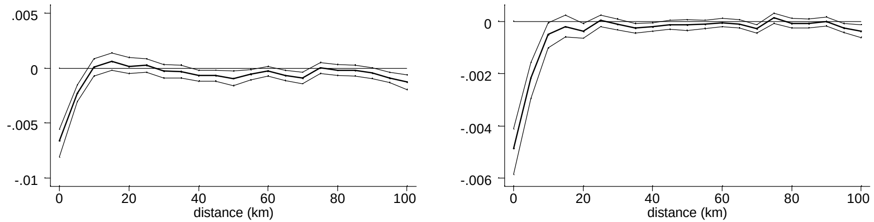


military on military

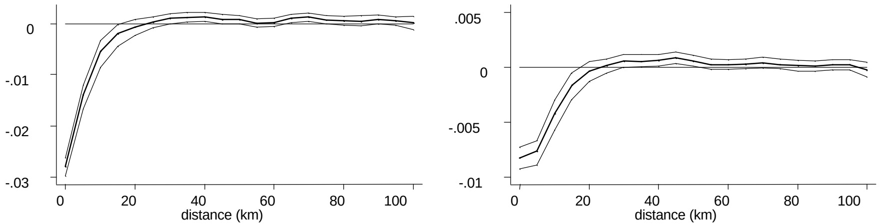


state/local on state/local

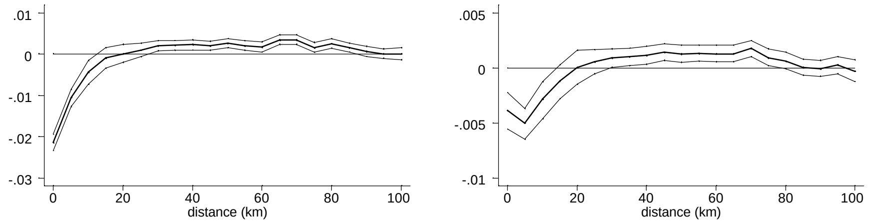
Figure 2: Effect of sectoral employment (logs) at different distances on sectoral employment growth (cont'd from Figure 1)



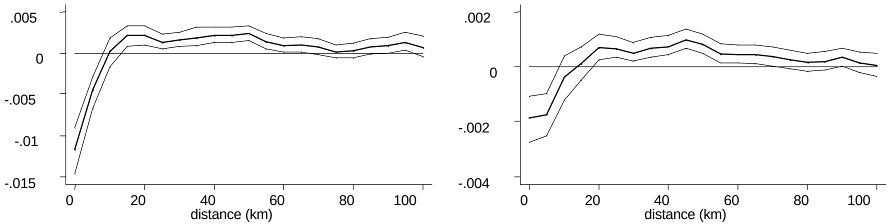
farming on farming farming on total



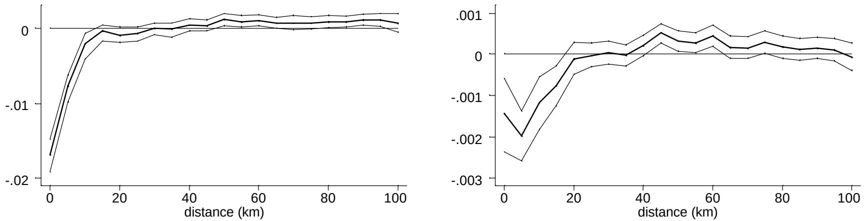
ag serv on ag serv ag serv on total



mining on mining mining on total

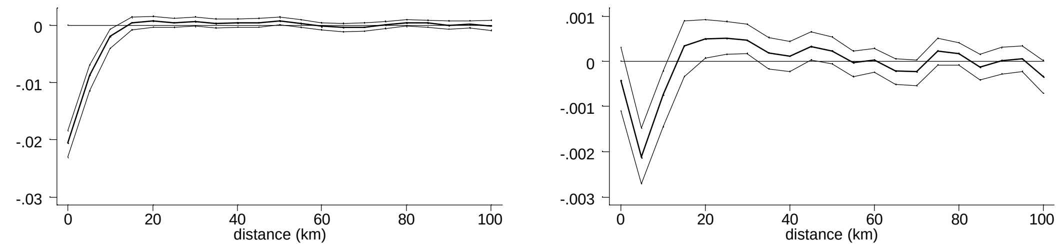


construction on construction construction on total



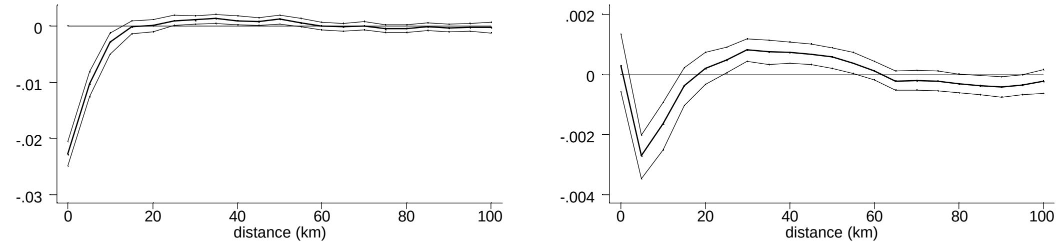
manufacturing on manufacturing manufacturing on total

Figure 3: Effect of sectoral employment shares (logs) and total employment (logs) at different distances on sectoral employment growth (cont'd in Figure 4)



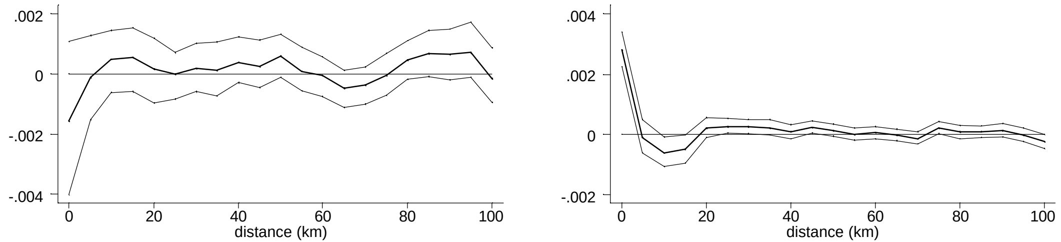
transp/util on transp/util

transp/util on total



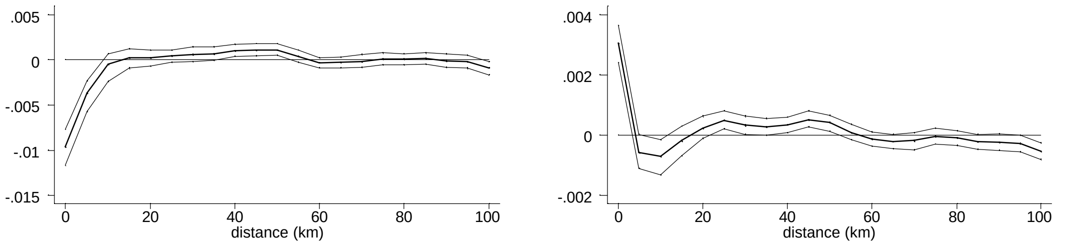
wholesale on wholesale

wholesale on total



retail on retail

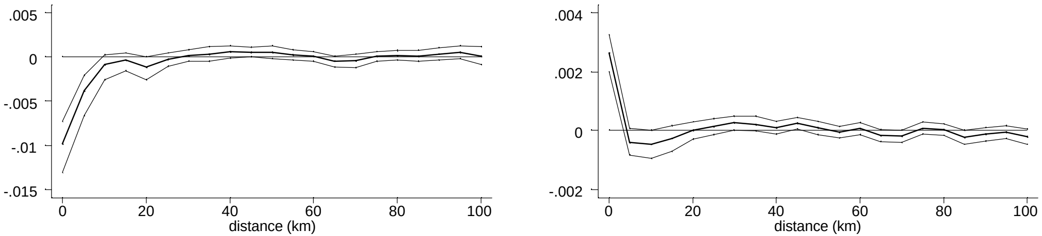
retail on total



FIRE on FIRE

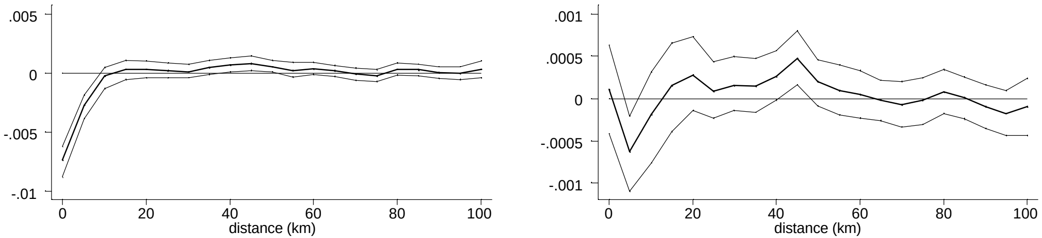
FIRE on total

Figure 4: Effect of sectoral employment shares (logs) and total employment (logs) at different distances on sectoral employment growth (cont'd in Figure 5)



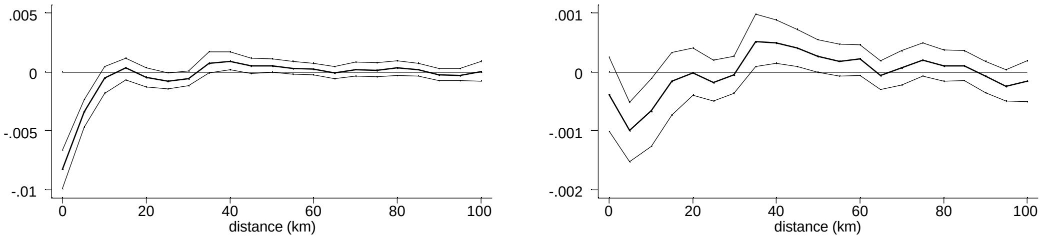
other serv on other serv

other serv on total



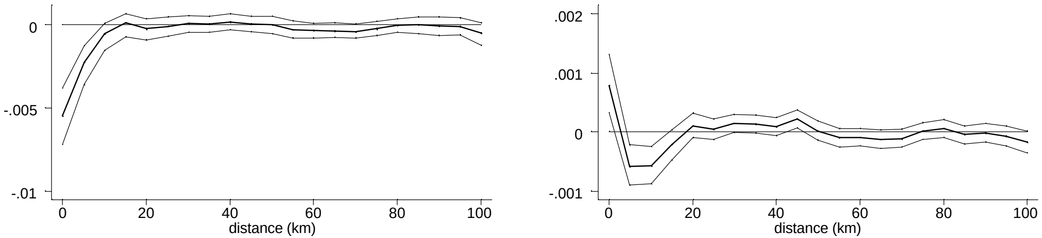
fed civ on fed civ

fed civ on total



military on military

military on total



sate/local on state/local

state/local on total

Figure 5: Effect of sectoral employment shares (logs) and total employment (logs) at different distances on sectoral employment growth.

Table 1: Sectoral employment in 1972 and 1992 (Summary statistics)

Sector	Employment 1972	Employment 1992	Growth rate
Total	30416	44947	47.77%
Farming	1228	981	-20.08%
Agricultural services	194	530	173.10%
Mining	275	392	42.78%
Construction	1547	2184	41.19%
Manufacturing	6452	6130	-4.98%
Transportation/Utilities	1666	2169	30.18%
Wholesale	1494	2247	50.40%
Retail	4657	7431	59.58%
FIRE	2191	3509	60.12%
Other services	5946	13233	122.54%
Federal civilian	922	1024	11.11%
Military	898	831	-7.41%
State/Local	3557	5050	42.00%

Source: REIS, Bureau of Economic Analysis

Table 2: Sectoral employment growth on sectoral employment and control variables

Dependent variable: annual growth rate in sectoral employment 1972-92							
	Total	Farming	Ag serv	Mining	Construction	Manuf	Transp/util
cons	-0.0024	0.0430	0.1326	0.0828	0.0850	0.0696	0.0888
	(0.43)	(8.19)	(12.03)	(3.83)	(9.77)	(6.39)	(10.22)
empl	0.0018	-0.0067	-0.0112	-0.0081	-0.0027	-0.0063	-0.0044
	(7.95)	(26.59)	(20.57)	(12.03)	(7.56)	(19.14)	(12.51)
area	1.13E-06	1.70E-06	1.88E-06	3.11E-06	1.21E-06	1.44E-07	1.41E-06
	(4.48)	(6.38)	(3.34)	(2.92)	(2.73)	(0.28)	(3.11)
lat	-0.0229	0.0038	-0.0193	-0.1487	-0.0297	-0.0213	-0.0434
	(6.23)	(0.96)	(2.22)	(8.76)	(4.63)	(2.80)	(6.66)
longit	0.0085	-0.0068	-0.0155	0.0357	-0.0218	0.0003	-0.0122
	(3.45)	(2.72)	(2.85)	(3.38)	(5.12)	(0.06)	(2.85)
ecoast	0.0058	-0.0061	0.0123	0.0287	0.0013	0.0024	0.0080
	(3.68)	(3.60)	(3.27)	(4.14)	(0.46)	(0.76)	(2.89)
lakes	0.0023	-0.0014	0.0054	0.0266	0.0066	0.0012	0.0027
	(1.34)	(0.77)	(1.33)	(3.42)	(2.16)	(0.35)	(0.88)
wcoast	0.0029	0.0045	0.0083	0.0071	0.0142	0.0067	0.0066
	(0.98)	(1.44)	(1.30)	(0.61)	(2.80)	(1.13)	(1.29)
gulf	0.0092	0.0006	0.0152	0.0023	0.0050	0.0052	0.0037
	(4.39)	(0.25)	(3.21)	(0.26)	(1.36)	(1.22)	(1.00)
mexico	-0.0009	-0.0040	0.0056	-0.0030	-0.0052	0.0082	0.0025
	(0.33)	(1.33)	(0.86)	(0.24)	(1.08)	(1.34)	(0.49)
canada	-0.0034	0.0001	-0.0093	0.0128	-0.0076	-0.0023	-0.0049
	(1.26)	(0.03)	(1.50)	(1.01)	(1.61)	(0.42)	(1.05)
estate	0.0050	-0.0042	-0.0039	-0.0110	0.0051	-0.0024	0.0053
	(5.45)	(4.32)	(1.79)	(2.44)	(3.23)	(1.31)	(3.27)
wstate	0.0066	0.0165	0.0262	-0.0008	0.0277	0.0064	0.0140
	(3.40)	(8.11)	(5.79)	(0.10)	(8.10)	(1.55)	(4.02)
R^2	0.1072	0.2230	0.1550	0.1097	0.0681	0.1466	0.0893

	Wholesale	Retail	FIRE	Other serv	Fed civ	Milit	State/Loc
cons	0.0487	0.0342	0.0220	0.0079	0.0418	0.0691	0.0285
	(4.64)	(5.34)	(3.22)	(1.09)	(6.67)	(11.72)	(5.92)
empl	-0.0058	0.0023	0.0011	0.0013	-0.0018	-0.0020	0.0005
	(15.16)	(8.42)	(3.99)	(4.59)	(6.99)	(7.94)	(2.23)
area	1.92E-07	1.57E-06	2.19E-06	1.26E-06	1.96E-06	1.20E-06	8.60E-07
	(0.33)	(4.95)	(6.01)	(3.51)	(5.71)	(3.93)	(3.68)
lat	0.0275	-0.0382	-0.0334	0.0133	-0.0382	-0.0331	-0.0637
	(3.43)	(8.25)	(6.43)	(2.56)	(7.64)	(7.37)	(18.74)
longit	-0.0027	-0.0063	0.0022	0.0021	-0.0035	-0.0236	0.0152
	(0.51)	(2.07)	(0.66)	(0.62)	(1.09)	(8.04)	(6.74)
ecoast	0.0021	0.0030	0.0113	0.0107	0.0070	0.0026	0.0035
	(0.62)	(1.51)	(5.16)	(4.86)	(3.28)	(1.32)	(2.39)
lakes	-0.0095	0.0057	0.0043	0.0033	0.0061	-0.0016	0.0017
	(2.56)	(2.60)	(1.78)	(1.33)	(2.59)	(0.78)	(1.05)
wcoast	0.0080	0.0054	0.0079	0.0073	-0.0031	0.0014	-0.0033
	(1.27)	(1.47)	(1.92)	(1.77)	(0.80)	(0.38)	(1.20)
gulf	0.0058	0.0103	0.0116	0.0180	0.0147	0.0090	0.0019
	(1.27)	(3.86)	(3.98)	(6.09)	(5.19)	(3.50)	(0.99)
mexico	-0.0096	0.0007	0.0018	0.0068	0.0143	0.0013	0.0020
	(1.57)	(0.19)	(0.42)	(1.69)	(3.83)	(0.36)	(0.78)
canada	-0.0242	0.0013	0.0042	-0.0065	-0.0024	-0.0070	-0.0022
	(4.22)	(0.37)	(1.13)	(1.70)	(0.65)	(2.15)	(0.88)
estate	0.0049	0.0086	0.0078	0.0026	0.0031	-0.0049	0.0088
	(2.45)	(7.51)	(6.08)	(2.00)	(2.52)	(4.47)	(10.47)
wstate	0.0136	0.0160	0.0056	0.0079	0.0187	0.0133	0.0047
	(3.14)	(6.55)	(2.05)	(2.88)	(7.20)	(5.61)	(2.62)
R^2	0.0946	0.1507	0.0995	0.0644	0.0907	0.0612	0.1969

Absolute values of t-statistics in brackets.

Table 3: Standard deviations of sectoral employment in 1972 and 1992 in logs

Sector	standard deviation (logs) 1972	standard deviation (logs) 1992
Farming	.94	.84
Agricultural Services	1.32	1.31
Mining	1.67	1.78
Construction	1.51	1.58
Manufacturing	1.97	1.88
Transportation/Utilities	1.54	1.57
Wholesale	1.73	1.67
Retail	1.42	1.58
FIRE	1.54	1.64
Other Services	1.50	1.62
Federal Civilian	1.57	1.60
Military	1.49	1.50
State/Local	1.31	1.36

Source: REIS, Bureau of Economic Analysis

Table 4: Sectoral employment growth on sectoral employment at different distances and control variables

Dependent variable: annual growth rate in sectoral employment 1972-92							
	Total	Farming	Ag serv	Mining	Construction	Manuf	Transp/util
cons	-0.0021981	0.0182922	0.0271476	0.0013742	0.0136244	0.0105708	0.0178793
	(0.70)	(5.62)	(4.14)	(0.12)	(2.58)	(1.69)	(3.39)
area	1.26E-06	1.09E-06	2.98E-06	6.02E-06	1.99E-06	9.30E-07	1.91E-06
	(4.63)	(3.70)	(4.98)	(5.58)	(4.19)	(1.73)	(3.95)
lat	-0.022969	0.0150381	-0.0027604	-0.1540322	-0.0198183	-0.0137093	-0.0356837
	(6.60)	(4.11)	(0.34)	(10.25)	(3.28)	(1.94)	(5.77)
longit	0.0090501	0.0021927	0.029197	0.0758084	0.0093409	0.0261786	0.0200724
	(4.94)	(1.12)	(7.08)	(9.89)	(2.92)	(6.87)	(6.15)
ecoast	0.0056855	-0.0049663	0.0127675	0.0333713	0.0049403	0.007777	0.0101269
	(3.53)	(2.91)	(3.34)	(4.82)	(1.77)	(2.41)	(3.59)
lakes	0.002663	-0.0016566	0.0139015	0.039808	0.0127471	0.006557	0.0084282
	(1.48)	(0.86)	(3.33)	(5.11)	(4.06)	(1.80)	(2.64)
wcoast	0.0026657	0.0029803	0.0040277	0.008798	0.0125361	0.0055171	0.0040809
	(0.91)	(0.95)	(0.63)	(0.77)	(2.48)	(0.93)	(0.80)
gulf	0.0097241	0.0025789	0.0244819	0.0119659	0.0115087	0.0122581	0.0089913
	(4.57)	(1.14)	(5.14)	(1.37)	(3.11)	(2.87)	(2.39)
mexico	-0.0012236	-0.003925	0.0106147	0.0060427	-0.0018081	0.0112277	0.0039715
	(0.44)	(1.31)	(1.61)	(0.48)	(0.37)	(1.85)	(0.79)
canada	-0.0023902	-0.0010467	0.0003061	0.027077	-0.0011318	0.0042028	0.0007381
	(0.88)	(0.36)	(0.05)	(2.16)	(0.24)	(0.75)	(0.16)
estate	0.0047934	-0.0012201	0.001386	-0.0008267	0.0087952	0.0001525	0.0102765
	(5.82)	(1.40)	(0.69)	(0.22)	(6.12)	(0.09)	(7.08)
wstate	0.0063916	0.0126599	0.0094853	-0.0108507	0.017397	-0.0008708	0.0028464
	(3.59)	(6.60)	(2.29)	(1.46)	(5.55)	(0.24)	(0.89)
R^2	0.1259	0.225	0.1763	0.1459	0.0806	0.1623	0.1002

	Wholesale	Retail	FIRE	Other serv	Fed civ	Milit	State/Loc
cons	0.0004683	0.0047589	0.0061139	-0.000884	0.0119423	0.0136526	0.0036666
	(0.07)	(1.23)	(1.46)	(0.21)	(2.93)	(3.67)	(1.28)
area	2.06E-06	1.71E-06	2.12E-06	1.59E-06	2.00E-06	1.63E-06	1.10E-06
	(3.44)	(5.01)	(5.43)	(4.13)	(5.48)	(4.99)	(4.38)
lat	0.0203211	-0.0332372	-0.0288006	0.013496	-0.0321485	-0.0235024	-0.0603058
	(2.72)	(7.55)	(5.85)	(2.76)	(6.75)	(5.58)	(18.70)
longit	0.0206716	0.006594	0.0098443	0.0066853	0.0097939	0.0004457	0.0258158
	(5.24)	(2.85)	(3.82)	(2.59)	(3.91)	(0.20)	(15.21)
ecoast	0.005605	0.0041128	0.0109504	0.0113371	0.0069169	0.0042576	0.0047957
	(1.66)	(2.03)	(4.91)	(5.01)	(3.16)	(2.16)	(3.23)
lakes	-0.001679	0.0075649	0.0051175	0.0046784	0.0078421	0.0024364	0.0036859
	(0.45)	(3.35)	(2.04)	(1.81)	(3.22)	(1.12)	(2.21)
wcoast	0.0062188	0.0047925	0.0067169	0.0069681	-0.0040952	-0.0000748	-0.004037
	(1.01)	(1.30)	(1.63)	(1.70)	(1.03)	(0.02)	(1.49)
gulf	0.0122986	0.0124964	0.0130602	0.0190917	0.0167503	0.013238	0.0038845
	(2.71)	(4.64)	(4.47)	(6.38)	(5.87)	(5.09)	(1.98)
mexico	-0.0059918	0.0012019	0.0013804	0.0069758	0.0151866	0.0031874	0.0028927
	(1.00)	(0.34)	(0.33)	(1.72)	(4.03)	(0.91)	(1.12)
canada	-0.0140143	0.0038695	0.0052333	-0.0045432	-0.0007471	-0.0028309	0.0002475
	(2.45)	(1.13)	(1.39)	(1.18)	(0.20)	(0.85)	(0.10)
estate	0.0053612	0.0105034	0.0091638	0.0028607	0.0053387	-0.0018973	0.0102155
	(3.05)	(10.18)	(7.99)	(2.45)	(4.78)	(1.88)	(13.41)
wstate	0.0081283	0.0110766	0.0020739	0.0066513	0.013561	0.0045266	0.0011632
	(2.06)	(4.95)	(0.82)	(2.64)	(5.62)	(2.07)	(0.71)
R^2	0.1368	0.1648	0.1129	0.0891	0.0904	0.0652	0.2115

Only control variables are reported. Employment regressors are presented in Figure 1. Absolute values of t-statistics in brackets.