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ABSTRACT

What are Falling Transport Costs doing to Spatial Concentration Across US Counties?

Theory is divided on whether falling transport costs lead to more or less spatial concentration of economic activity. Using US county-level data we find that aggregate employment became more concentrated between 1972-92. This aggregate picture hides important differences between sectors though. Whereas non-service sectors have been spreading out, service sectors have become increasingly concentrated by absorbing jobs from nearby areas. This cross-sectional variation lends support to Krugman and Venables (1995), who suggest that falling transport costs initially lead to more concentration, and later on to more dispersion.

JEL Classification: R11 and R12
Keywords: location, spatial concentration, transport costs and US counties

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1 Introduction

Do falling transport costs lead to more or to less concentration of economic activity across space? While certain authors have asserted that lower transport costs imply more spatial concentration (Krugman, 1991), others have gone to the opposite extreme by claiming that falling transport costs will cause the demise of cities (Gilder, 1994). According to Krugman and Venables (1995), both views may be partly right: they suggest that as transport costs drop, spatial concentration first increases, and then decreases.

The same conflicting views are present in the empirical literature on urban economics: while much attention has been devoted to the phenomenon of suburbanization (Mills, 1972; Macauley, 1985; Thurston and Yezer, 1994; Jordan, Ross and Usowski, 1998), the more recent evidence has shown that cities are in fact thriving (Kolko, 1999). Again, these views need not be contradictory. By focusing on county data, our paper finds evidence largely consistent with the non-monotone relation between transport costs and spatial concentration of Krugman and Venables (1995).

More particularly, we analyze spatial concentration across U.S. counties between 1972 and 1992, a period marked by falling transport costs. Continuing its secular trend, freight expenditure dropped from 8.1% of GDP at the beginning of the 1970s to 5.9% of GDP in 1992; over the same time period, the share of disposable income dedicated to transportation fell from 11% to 9.7% (Bureau of Transportation Statistics).

At the aggregate level we find that employment became more concentrated, confirming the good health of cities. However, behind the veil of aggregation lies a world more like the one described by Krugman and Venables (1995). In non-service sectors, such as manufacturing, activity has been spreading out, making counties more alike; in service sectors the opposite has been happening: they have become increasingly concentrated.

To see how this fits in with the Krugman and Venables (1995) story, we briefly review their argument. At prohibitively high transport costs, goods are essentially non-tradeable. This obliges production to locate close to customers, leading activity to remain spread out.[1] As transport costs fall, goods become tradeable, allowing production to take advantage of agglomeration economies by concentrating. However, if transport costs continue to drop, those agglomeration economies reach out farther in space, leading activity to spread back out to less congested areas.

While our time series is too short to uncover the Krugman-Venables relation at the aggregate level, the cross-sectional variation allows us to get around this problem. To clarify this point, assume that transport costs declined across all sectors.[2] If a sector had initially high transport costs, we would expect concentration to have increased; if, on the contrary, a sector had already low transport costs to start with, we would expect concentration to have decreased.

This is exactly what we see when we compare the service to the non-service sectors. Due to their non-tradeable nature, services have traditionally been spread out. Falling transport costs are now allowing them to agglomerate.[3] Manufacturing, however, already became highly concentrated during the nineteenth century (Kim, 1995; Glaeser, 1998); the more recent drop in transport costs has been weakening the benefits from agglomeration, leading manufacturing activity to spread out.

Now take this argument one step further. If services are becoming more tradeable, we would expect service centers to sprout up by aborbing service jobs from the hinterland. Similarly, if agglomeration economies in the manufacturing sector are reaching out farther, we would expect areas close to existing clusters to benefit. We can only study these issues if we explicitly take into account the spatial dimension of agglomeration economies. To

[1] In the Krugman-Venables model this result depends on workers being immobile, an assumption which hardly makes sense in our framework, where counties are the unit of analysis. However, it is straightforward to see that their intuition goes through as long as one factor of production, such as land, is immobile.

[2] While the decline of transport costs in manufacturing is well documented (Smith, 1989), the evidence for services is more anecdotal. For instance, Kolko (1999) argues that the need for face-to-face interaction in services, such as consumer banking, has been greatly decreased due to technological advances. Not everyone agrees though: Glaeser (1998) makes the point that, although transport technologies have improved, higher incomes have increased the opportunity cost of losing time in transportation. Overall, however, it remains true that, as we mentioned before, the share of disposable income dedicated to transportation has declined.

[3] For an alternative explanation of the concentration of services, based on the increasing need to be close to specialized workers, see Kolko (1999).

do so, we regress county employment growth on initial employment at different distances from the county under consideration.

The results are consistent with the Krugman-Venables hypothesis. In service sectors growth was higher in centers of high aggregate employment, but lower 5 to 20 kilometers away; in non-service sectors, growth was lower in aggregate employment centers, but higher in areas 20 to 80 kilometers away. This suggests service employment concentrating in centers of high economic activity at the cost of service jobs in the hinterland. Non-service sectors, instead, moved out of economic centers to less congested areas 20 to 80 kilometers away.

Our paper is closely related to the urban economics literature. The results fit the picture of cities losing manufacturing employment, and becoming service centers (Glaeser, 1998). For example, textiles and publishing moved out of New York City during the 1970s and the 1980s, leaving it to be mainly a financial center (Glaeser and Kahn, 2001). However, some of our findings collide with the accepted wisdom in urban economics. Whereas we find that services and total employment became increasingly concentrated in high employment centers, studies on metropolitan areas suggest that suburbanization has not just affected some sectors, such as manufacturing, but the entire economy, including services (Macauley, 1985).

Clearly, some of these differences may stem from our focus on counties, rather than cities. In addition to leading to certain novel results, looking at counties has the further advantage of avoiding selection bias,[4] increasing the number of observations, and augmenting cross-sectional variation. Though there has been similar work on France (Combes, 2000), studies on changes in spatial concentration across the entire U.S. have generally focused on larger geographical units: Kim (1995), for instance, analyzed census regions, whereas Dumais, Ellison and Glaeser (2002) looked at U.S. states. Our finer level of disaggregation is preferable because static estimates of externalities suggest they have limited geographical reach. Ellison and Glaeser (1997), for instance, found that spillovers

[4]As pointed out by Beeson, DeJong and Troesken (2001), focusing on cities, rather than counties, introduces a bias by only considering those place which experienced successful growth in the past.

are stronger within counties than within states. Micro-based studies have come to similar conclusions (Jaffe, Trajtenberg and Henderson, 1993; Wallsten, 2001).

Returning to Combes (2000), many of our results on U.S. counties reinforce his findings on the differences between service and non-service sectors in France. As in Combes, we distinguish between localization economies, benefits which derive from being located close to other firms in the same industry, and urbanization economies, associated with closeness to overall economic activity. This ties in with previous work by Glaeser, Kallal, Scheinkman and Shleifer (1992) and Henderson, Kuncoro and Turner (1995). However, our paper differs from Combes on several accounts. First, Combes focuses on the sources of employment growth, whereas we are interested in the relation between transport costs and spatial concentration. Second, whereas Combes limits himself to studying local externalities, we explicitly take into account the spatial dimension of agglomeration economies.

Following up on that last point, studies based on metropolitan data are forced to implicitly assume that cities are islands, where the hinterland does not matter. However, when using county data covering the entire U.S. there is no need to place artificial bounds on agglomeration economies. Our paper therefore takes the view that a county's employment growth is not only affected by the county under consideration, but also by all 'nearby' counties, where we let the data tell us what 'nearby' means. As argued before, this allows us to further test some of the predictions of Krugman and Venables (1995). For instance, if dropping transport costs have weakened agglomeration economies in manufacturing, this should benefit counties close to existing clusters.

Of course taking into account the spatial aspect of externalities 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.

Note, however, that estimating a simple spatial decay function, as in Harris (1954), will not do for our purposes. 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 service growth was greater in high employment counties and smaller in the immediate hinterland. 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

2.1 A simple benchmark model

In a 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. Geographical features may also affect location through people's preferences: if workers like to live at the beach or in a warm climate, firms will follow.

Further clustering arises when spatial externalities are introduced (Marshall, 1890; Mills, 1967; Henderson, 1974; Rodríguez Clare, 1996; Fafchamps, 1997; Fujita, Krugman and Venables, 1999). These positive feedback mechanisms reinforce the initial patterns of specialization. This implies a role for path dependence — and thus also for random events — in determining the spatial distribution of economic activity. Whether initial location is driven by geographical features or by random events, clustering creates advantages of its own, irrespective of initial conditions. Although originally people migrated to California in search of gold, path dependence (and the sun) have kept them there, even if gold has all but disappeared.

For our estimation purposes these insights translate into the following equation:

$$\log L^{is}_{1992} = \alpha^s + (1+\beta^s)L^{is}_{1972} + \delta^s H^i + \varepsilon^{is}$$

where α^s is a sector-specific constant; L^{is} is employment in county i and sector s;[5] H^i is a vector of geographical features of county i, such as being located at the coast or a waterway; and ε^{is} is an error term.

Re-writing the above equation in terms of sectoral employment growth gives us:

$$\log L^{is}_{1992} - \log L^{is}_{1972} = \alpha^s + \beta^s L^{is}_{1972} + \delta^s H^i + \varepsilon^{is} \tag{1}$$

In the empirical section we will refer to equation (1) as **Model 1**. When estimating the model, we account for the possibility that disturbances ε^{is} are correlated across space. To this effect, we correct standard errors using the method proposed by Conley (1999), which is essentially an extension of the Newey-West correction of standard errors in time series, itself based on White robust standard errors. The advantage of this method is that it does not impose any extraneous structure on the shape of spatial autocorrelation.

To interpret the coefficients in equation (1), assume for now that capital and labor are sufficiently mobile across counties so that the economy is in steady state at all times.[6] In that case, if conditions did not change between 1972 and 1992, the spatial distribution of employment would not have changed either, so that $\alpha^s = \beta^s = \delta^s = 0$.

But of course changes did occur over those twenty years. Our simple theoretical framework allows us to distinguish between four different types of changes — corresponding to the four terms in (1) — that may have affected the spatial distribution of employment: weakening or strengthening agglomeration or congestion effects; changes in the role of geographical features; sector-specific changes; and random county-specific sectoral shocks. We now look in turn at each one of these possibilities to see how they would show up in equation (1).

[5] For now we only consider the effect of past sector-specific employment; later we will also take into account past aggregate employment. In other words, we will distinguish between specialization and urbanization economies.

[6] This allows us to abstract from transitional dynamics, familiar from the empirical growth literature; we will return to this alternative interpretation later.

If agglomeration economies weakened, β^s would be negative, reflecting employment having become more equally spread across counties. Likewise, if agglomeration economies strengthened — or, alternatively, congestion effects weakened — β^s would be positive, suggesting further clustering of employment. The literature has pointed to the drop in transport costs as one of the main forces affecting the nature of agglomeration economies (Glaeser, 1998; Kolko, 1999).[7] To contribute to resolving the theoretical debate about how changing transport costs relate to the changing concentration of economic activity, our paper aims to determine which theory fits the data better. For instance, according to Krugman (1991), falling transport costs should lead to more concentration, and thus to positive values of β^s across all sectors. In contrast, the later work by Krugman and Venables (1995) claims that lower transport costs should only increase spatial concentration in those sectors with high initial costs, such as services. In other sectors, such as manufacturing, with low initial transport costs, we should see activity spreading out, giving negative values of β^s. This is of course a very indirect way of looking at the effect of falling transport costs on spatial concentration. However, for want of time series data on sectoral transportation costs, our approach seems justified.

An example of the changing role of geographical features could be the decreasing relevance of waterways, showing up as a negative coefficient δ^s for waterways. Another example would be the increased attraction of firms to warm weather, giving a positive coefficient δ^s to being located in the South. This phenomenon could be explained by workers in warm weather having become more productive, following the introduction of air conditioning. Or shifting preferences could have played a role: people have been moving South and West, with firms following suit (Glaeser and Shapiro, 2001).

As for sector-specific shocks, we could think of the oil shocks of the 1970s having had a negative effect on automobile producers, and a positive effect on the oil industry: this would show up in a negative α^s for the automobile industry and a positive α^s for the oil industry. Another possibility would be that the sector-specific coefficient α^s picked up

[7] Of course other reasons may have contributed to changes in the concentration of industries, such as technological change (Carlino, 1985).

changes in comparative advantage, epitomized by the rise of services and the demise of manufacturing.

Finally, county-specific sectoral shocks may also have affected the spatial distribution of employment. For instance, if Los Angeles residents voted a resolution on restricting industrial pollution, this would give us a negative ε^{is} for contaminating activities in Los Angeles county.

As mentioned before, our interpretation of (1) is one where changes in underlying conditions make the economy move from one steady state or equilibrium in 1972 to another equilibrium in 1992. An alternative reading, in line with the empirical growth literature, would take a transitional dynamics view, where the economy moves to a steady state over time (Mankiw, Romer and Weil, 1992; Barro and Sala-i-Martin, 1995). Although both approaches indicate the same economic reality — a negative coefficient on past employment suggests employment spreading out more evenly across space, and a positive coefficient points to further geographical clustering — the interpretation of why this happens differs: whereas we view the coefficient on past employment as indicative of changing agglomeration or congestion effects, the Barro-Sala-i-Martin approach would interpret the coefficient as the speed at which the economy moves towards its steady state.

Given the focus on counties, our interpretation seems appropriate: contrary to larger units of analysis, such as states or countries, mobility of capital and labor is high across U.S. counties, so that arguably the economy is never too far away from its steady state or equilibrium. Not surprisingly, Combes (2000), who studies similar issues for France, differs in the reading of his results, given the limited labor mobility in European countries.

2.2 Distinguishing between sectoral and aggregate externalities

Uptil now we have only considered sector-specific externalities. However, some spatial effects — such as market potential and land prices — come from aggregate externalities. The literature has long distinguished between these two types of externalities: localization economies, based on the proximity to other firms in the same sector, and urbanization economies, coming from overall economic activity or diversity. In its dynamic version, this distinction is better known as the difference between Marshall-Arrow-Romer (MAR) and Jacobs externalities.

To distinguish between urbanization and localization economies in our simple model, take equation (1), and replace $(L^{is}_{1972})^{\beta^s}$ with $(L^{is}_{1972})^{\beta^s}(L^{i}_{1972})^{\gamma^s-\beta^s}$. We are thus considering total and sectoral employment to be imperfectly substitutable in their agglomeration and congestion effects. After re-writing $(L^{is}_{1972})^{\beta^s}(L^{i}_{1972})^{\gamma^s-\beta^s}$ as $(\frac{L^{is}_{1972}}{L^{i}_{1972}})^{\beta^s}(L^{i}_{1972})^{\gamma^s}$, and taking logs, we get the following expression:

$$\log L^{is}_{1992} - \log L^{is}_{1972} = \alpha^s + \beta^s \log \frac{L^{is}_{1972}}{L^{i}_{1972}} + \gamma^s \log L^{i}_{1972} + \delta^s H^i \qquad (2)$$

In the empirical section we will refer to (2) as **Model 2**. As before, standard errors will be calculated by applying the Conley correction for spatial autocorrelation.

Estimating equation (2) is reminiscent of Glaeser et al. (1992) who studied the relative importance of MAR and Jacobs externalities for economic growth in a cross-section of cities. Their work has been further extended by Henderson et al. (1995) and Combes (2000), amongst others. However, in line with what we said before, our reading of (2) will be different. More particularly, we will interpret the coefficients β^s and γ^s as reflecting changes in agglomeration economies. One further difference is worth pointing out: we take urbanization economies as coming from aggregate economic activity. Another commonly held view emphasizes the diversity of activities, rather than their overall size. But given that we are using a data set with only 13 sectors, calculating diversity indices makes little sense.

2.3 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 the vicinity of the San Francisco Bay Area still benefits from its proximity to Silicon Valley, whereas a rural county in the middle of nowhere does not. When lower transport costs increase the span of agglomeration economies, we would expect counties in the proximity of existing clusters to profit.

To take into account the effect of neighboring locations, we re-write equation (2) in the following way:

$$\log L^{is}_{1992} - \log L^{is}_{1972} = \alpha^s + \int_0^\infty \beta^s(m) \log \frac{L^{is}_{1972}(m)}{L^{i}_{1972}(m)} dm + \int_0^\infty \gamma^s(m) \log L^{i}_{1972}(m) dm + \delta^s H^i + \varepsilon^{is}$$

where $L^{is}(m)$ denotes sectoral employment in counties situated m kilometers from county i.

If the dependent variable were the level of employment, it would be natural to model $\beta^s(.)$ and $\gamma^s(.)$ as simple decay functions. However, given that the dependent variable is the growth of employment, we have no strong prior about the shapes of $\beta^s(.)$ and $\gamma^s(.)$. 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 $\gamma^s(.)$ 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 shapes of $\beta^s(.)$ and $\gamma^s(.)$. The same is true for the pattern of spatial autocorrelation in the disturbances.

For estimation purposes we replace the continuous functions $\beta^s(.)$ and $\gamma^s(.)$ with discrete approximations and obtain the following regression:

$$\log L^{is}_{1992} - \log L^{is}_{1972} = \alpha^s + \sum_{m=0}^{D} \beta^s(m) \log \frac{L^{is}_{1972}(m)}{L^{i}_{1972}(m)} + \sum_{m=0}^{D} \gamma^s(m) \log L^{i}_{1972}(m) + \delta^s H^i + \varepsilon^{is} \tag{3}$$

where each value of index m now 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. 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 (3) will be referred to as **Model 3**.

To improve efficiency, we impose a certain smoothness on functions $\beta^s(.)$ and $\gamma^s(.)$ by adopting a roughness penalty approach. This method, pioneered by Good and Gaskins (1971) and Silverman (1982), prevents the slopes of $\beta^s(.)$ and $\gamma^s(.)$ from changing too rapidly by adding a penalty function to the standard least square criterion. For instance, in the case of $\gamma^s(.)$, this penalty function is:

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

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 $\gamma^s(.)$.[8] With the roughness penalty correction, we should in principle bootstrap standard errors. This is not feasible here because computing the Conley correction for spatially autocorrelated errors takes over one hour per regression; bootstrapping them would take weeks, if not months, of computer time. However, comparison between OLS standard errors and bootstrapped standard errors (without the Conley correction) reveal very little difference between the two. This is because the roughness penalty correction does not affect estimated coefficients much. We can therefore reasonably assume that the bias introduced by not bootstrapping Conley standard errors is negligible.

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,[9] we are left with 3092 counties. Sectoral employment data are missing

[8] In practice, the roughness penalty correction can be implemented by 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 $L^i_{1972}(n - T - 1) = \lambda$, $L^i_{1972}(n - T) = -2\lambda$, and $L^i_{1972}(n - T + 1) = \lambda$. Applying the standard OLS formula to the modified sample yields the roughness penalty estimator.

[9] 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).

for some counties, either because they are unavailable or because they are not disclosed.[10]

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 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).[11] 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:

$$d_{ij} = \frac{10000}{90} \arccos[\sin lat_i \sin lat_j + \cos lat_i \cos lat_j \cos(long_j - long_i)] \tag{4}$$

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 $L^{is}(m)$. 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.[12] For each distance interval (or 'donut') we sum the sectoral

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The mobility of capital and labor is probably less with the rest of the economy than among contiguous US states and we expect model parameters to be different. Pooling them with continguous US is thus not appropriate.

[10] 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.

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

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

employment of all counties (for which the county seat is) located in that particular 'donut'. This procedure, performed with the help of a Fortran program, yields a vector of 20 employment variables $L^{is}(m)$, in addition to the county's own employment. In case there is no county seat in a given 'donut', $L^{is}(m)$ 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 to other county seats. To correct for this phenomenon, county area is included as a separate regressor.[13] 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 might benefit; if tariffs come down, counties on the U.S. border may attract more jobs. 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 Shleifer, 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.

[13] 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.

4 Empirical results

4.1 A model with sector-specific externalities

Our starting point is **Model 1**, which regresses annual sectoral employment growth on initial sectoral employment, without taking into account aggregate externalities and spatial spillovers. In *Table 2* we present OLS point estimates of regression (1), and we report t-values based on spatially corrected standard errors. 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.[14]

Whereas non-service sectors became more spread out between 1972 and 1992, service sectors became geographically more concentrated. This is reflected by the signs of the coefficients on initial employment: negative in non-service sectors, and positive in service sectors. The overall economy behaved like the service sectors. In contrast to our findings, most studies on metropolitan areas point to a spreading out of employment across all sectors (Macauley, 1985).

Interpreting our results in the light of the decline in transport costs, they seem to confirm the view of Krugman and Venables (1995). Sectors with initially high transport costs, such as services, became more concentrated; other sectors with initially lower transport costs, such as manufacturing, became more spread out. The intuition is straightforward. Faced with high transport costs, services have traditionally been non-tradeable, forcing them to locate close to all consumers. The drop in transport costs has now been allowing them to reap the benefits of agglomeration economies by concentrating. Manufacturing, in contrast, already reached high levels of concentration in the 19th century. The drop in transport costs has been expanding the reach of agglomeration economies, causing manufacturing to spread out once again.

[14] 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 is the correct interpretation.

Considering service sectors as being less tradeable than non-service sectors is supported by *Table 3*. It shows that the standard deviation of log employment in 1972 was lower in services than in manufacturing, pointing to services being less tradeable and more equally spread across counties than manufacturing. In 1992 this difference continued to exist, although — consistent with our regression results — services had become more clustered, and manufacturing less. Here again, counties behaved differently from cities: compared to other sectors, we find that services are more equally spread across counties, whereas standard results from urban economics suggest they are more concentrated (Glaeser and Kahn, 2001).[15]

Returning to *Table 2*, the coefficients on initial employment are easy 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 an annual decrease in manufacturing employment growth of 0.006%. Maybe more tellingly, if county A started out with twice the manufacturing employment of county B, manufacturing employment growth between 1972 and 1992 would have been a total of 8% lower in A than in B.

As mentioned before, though we prefer to think of changes in the spatial distribution as movements from one steady state to another, the same distributional changes can be interpreted in a convergence framework (Barro and Sala-i-Martin, 1995) or a mean reversion setup (Quah, 1993). These alternative views are hard to reconcile with some of our regression results though.

Take, for instance, the positive coefficient on initial employment in the regression for total employment (the first column in *Table 2*). According to the convergence view, this would mean that eventually all economic activity will concentrate in Los Angeles county,[16] a hardly credible prediction. The positive coefficient on initial total employment also clashes with the mean reversion idea, which assumes that random shocks move

[15] Kolko (1999) already noted that services tend to be less clustered than manufacturing, but more urbanized.

[16] Los Angeles is the county with the highest total employment in 1972.

counties temporarily away from the U.S. average: mean reversion should therefore lead to lower growth in high employment counties, implying negative coefficients on initial employment — in contradiction with our findings.

But even for those sectors with negative coefficients on initial employment, mean reversion cannot have been the entire explanation. Mean reversion alone would have left 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 having become more equally spread across counties. Lastly, the standard errors on initial employment are lower than would be expected in a stochastic mean reversion setup.

In contrast, our framework does not pose any interpretational problems. A negative coefficient on initial employment indicates that some change in conditions led employment to become more spread out; a positive coefficient means that employment became more concentrated. Since we view these changes as driven by exogenous changes in economic conditions between 1972 and 1992, there is no presumption that these trends will persist. From historical evidence on spatial concentration we know that extrapolating trends into the future makes little sense. 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.

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 coefficients on 'latitude' for most sectors indicate jobs having moved South, a well documented finding (Blanchard and Katz, 1992; Glaeser, Scheinkman and Shleifer, 1995; Hanson, 1998). The evidence on 'longitude' is more mixed: whereas the overall economy has been moving West, as reflected by the positive coefficient on 'longitude', quite a few sectors — such as farming, construction, and retail — have been moving East. These results obtain after we control for being located on one of the coasts. The longitude and latitude 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 having affected the spatial distribution of activity within the US (albeit it might have affected it in Mexico).

4.2 Distinguishing between sectoral and aggregate externalities

Not all externalities come from sector-specific effects: market potential, for instance, derives from aggregate, rather than sectoral, activity. As pointed out earlier, this distinction between localization (sector-specific) and urbanization (aggregate) externalities is common in the literature. To separate out these two effects, we turn to **Model 2**, and regress sectoral employment growth on both the initial sectoral employment share and on initial aggregate employment. The results are reported in *Table 4*; as before, t-values are based on spatially corrected standard errors.

To avoid repetition, we limit ourselves to highlighting those results which differ from our previous findings. Whereas Model 1 suggested that services became increasingly concentrated in sector-specific clusters, this is no longer true once we control for aggregate employment: we now find that *all* sectors — including services — have been moving out of sector-specific clusters. This does not necessarily imply that services have become more spread out though. Indeed, the raw data in *Table 3* show that services became more concentrated between 1972 and 1992. The answer to this apparent contradiction lies in the positive coefficient on aggregate employment. Though services have been moving away from sector-specific clusters, they have become increasingly concentrated in areas of high aggregate employment, such as cities. If, as is the case, services already started off being over-represented in cities, then these results are consistent with service employment having become overall more concentrated.

The stark difference between service and non-service sectors therefore persists:

whereas services have been moving out of sector-specific clusters into areas of high aggregate employment, non-service sectors have been moving away from both sector-specific and aggregate clusters. In other words, if it had not been for services, counties would have become increasingly alike both in employment size and structure. However, services have been pushing the other way by further concentrating in high employment areas. Adding to that the increasing weight of services,[17] it is not surprising to find that cities have been thriving. The vanishing importance of distance and geography, suggested by the developments in the manufacturing sector, has been more than offset by the behavior of services.

Again, interpreting our results in the light of the drop in transport costs, our findings are suggestive of Krugman and Venables (1995). To avoid too much repetition, we briefly focus on the case of services. Traditionally with limited opportunities to cluster due to prohibitively high transport costs, more recently services have started to concentrate. To make the most out of agglomeration economies, it makes sense for services to cluster in areas of high aggregate employment.

Though our focus is on transport costs, there exist alternative explanations for the increasing concentration of services and the decreasing concentration of manufacturing in high employment areas. Carlino (1985), for instance, remarks that manufacturing has become more land-intensive (increasing the cost of congestion) and more automized (decreasing the necessity to be close to a pool of skilled workers). Both effects point to less spatial concentration. Kolko (1999) makes the reverse argument for services, claiming an increased need to be close to qualified workers. It is not our goal in this paper to distinguish between these competing explanations. Rather, we limit ourselves to interpreting our findings against the background of falling transport costs. More particularly, our aim is to see which of the theories relating transport costs to spatial concentration fits the data better.

[17] In contrast to our findings in Model 1, note that certain sectors, such as wholesale and transportation & utilities, are now behaving like services. This should not be viewed as unusual, given the imprecise definition of what characterizes services.

4.3 Including spatial spillovers

The next set of regressions examines the effect of neighboring counties **(Model 3)**. We use the roughness penalty approach to determine point estimates; standard errors are calculated by applying the Conley correction for spatial autocorrelation.[18] As in Model 2, we again distinguish between localization and urbanization economies, with the difference that we now take into account spatial spillovers: *Figure 1* shows the effect of sector-specific employment at different distances, whereas *Figure 2* gives the effect of aggregate employment at different distances. The effect of geographical features largely confirm the results of Model 1, so we refrain from reporting them here.

Including spatial spillovers allows us to complete our description of location dynamics. Take, for instance, services. If declining transport costs paved the way for spatial concentration, we would expect service centers to have emerged by absorbing jobs from the surrounding hinterland. At least this is what central place theory would tell us (Christaller, 1933). By explicitly taking into account spatial effects, our regressions are able to check the consistency of that prediction. Likewise, if falling transport costs have been weakening agglomeration economies in manufacturing, we would expect manufacturing jobs to have moved out of clusters to nearby less congested areas. Again, our empirical analysis can verify this prediction.

Figure 1 shows the effect of aggregate employment at different distances on sectoral employment growth. The results are consistent with what we expected. The pattern for most non-service sectors — such as manufacturing and construction — shows employment having moved away from centers of high aggregate employment to nearby locations. Look, for instance, at 'construction' in *Figure 1*: whereas the coefficients are negative for distances below 15 kilometers, they are slightly positive for distances between 15 and 60 kilometers. These results are significant at the 10% level. In other words, the presence of high aggregate employment in a radius of 15 kilometers had a negative effect on con-

[18] As we pointed out in the first section, bootstrapping the Conley standard errors is not feasible. Without the Conley correction, bootstrapped and OLS standard errors are virtually identical. This suggests that the bias introduced by not bootstrapping the Conley standard errors (to account for roughness penalty correction) is negligible.

struction growth, whereas the presence of high aggregate employment 15 to 60 kilometers away had a positive effect on construction growth. Put differently, aggregate employment clusters (and nearby areas) have experienced a relative decline in construction activity, whereas areas slightly farther out have grown relatively faster.

Service sectors exhibit a different pattern: services grew faster in aggregate clusters and slower in nearby areas. Look, for instance, at 'FIRE' in *Figure 1*: the coefficients are positive at distances below 5 kilometers, and slightly negative at distances between 5 and 20 kilometers. This implies that services grew faster in areas of high aggregate employment, and slower in nearby areas. One interpretation is that FIRE employment has been concentrating in places of high economic activity by attracting jobs from the surrounding areas.

Figure 2 focuses on localization externalities by showing the effect of sectoral employment share at different distances on sectoral employment. Results look similar across the board with negative coefficients at short distances and slightly positive coefficients at intermediate distances. After controling for the effect of aggregate employment, this points to sectoral employment clusters having become more spread out.

5 Conclusion

In this paper we have studied the changing spatial distribution of employment across U.S. counties between 1972 and 1992. Given the falling cost of transportation, our underlying aim was to see whether economic activity became more or less concentrated. Analyzing this question empirically is important, since there exists substantial theoretical agreement about how transport costs affect the degree of spatial concentration. Our findings are consistent with the Krugman and Venables (1995) view: sectors with initially high transport costs, such as services, became more concentrated; whereas sectors with initially low transport costs, such as manufacturing, became more dispersed.

When analyzing whether employment became more or less concentrated, we distinguished between sector-specific and aggregate clusters. Moreover, we explicitly took into account spatial spillovers. This is just one advantage of using county, rather than urban, data: by covering the entire U.S., county data do not oblige us to put artificial bounds on the spatial reach of agglomeration economies. Two concluding caveats are in place though. First, our analysis falls short on testing the transport explanation against possible alternative theories. Second, for want of time series data on sectoral transport costs, we were unable to directly estimate the effect of changing transport costs on spatial concentration.

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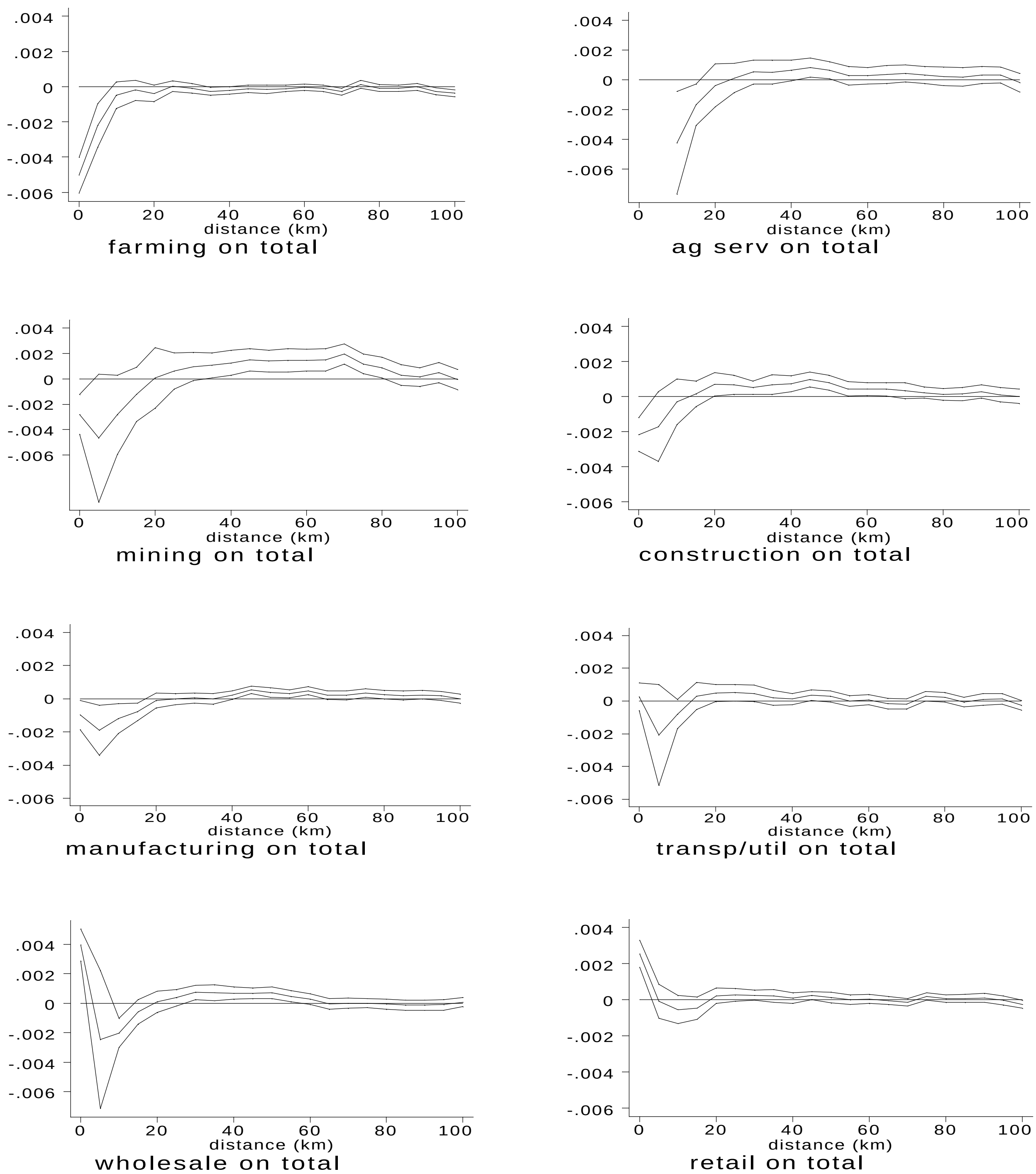

Figure 1: Effect of aggregate employment (logs) on sectoral employment growth with 90% confidence interval

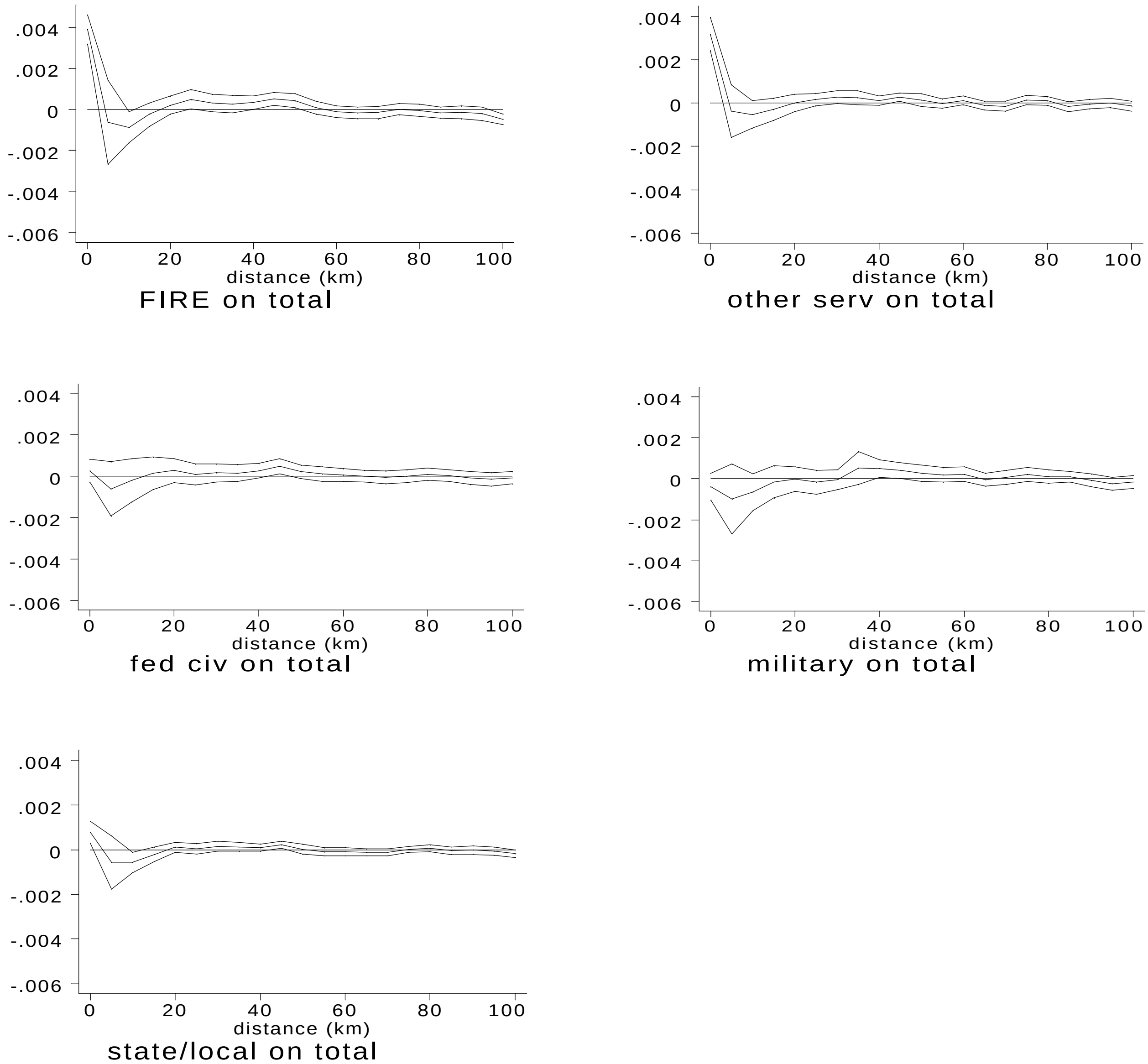

Figure 1: Effect of aggregate employment (logs) on sectoral employment growth with 90% confidence interval

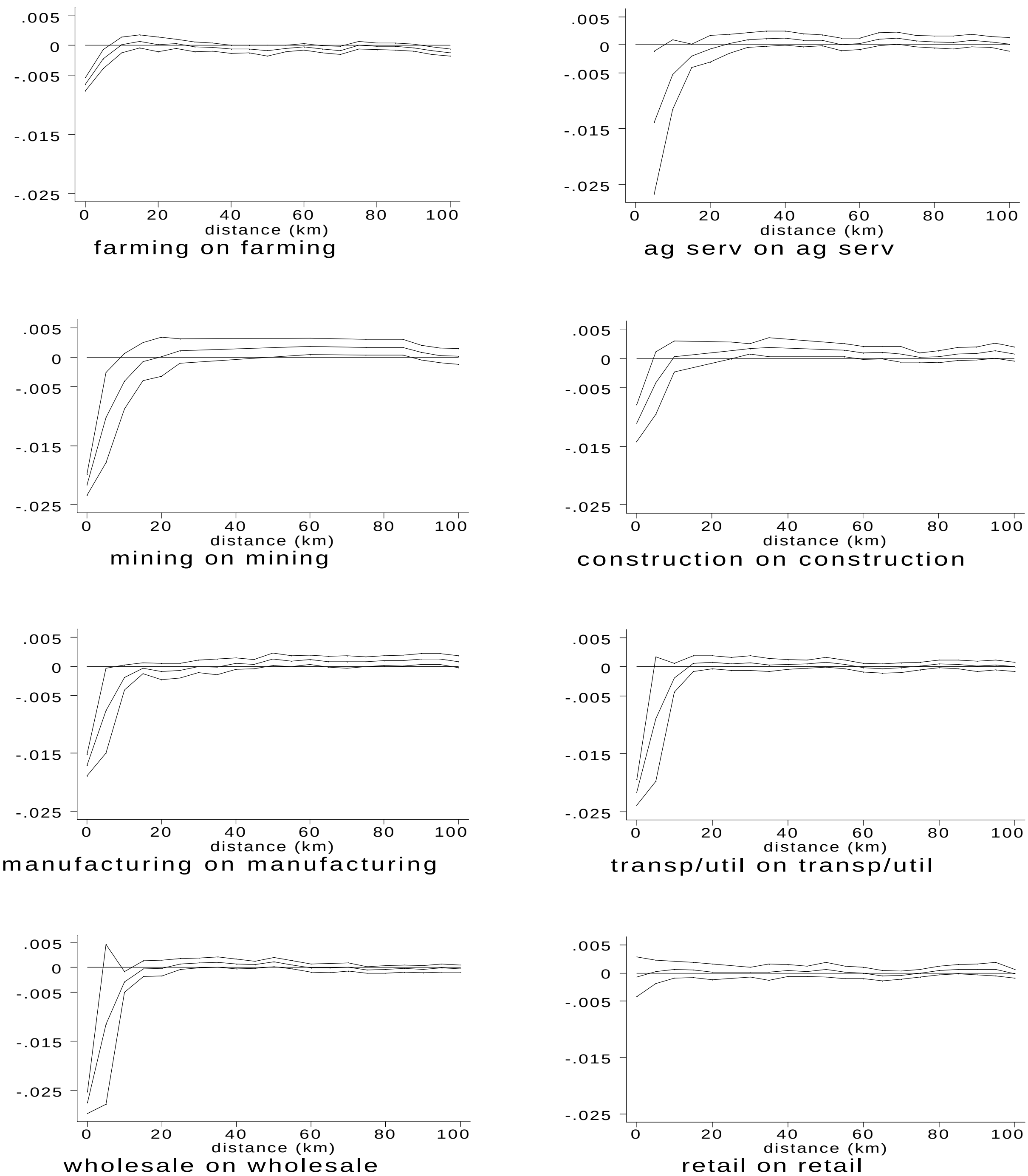

Figure 2: Effect of sectoral employment share (logs) on sectoral employment growth with 90% confidence interval

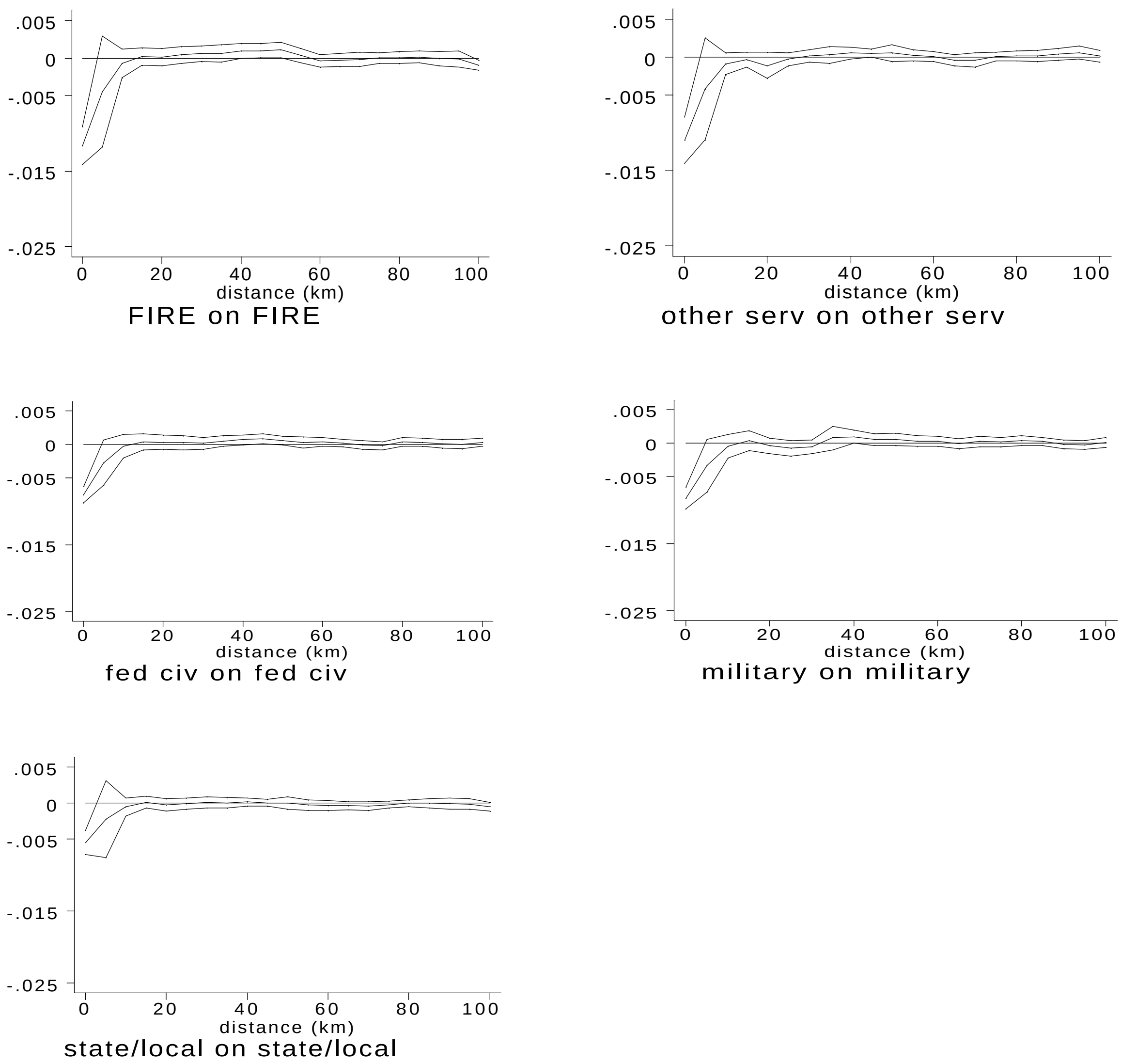

Figure 2: Effect of sectoral employment share (logs) on sectoral employment growth with 90% confidence interval

Table 1: Average county 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**	**Constr**	**Manuf**	**Trans/util**
const	-0.0024	0.0430	0.1326	0.0828	0.0850	0.0696	0.0888
	(0.27)	(4.42)	(8.70)	(3.17)	(6.74)	(4.31)	(7.49)
empl	0.0018	-0.0067	-0.0112	-0.0081	-0.0027	-0.0063	-0.0044
	(5.62)	(10.56)	(15.24)	(10.55)	(5.81)	(11.82)	(9.62)
area	1.13E-06	1.70E-06	1.88E-06	3.11E-06	1.21E-06	1.44E-07	1.41E-06
	(3.82)	(5.61)	(3.85)	(2.79)	(2.30)	(0.24)	(2.99)
lat	-0.0229	0.0038	-0.0193	-0.1487	-0.0297	-0.0213	-0.0434
	(3.96)	(0.55)	(1.67)	(6.95)	(3.35)	(2.26)	(5.42)
longit	0.0085	-0.0068	-0.0155	0.0357	-0.0218	0.0003	-0.0122
	(2.08)	(1.70)	(2.12)	(2.89)	(3.61)	(0.05)	(2.02)
ecoast	0.0058	-0.0061	0.0123	0.0287	0.0013	0.0024	0.0080
	(2.38)	(1.77)	(3.23)	(3.52)	(0.50)	(0.83)	(2.34)
lakes	0.0023	-0.0014	0.0054	0.0266	0.0066	0.0012	0.0027
	(1.31)	(0.73)	(1.12)	(2.82)	(3.23)	(0.53)	(1.01)
wcoast	0.0029	0.0045	0.0083	0.0071	0.0142	0.0067	0.0066
	(0.87)	(1.13)	(1.51)	(0.69)	(2.26)	(1.10)	(1.49)
gulf	0.0092	0.0006	0.0152	0.0023	0.0050	0.0052	0.0037
	(3.10)	(0.12)	(3.58)	(0.27)	(1.17)	(1.06)	(1.09)
mexico	-0.0009	-0.0040	0.0056	-0.0030	-0.0052	0.0082	0.0025
	(0.35)	(1.49)	(0.93)	(0.24)	(0.79)	(0.91)	(0.60)
canada	-0.0034	0.0001	-0.0093	0.0128	-0.0076	-0.0023	-0.0049
	(1.39)	(0.04)	(1.56)	(1.17)	(1.24)	(0.38)	(1.66)
estate	0.0050	-0.0042	-0.0039	-0.0110	0.0051	-0.0024	0.0053
	(3.01)	(1.93)	(1.18)	(1.97)	(2.34)	(1.16)	(2.29)
wstate	0.0066	0.0165	0.0262	-0.0008	0.0277	0.0064	0.0140
	(2.32)	(5.48)	(4.55)	(0.09)	(4.71)	(1.23)	(3.34)
	Wholesale	**Retail**	**FIRE**	**Other serv**	**Fed civ**	**Milit**	**State/Loc**
const	0.0487	0.0342	0.0220	0.0079	0.0418	0.0691	0.0285
	(3.79)	(3.45)	(2.23)	(0.71)	(5.57)	(8.14)	(3.76)
empl	-0.0058	0.0023	0.0011	0.0013	-0.0018	-0.0020	0.0005
	(12.70)	(5.36)	(2.88)	(3.32)	(5.18)	(5.28)	(1.55)
area	1.92E-07	1.57E-06	2.19E-06	1.26E-06	1.96E-06	1.20E-06	8.60E-07
	(0.30)	(4.35)	(5.26)	(3.28)	(5.55)	(2.80)	(3.42)
lat	0.0275	-0.0382	-0.0334	0.0133	-0.0382	-0.0331	-0.0637
	(2.73)	(5.76)	(5.00)	(1.67)	(5.80)	(5.14)	(12.29)
longit	-0.0027	-0.0063	0.0022	0.0021	-0.0035	-0.0236	0.0152
	(0.40)	(1.28)	(0.45)	(0.40)	(0.90)	(5.24)	(4.29)
ecoast	0.0021	0.0030	0.0113	0.0107	0.0070	0.0026	0.0035
	(0.62)	(0.89)	(4.29)	(3.38)	(1.98)	(0.71)	(1.89)
lakes	-0.0095	0.0057	0.0043	0.0033	0.0061	-0.0016	0.0017
	(2.06)	(2.64)	(1.97)	(1.93)	(2.77)	(0.62)	(1.24)
wcoast	0.0080	0.0054	0.0079	0.0073	-0.0031	0.0014	-0.0033
	(1.52)	(1.24)	(2.14)	(2.34)	(0.67)	(0.21)	(1.07)
gulf	0.0058	0.0103	0.0116	0.0180	0.0147	0.0090	0.0019
	(1.20)	(3.17)	(5.36)	(4.33)	(3.95)	(2.47)	(0.72)
mexico	-0.0096	0.0007	0.0018	0.0068	0.0143	0.0013	0.0020
	(1.15)	(0.20)	(0.44)	(1.63)	(2.81)	(0.31)	(0.82)
canada	-0.0242	0.0013	0.0042	-0.0065	-0.0024	-0.0070	-0.0022
	(4.70)	(0.43)	(1.23)	(2.61)	(0.52)	(1.76)	(0.86)
estate	0.0049	0.0086	0.0078	0.0026	0.0031	-0.0049	0.0088
	(1.67)	(4.29)	(4.11)	(1.01)	(2.02)	(3.20)	(6.37)
wstate	0.0136	0.0160	0.0056	0.0079	0.0187	0.0133	0.0047
	(2.89)	(4.64)	(1.70)	(2.22)	(6.95)	(3.70)	(2.36)

Absolute values of t-statistics (corresponding to spatially corrected standard errors) 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 share, total employment, and control variables

Dependent variable: annual growth rate in sectoral employment 1972-92						
	Farming	**Ag serv**	**Mining**	**Constr**	**Manuf**	**Trans/util**
const	0.0238	-0.0652	-0.0671	0.0366	0.0221	-0.0611
	(2.21)	(3.96)	(2.10)	(2.26)	(1.47)	(4.00)
sect share	-0.0072	-0.0277	-0.0130	-0.0110	-0.0149	-0.0250
	9.78	26.30	12.54	5.51	14.46	17.99
tot emp	-0.0056	-0.0066	0.0009	-0.0010	-0.0004	0.0015
	(8.98)	(10.28)	(0.86)	(1.63)	(0.64)	(2.83)
area	0.0014	0.0004	0.0025	0.0012	-0.0008	0.0014
	(4.74)	(0.90)	(2.20)	(2.37)	(1.44)	(3.62)
lat	0.0029	-0.0411	-0.1724	-0.0291	-0.0335	-0.0319
	(0.43)	(4.05)	(8.15)	(3.25)	(3.59)	(4.29)
longit	-0.0014	0.0394	0.0727	-0.0177	-0.0097	0.0011
	(0.31)	(5.90)	(5.13)	(2.93)	(1.27)	(0.21)
ecoast	-0.0078	0.0188	0.0181	0.0011	-0.0088	0.0066
	(2.31)	(4.06)	(2.50)	(0.40)	(3.00)	(2.10)
lakes	-0.0024	0.0045	0.0179	0.0055	0.0008	-0.0014
	(1.20)	(1.11)	(1.78)	(2.49)	(0.30)	(0.64)
wcoast	0.0018	0.0011	-0.0059	0.0121	-0.0002	0.0004
	(0.43)	(0.21)	(0.65)	(1.95)	(0.05)	(0.10)
gulf	-0.0010	0.0195	-0.0052	0.0072	-0.0031	0.0092
	(0.22)	(4.78)	(0.68)	(1.68)	(0.73)	(2.82)
mexico	-0.0046	0.0047	-0.0149	-0.0056	0.0015	0.0015
	(1.86)	(0.77)	(1.16)	(0.91)	(0.18)	(0.43)
canada	0.0012	-0.0004	0.0245	-0.0076	-0.0012	-0.0032
	(0.47)	(0.10)	(2.15)	(1.35)	(0.20)	(1.09)
estate	-0.0040	0.0057	-0.0163	0.0060	-0.0017	0.0011
	(1.84)	(1.83)	(2.94)	(2.56)	(0.82)	(0.46)
wstate	0.0136	0.0141	-0.0273	0.0242	0.0115	0.0052
	(4.57)	(3.01)	(3.11)	(4.09)	(2.45)	(1.53)

	Wholesale	**Retail**	**FIRE**	**Other serv**	**Fed civ**	**Milit**	**State/Loc**
const	-0.2314	0.0161	-0.0950	-0.0584	-0.0333	0.0117	0.0055
	(13.81)	(1.13)	(7.50)	(4.61)	(3.74)	(1.09)	(0.70)
sect share	-0.0316	-0.0023	-0.0145	-0.0160	-0.0078	-0.0086	-0.0072
	23.44	1.11	9.33	8.89	10.35	8.85	6.96
tot emp	0.0065	0.0028	0.0050	0.0041	0.0006	-0.0001	0.0007
	(9.56)	(5.26)	(11.56)	(9.05)	(1.59)	(0.31)	(2.19)
area	-0.0019	0.0016	0.0013	0.0013	0.0021	0.0010	0.0009
	(3.02)	(4.39)	(3.49)	(3.54)	(5.77)	(2.52)	(3.75)
lat	0.0370	-0.0355	-0.0198	0.0101	-0.0317	-0.0365	-0.0618
	(4.48)	(5.11)	(3.07)	(1.32)	(5.15)	(5.81)	(12.05)
longit	0.0370	-0.0044	0.0178	0.0081	0.0111	-0.0138	0.0177
	(6.56)	(0.87)	(3.78)	(1.51)	(2.87)	(3.10)	(5.08)
ecoast	0.0002	0.0032	0.0124	0.0102	0.0099	0.0056	0.0024
	(0.06)	(0.94)	(4.50)	(3.31)	(2.73)	(1.47)	(1.27)
lakes	-0.0140	0.0058	0.0027	0.0033	0.0037	-0.0029	0.0024
	(4.17)	(2.62)	(1.11)	(1.57)	(1.60)	(1.22)	(1.82)
wcoast	-0.0092	0.0051	0.0058	0.0064	-0.0071	0.0015	-0.0039
	(2.37)	(1.14)	(1.41)	(1.85)	(1.52)	(0.24)	(1.18)
gulf	0.0067	0.0107	0.0130	0.0179	0.0132	0.0093	0.0024
	(1.79)	(3.26)	(5.29)	(4.27)	(3.51)	(2.76)	(0.93)
mexico	-0.0064	0.0009	-0.0003	0.0049	0.0153	0.0025	0.0020
	(1.00)	(0.27)	(0.08)	(1.30)	(3.13)	(0.64)	(0.78)
canada	-0.0160	0.0009	0.0008	-0.0059	0.0009	-0.0034	-0.0020
	(3.24)	(0.30)	(0.28)	(2.31)	(0.21)	(0.91)	(0.74)
estate	0.0070	0.0083	0.0084	0.0039	0.0045	-0.0036	0.0093
	(2.58)	(4.16)	(4.33)	(1.63)	(2.95)	(2.33)	(6.92)
wstate	-0.0085	0.0147	0.0001	0.0045	0.0130	0.0087	0.0045
	(2.39)	(4.18)	(0.03)	(1.22)	(4.85)	(2.51)	(2.26)

Absolute values of t-statistics (corresponding to spatially corrected standard errors) in brackets.