# *Industrial Structure and Economic Success at the Local Level*

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## 1. Introduction and Summary

Over the past decade or so, a great deal of attention – and taxpayers' money – has been devoted to local and regional economic development. The main emphasis was made clear in the Lisbon Agenda issued by the EU Heads of State in March 2000. It was intended to mark the turning point for European enterprise and innovation policy. The goal was set to make the EU "the most competitive and dynamic knowledge-based economy in the world." Central to this aim was the strategy of developing the "knowledge-based economy".

This same theme is repeated endlessly in regional and local economic development strategies. Every local authority in the country appears to want to develop and attract companies in 'knowledge-based' sectors.

One obvious and immediate drawback of such an approach is that not every area can achieve such an aim. Resources are limited, and the development which has been seen around Cambridge, say, cannot be replicated everywhere. Still, this has not prevented fierce competition amongst local and regional policymakers to attract firms in 'knowledge-based' sectors.

The aim of this paper is to examine at a detailed, local level the relationship between industrial structure and the growth of employment in the medium to longer term. The data base used in the analysis is highly disaggregated, both geographically and by region. It covers the 400-plus local authority economic areas in England,Wales and Scotland at the level of 58 industries.

I examine the structures as they existed in 1983, and see to what extent different kinds of structure were associated with different rates of overall employment growth over the subsequent period 1983 - 2002.

The evidence suggests that industrial structure itself is of only second-order importance in determining employment growth. On average, certain types of structure are associated with faster subsequent growth of employment than other types. But the differences **within** the experiences of local areas with very similar structures in 1983 are much greater than the differences **between** the averages for the various types of structure.

In other words, there is a wide variety of industrial structures which are capable of generating local employment growth and economic success. By implication, it is the nature of the companies within each industrial sector which is important, rather than the type of industrial sector as such. The present policy emphasis on the 'knowledge-based' sectors is therefore misplaced. A successful local economy can in principle be built upon almost any industrial structure.

## 2. The Data

Data is available in the Census of Employment for employment[1] at the level of the 2-digit SIC level industries for each of the 459 pre-1996 local authority economic areas in England, Wales and Scotland. There are 58 such industries. The numbers employed in the various industries in any given area as a percentage of total employment in the area is the basic information which we analyse. This is a reasonable proxy for both the distribution of output across the industries, and the skill and capital endowments of an area at any point in time.

A fairly long-term perspective is needed in order to assess any potential relationship between industrial structure and employment growth, not least to avoid any distorting effects of the economic cycle on the relative growth rates of different industries. The

[1] The data is available for male and female employment, both full- and part-time. These are aggregated into a single series for overall employment. The distinction between full and part-time employment has become increasingly blurred in recent years.

deep recession of 1979-81 had a devastating impact on the old manufacturing areas of the UK, but by 1983 a gradual recovery had begun. I therefore take 1983 as the base year in the analysis, and examine the growth in employment over the 1983-2002 period.

Over this twenty year period, there has been a very wide range of outcomes in terms of employment growth at the local level. The area that grew fastest, for example, Hart, saw a rise of 140 per cent. At the opposite end of the spectrum, Barking and Dagenham experienced a fall of 26.8 per cent, reflecting the closure of Ford's car plant.

Figure 1 describes the distribution of the data on the percentage change in total employment in the 459 local economic areas.

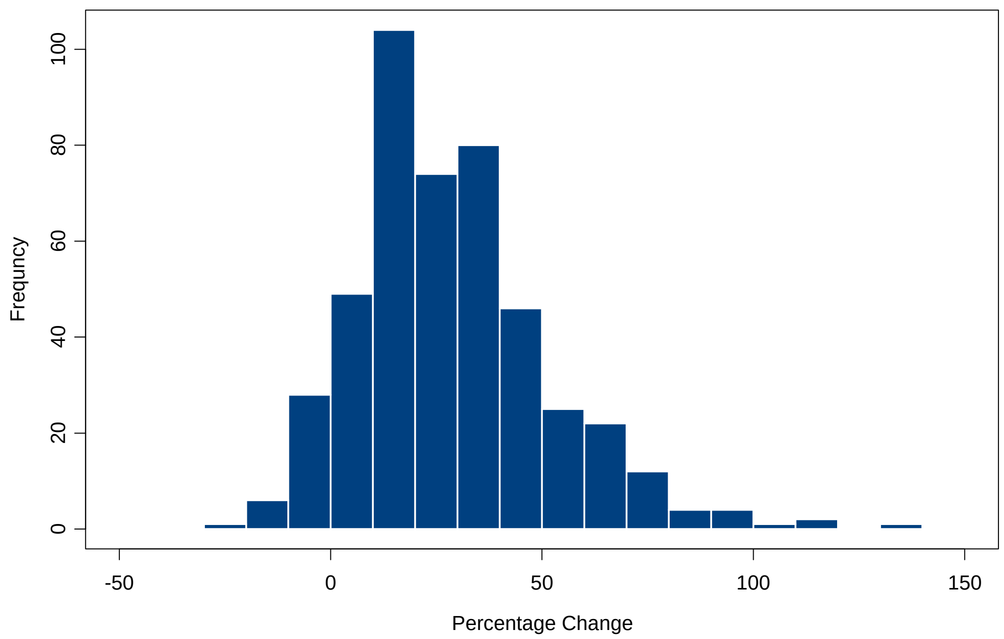


**Figure 1** *Percentage change in employment, 1983-2002, 459 local authority districts in the UK*

An important feature of the distribution of the data is that it does not follow a normal distribution. The right-hand tail of the distribution is too 'fat' for this to be the case.

In other words, there are considerably more areas which exhibited high growth rates than would have been the case if the growth rates were distributed normally.

The same property is known to characterise the distributions of growth rates of individual firms. Recent papers have presented decisive evidence on this for US data, for example, for Italy and for the international pharmaceutical industry. An excellent summary of this work is set out in a recent paper by Giovanni Dosi[2]. Dosi notes that "growth rates display distributions which are *at least exponential (Laplace) or even fatter in their tails*... This property holds across (i) levels of aggregation; (ii) countries; (iii) different measures of size (e.g. sales, employees, value added, assets)".

The generalized presence of fat tails in the distribution, whether of firm growth or local area growth, implies considerable structure in the underlying growth dynamics. More specifically, fat tails are a sign of some underlying correlating mechanism, which one would rule out if growth events were normally distributed, small, and independent. There are obvious examples of such mechanisms. For example, the very process of competition induces correlation. Market shares must obviously add up to one: someone's gain is someone else's loss. Second, in an evolutionary world one should indeed expect "lumpy" growth events (of both positive and negative sign) such as the introduction of new products, the construction/closure of plants, entry to and exit from particular markets or areas.

The question is whether the specific industrial structures of areas are also one of these mechanisms in terms of understanding the distribution of employment growth outcomes.

For the moment, in terms of describing the data, the individual local areas have a wide variety of distributions of structure across the 58 industries. In 1983, in Barking and Dagenham 23 per cent of the total labour force were employed in the manufacture of motor vehicles In Cynon Valley 22 per cent of the total labour force were employed in the coal industry, whilst in Easington this figure was over 40 per cent. In Hart, the

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[2] 'Statistical Regularities in the Evolution of Industries' LEM Working Papers 2005/17, Sant'Anna School of Advanced Studies, Pisa, 2005

spread across industries was more even. Perhaps surprisingly, however - at least to believers in Silicon Valley-type clusters - its biggest sectors of employment, each with over 7.5 per cent of total employment in the area, were construction, hotels, retail, public administration and education. Only 4 per cent were engaged in computers and there was no research sector at all[3]. Even South Cambridgeshire, another rapidly growing area over the 1983-2002 period and now closely associated with knowledge industries, had a wide dispersion of industries in 1983. Its biggest sectors of employment, each with over 7.5 per cent of total employment in the area, were agriculture, chemicals, construction and the health and social sector. Only 3.5 per cent were engaged in the research sector and a mere 0.3 per cent in computers.

The two largest sectors in terms of the averages of the percentage of employment in each area are retail and health and social services, with 8.7 and 8.8 per cent respectively. But the diverse nature of the local areas is illustrated by the distribution of these percentages across the 459 areas. For example, the lowest percentage in retail was 1.6 per cent, and the highest 17.8 per cent. For health and social services, the spread is even wider, the lowest being 1.2 per cent and the highest as much as 35.6 per cent.

In short, not only was there a very wide mix of industrial structures in 1983 across the local authority areas, there has also been a very wide spread of outcomes of employment growth over the 1983-2002 period.

## 3. The Methodology

The essential idea underlying the analysis is to examine local areas which had similar industrial structures in 1983, and to see whether they experienced similar employment growth rates over the 1983-2002 period.

The growth rate data is easy to examine, but a measure of similarity of industrial structure is also needed. Fortunately, this can be defined in a rather straightforward way. The distribution of employment in any given area can be arranged as a vector

[3] The national averages for these two sectors in 1983 both being 0.5 per cent

with 58 elements. Each element shows the percentage of total employment in the areas which is in the relevant industrial sector. The degree of similarity to, or difference from depending on which way we look at it, any other area can be quantified by the distance between these two vectors. Areas which are rather similar to each other will have a smaller distance between them than areas which are quite different.

In order to formalise the concept of the degree of similarity between the industrial structures of any pair of local areas, a measure of distance needs to be defined. There are a number of ways of measuring the distance between any two vectors. Two of these have quite natural interpretations in this context. First, the Euclidean norm, and second the Manhattan norm. The Euclidean norm of the distance between any two vectors x and y is given by

$$[\ \Sigma_i ( x_i - y_i )^2 \ ]^{0.5}$$

where $x_i$ and $y_i$ are the individual elements of the vectors.

The Manhattan norm is given by

$$[\ \Sigma_i \text{abs} (x_i - y_i) \ ]$$

The Euclidean norm, by squaring the difference between each element of the vectors, gives more weight to a few large differences, and the Manhattan norm gives more weight to lots of small differences.

As it happens, there is very little difference between the eventual results obtained in this context regardless of which of the two measures of distance we use. I report the results for the Manhattan norm[4].

This approach takes into account the whole structure of a local area in determining how similar it is to every other area in the country.

[4] details of the (very similar) results obtained with the Euclidean norm are available from the author

The k nearest neighbours of any given area can then be identified, in other words the k local areas whose industrial structure is most similar to that of any given area. This is *not*, it must be stressed, a concept of geographical nearness. Rather, *it shows which other areas are nearest to it in terms of their industrial structures*. Those which are most similar are a lower mathematical distance from the area than those which are most different.

## 4. The Results

The k nearest neighbours in terms of similar industrial structure of any individual area, or groups of areas, can be identified, and their subsequent experience of employment growth examined. If industrial structure is a powerful determinant of economic performance, one would expect to see considerable similarities between the employment growth record of areas whose structures were similar, and considerable differences between these and areas with different industrial structures.

The values of the calculated distances are of no consequence in themselves, for they will depend upon the units in which the original data is expressed. It is the *relative* sizes of the distances which are important. Figure 2 plots the average distance of the nearest neighbours of all areas, from the very nearest to the 30th nearest.

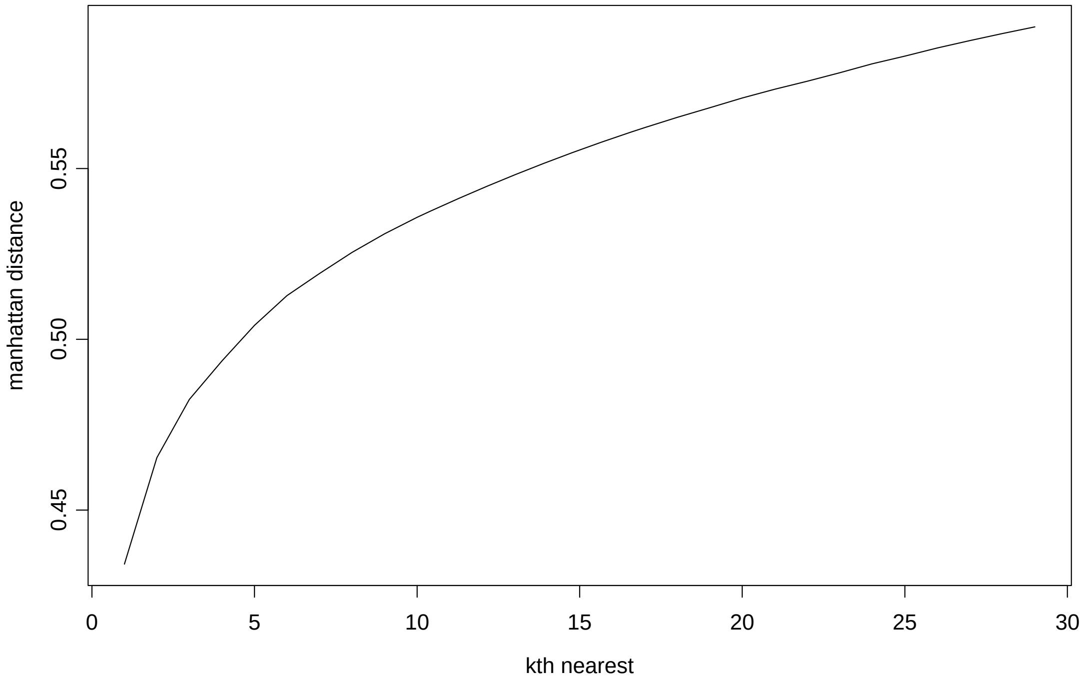



*Figure 2* *Average distance of kth nearest neighbour from all other areas*

In other words, given the units in which the data is measured, the average distance of the nearest neighbour to each authority is around 0.43. The distance rises quite sharply to around the fifth nearest neighbour.

I therefore based the calculations on the closest one and the closest five nearest neighbours to the industrial structure of any given area, though I also used the closest twenty to verify that the results are robust to the choice of k, which indeed they are.

The next step was to divide the areas into groups depending upon their experience of employment growth over the 1983-2002 period. I divided the sample into quartiles. The lower quartile of the percentage growth in employment is 13.1 per cent, the mean 28.4 per cent, and the upper quartile 40.3 per cent.

The average percentage growth in employment of the k nearest neighbours in terms of similarity of industrial structure of all of the areas within each quartile was calculated, and the results are reported in Table 1.

*Table 1. Average percentage growth of employment 1983-2002, k nearest neighbours of areas in each quartile of growth*

| | nearest 1 | nearest 5 | nearest 20 |
|---|---|---|---|
| lowest growth quartile | 18.6 | 20.5 | 23.5 |
| second quartile | 26.6 | 26.4 | 28.8 |
| third quartile | 31.1 | 31.7 | 32.7 |
| highest quartile | 40.9 | 39.1 | 38.1 |

The average percentage employment growth of the k nearest neighbours in terms of industrial structure does rise, though not dramatically, with the employment growth quartile. So, for example, consider the 115 local areas in the lowest growth quartile. The first column of Table 1 shows that the average growth in the area most similar in its industrial structure to each of these 115 areas is 18.6 per cent. The second column says that the average growth in the 5 areas most similar to each of these areas is 20.5 per cent.

The differences between each of the neighbouring quartiles - and by extension between those which are further apart - are statistically significant at the conventional level of 5 per cent[5].

These results do indicate that certain types of local area industrial structure in 1983 were associated with different rates of employment growth over the 1983-2002

[5] a formal Kolmogorov-Smirnov test rejects the null hypothesis of normality in each case. The test of equality of the means reported in Table 1 is therefore carried out using the nonparametric Wilcoxon rank sum test statistic. Details of the calculations are available from the author. The calculated values of the statistic are virtually the same when a conventional t-test is used

period. Certain types of structure tended to be associated with low growth, and others with high growth.

But the range *within* each quartile of k nearest neighbours in terms of similarity of industrial structure is very much greater than the differences *between* the means of these data sets.

This is shown in Table 2, which sets out summary statistics for the range of experience for the 5 nearest neighbours within each quartile.

*Table 2. Range of growth in percentage growth in total employment 1983-2002* ***within*** *the 5 nearest neighbour quartiles*

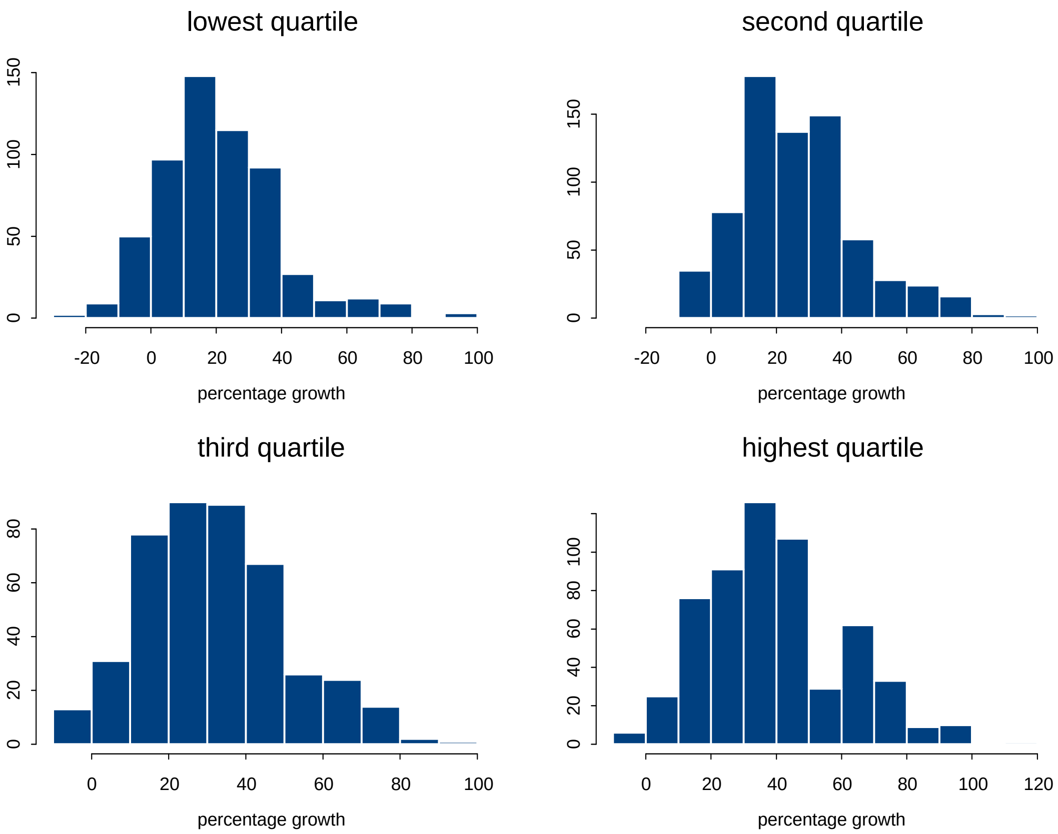
| | first quartile | mean | third quartile |
|---|---|---|---|
| lowest growth quartile | 7.7 | 20.5 | 31.0 |
| second growth quartile | 13.4 | 26.4 | 37.1 |
| third growth quartile | 17.9 | 31.7 | 41.6 |
| highest growth quartile | 23.5 | 39.1 | 49.9 |

This shows both a dramatic spread of experience within each quartile, and considerable overlap between the outcomes for the nearest neighbours of the areas in each quartile. For example, *within* the areas whose industrial structure in 1983 was most similar to those in the lowest quartile of subsequent employment growth, 25 per cent exhibited a growth in employment of no more than 7.7 per cent, but 25 per cent showed growth of more than 31.0 per cent. Amongst areas most similar to the fastest growing quartile, 25 per cent showed growth of more than 49.9 per cent, but 25 per cent showed growth of less than 23.5 per cent.

So the areas most similar in structure to the fastest and slowest growing areas differed in their subsequent experience, but there is very considerable overlap in the growth rates exhibited in these similar areas.  Many of the areas most similar in industrial structure to areas in the lowest growth quartile showed faster rates of growth than those most similar to areas in the highest growth quartile.

The histograms of the distributions are set out in Figure 3.

*Figure 3.  Histograms of employment growth of 5 nearest neighbours by quartiles of employment growth*



The summary statistics and histograms can be brought to light by examining in detail the outcomes for the two fastest growing areas 1983-2002, Hart and Milton Keynes, with the two slowest, Barking and Dagenham and Cumnock and Doon Valley.

*Table 4. Percentage employment growth 1983-2002 in the 5 areas most similar in industrial structure in 1983 to the fastest and slowest growing areas 1983-2002*

| Hart | Milton Keynes | Cumnock and Doon Valley | Barking and Dagenham |
|---|---|---|---|
| 42.0 | 84.7 | -17.7 | 1.6 |
| 49.5 | 34.9 | -0.2 | 14.6 |
| 34.4 | 3.7 | -9.0 | 28.2 |
| 46.6 | 22.0 | 3.9 | 37.1 |
| 23.5 | 20.3 | -0.7 | 1.5 |

Undoubtedly, it was better on average to have a structure similar to Hart in 1983 than it was to have one similar to that of Barking and Dagenham. But one of the five areas most similar to Barking and Dagenham in 1983 experienced faster growth of employment than two of the five areas most similar to Hart. And one of the five areas most similar to Cumnock and Doon Valley experienced growth faster than one of the five most similar to Milton Keynes.

## 5. Conclusion

I have examined the relationship between the detailed industrial structure of an area at local levels and the employment growth in that area over the medium term. Data was used for the growth in employment in the 459 local authorities in England and Wales over the 1983 - 2002 period. The employment structure is measured by the percentage of the labour force in each of 58 industries in 1983.

The degree of similarity of industrial structure between areas in 1983 is formalised by the concept of k-nearest neighbours. The distribution of employment in any given is arranged as a vector with 58 elements and the degree of similarity to, or difference from depending on which way we look at it, any other area is quantified by the distance between these two vectors. Areas which are rather similar to each other have a smaller distance between them than areas which are quite different.

Certain types of local area industrial structure in 1983 *were* subsequently associated with different rates of employment growth over the 1983-2002 period. The nearest neighbours of all areas in terms of industrial structure in the top quartile of employment growth showed on average higher growth than areas in the third quartile, the third in its turn more than the second, and the second more than the bottom.

But the range of employment growth experienced *within* each quartile of k nearest neighbours in terms of industrial structure is very much greater than the differences between the means of these data sets. For example, Hart showed the fastest employment growth over the 1983-2002 period, and Barking and Dagenham the lowest. But in terms of 1983 industrial structure, one of the five areas most similar to Barking and Dagenham showed subsequent faster employment growth than one of the five areas most similar to Hart.

These results suggest that a wide variety of industrial structures are compatible with employment growth and economic success. The current policy obsession with attracting and developing 'knowledge-based' industries is misplaced. In so far as policy can have a positive impact in this area, it should focus instead on the quality of the firms in *any* industry in a locality. Even apparently 'old' industrial structures can be associated with subsequent economic success.