Department for
Business, Energy
& Industrial Strategy

DENSITY-BASED SPATIAL CLUSTERING

Identifying industrial clusters in the UK

Methodology Report

November 2017

Contents

Executive Summary

This report describes analysis undertaken by the Data Science Team and the Business Growth Directorate at the Department for Business, Energy and Industrial Strategy. The purpose was to **identify groups of businesses across the UK which could be considered clusters for a particular sector**.

Why focus on business clusters?

Research shows that businesses in clusters benefit from agglomeration externalities[1] such as knowledge spillovers, better access to relevant skills, and reduced costs due to supply chain integration. The concept of an economic cluster can also extend beyond simple co-location however this analysis focuses on this aspect.

Being able to identify business clusters could help provide evidence for the location of sector strengths across the UK. The analysis described in this document uses an innovative approach building clusters from the bottom up using location data for individual business premises from the Inter-Departmental Business Register (ONS).

Traditional approaches for cluster identification

Clusters have often been examined using case studies. These can provide detailed information on the relationships within a sector or specific geographic area however the findings may not hold across the whole of the UK.

Other approaches have used data on the concentration of activity within existing administrative boundaries. Clusters however frequently form across multiple areas. Analysis restricted to local boundaries therefore may not provide evidence of these clusters as their effect will be diluted across different areas.

Variation within boundaries is also lost under this approach. Certain sectors may be concentrated around particular infrastructure however this precision is lost.

[1] Porter, M. (1998) Clusters and the New Economics of Competition, https://hbr.org/1998/11/clusters-and-the-new-economics-of-competition

A new approach

Any new approach to identify business clusters needed to overcome the limitations of its predecessors. It was also important that the methodology:

- Was able to make use of location data for individual businesses;
- Did not prescribe the number of clusters in advance;
- Was based on business density rather than the distance between them;
- Did not force all locations into a cluster; and,
- Produced results which reflected the true shape of the cluster.

The approach identified as the best solution was Density-Based Spatial Clustering of Applications with Noise[2] (DBSCAN). A more detailed description as well as the main advantages and limitations of the methodology are outlined in this report.

This was supplemented by another method, Kernel Density Estimation (KDE), which was used to produce a heat map of employment in each sector.

Results and Conclusions

The new approach was applied to 15 sectors. A full set of results can be found in the accompanying spreadsheet. The main outputs are a series of maps showing the outline of the clusters for each sector as defined by the DBSCAN algorithm. There are also maps showing the distribution of sector employment and the growth in employment within each cluster area over time. The new approach worked best for sectors which are more heavily reliant on fixed infrastructure.

[2] Ester et al. (1996) A density-based algorithm for discovering clusters in large spatial databases with noise.

Introduction

This report describes analysis undertaken by the Data Science Team and the Business Growth Directorate at the Department for Business, Energy and Industrial Strategy. The purpose was to **identify groups of business across the UK which could be considered clusters for a particular sector**. The approach identifies areas with high concentrations of businesses and employment. This differs from the traditional approaches which predominantly rely on existing administrative boundaries.

What is an industrial cluster?

The prevailing notion of economic clusters and their role in competitive advantage stems from the work of Michael Porter[3] in the late 1990s, although the merits of agglomeration externalities had been widely praised prior to this, notably since Alfred Marshall's Principles of Economics in 1890[4].

Agglomeration economies benefit firms located in close proximity with other firms and related industries through knowledge spillovers, thicker labour markets, and reduced costs of value chain integration. Economic clusters however have been found to be more complex than just co-location of industries related through their value chain, to include higher value knowledge and information services, and institutions that foster innovation and growth (Delgado et al, 2014[5]).

We now define a competitive economic cluster as a concentration of related industries and services in a location, including companies, their suppliers and clients; providers of knowledge services such as education, information, research, and technical support; and government agencies.

A high concentration of industries in a location is a necessary albeit not sufficient condition for an economic cluster, but cluster performance is often evaluated as firm growth or economic prosperity in the locality (Delgado et al (2014)[3]). This report offers an up-to-date understanding of the relative density of industrial activity across the UK that can help establish the location of potential economic clusters.

[3] He published a non-technical explanation in the Harvard Business Review in 1998 https://hbr.org/1998/11/clusters-and-the-new-economics-of-competition.
[4] Marshall A. (1890) Principles of Economics. London: McMillan & Co.
[5] Delgado et. al (2014) "Clusters, Convergence, and Economic Performance" Research Policy 43(10) http://www.sciencedirect.com/science/article/pii/S0048733314001048.

Importantly, what is a “high” concentration and what is a “location” need not mean exactly the same magnitude or the same physical distance for each industry. Some activities are space intensive, others are knowledge intensive. This report follows a tailored approach to capture the breadth and depth of industrial concentration across different sectors in the UK.

Links with policy

The Green Paper *Building our Industrial Strategy*[6] committed industrial policy to build on our strengths and close the gaps between front runners and runners up, with the goal of making the UK a world leader for business growth.

Industry concentration and economic clustering are key pieces of evidence for identifying the location of industrial strengths, and the evidence shows that businesses located within strong clusters perform better.

This report uses an experimental approach to identify industrial clusters across the UK.

Traditional approaches for cluster identification

Case Studies

Clusters have often previously been identified using case studies. These provide detailed information on the particular relationships within a sector or geographic area however they often cannot be applied across the UK.

A good example of clustering applied to a specific area was produced by Cambridge Ahead. The output is an interactive tool showing information on the cluster of business around Cambridge[7].

Location Quotient

Another method for identifying high concentrations of businesses in particular industries is using a location quotient (see Box 1). The Witty Review[8] used this approach to identify industrial clusters for Local Enterprise Partnerships.

The location quotient indicates whether the proportion of local employment in a sector is higher relative to the proportion of employment in that sector nationally. In other words are

[6] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/611705/building-our-industrial-strategy-green-paper.pdf

[7] http://www.camclustermap.com

[8] Witty, A. (2013) https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/291911/bis-13-1241-encouraging-a-british-invention-revolution-andrew-witty-review-R1.pdf

there greater than average concentrations of a specific sector employment within some local areas. The approach is usually applied to areas defined by existing administrative boundaries, for example Local Authorities or Local Enterprise Partnerships.

Box 1: Location Quotient for Employment

For a given sector (S), the location quotient is defined as:

$$\frac{\text{Sum of Local Employment in S / Total Local Employment}}{\text{Sum of National Employment in S / Total National Employment}}$$

One advantage of this approach is the ability to compare the relative strength of different sectors across the same local area. Location quotient suffers where the administrative boundaries chosen do not accurately represent the distribution of the feature being captured.

Administrative Boundaries

While they can be beneficial for statistical collection and presentation, in reality clusters are likely to form over multiple administrative boundaries. Approaches which restrict to these boundaries may lose local relationships because neighbouring areas are treated independently rather than considered as part of the whole area.

The variation within boundaries is also lost. The influence of some sectors can be diluted when the concentration is compared with the wider region.

Ideal features of a new cluster identification method

Some of the limitations associated with the traditional approaches to cluster identification identified above were:

- They rely too heavily on existing administrative boundaries; and,
- They are largely anecdotal and qualitative

These can both be overcome by using analytical techniques which build industrial clusters from the bottom up based on individual business location data. Additionally we wanted a method which:

- Did not require the user to know the number of clusters in advance;
- Was based on business density rather than the distance between locations;

- Did not force all locations into a cluster, i.e. had a robust approach to outliers;
- Produced clusters which reflected the true shape of the area.

The algorithm Density-Based Spatial Clustering of Applications with Noise was identified as the best solution.

Notes on the Data

Inter-Departmental Business Register

The main data source for this analysis was the Inter-Departmental Business Register (IDBR). This is a comprehensive list of UK businesses registered for either Value Added Tax (VAT) or Pay As You Earn (PAYE), produced by the Office for National Statistics (ONS). The data is primarily used as a sampling frame for business surveys but is also used for analysis of business activities.

The main sources of data for the IDBR are the Annual Business Survey, Business Register and Employment Survey, VAT from HMRC (Customs) and PAYE from HMRC (Revenue). Additional input comes from Companies House, Dun and Bradstreet and other ONS business surveys.

The IDBR covers 2.6 million businesses across all sectors of the UK economy. These account for around 97% of UK turnover. This includes 2.5 small businesses, including some with no employees, however an additional estimated 3 million micro businesses not registered for VAT or PAYE are not captured.

Further notes on the data can be found in the accompanying results as well as in Annex A.

BEIS access to the data

BEIS has received quarterly snapshots of the IDBR from 2007. This allows the department to perform longitudinal analysis.

In accordance with BEIS' data agreement with the ONS disclosure rules are applied to all outputs which use the IDBR. This is to ensure that individual businesses cannot be identified in the results. Figures in all the results tables are also rounded.

Likely date for the data

This project mainly used data from the 2015 (quarter 1) snapshot of the IDBR. We consider this data refers to the state of businesses in 2014 due to time lags in collecting and uploading the data. Throughout the report this will be referred to as '2015 data' to make it clear this was the IDBR snapshot used. The analysis also uses 2010 data from the 2010 (quarter 1) snapshot (likely to refer to 2009).

Features used for this analysis

The IDBR holds data for a number of different statistical units. This analysis is based on information at **local unit** level which refers to individual business premises rather than an enterprise's headquarters. Businesses can have multiple local units if they have employees in more than one location.

The main variables used in the analysis were postcode, SIC 2007 (Standard Industrial Classification) and employment.

National Statistics Postcode Lookup (NSPL)

The NSPL is a database of location information associated with every postcode in the UK, produced by the ONS (https://data.gov.uk/dataset/national-statistics-postcode-lookup-uk).

The NSPL was matched with data from the IDBR using the postcode associated with each local unit. This process is known as geocoding and allowed the data points to be plotted onto a map more precisely.

Map Templates

The map outlines for the UK and Local Enterprise Partnerships used in the results of this analysis were obtained via the ONS Open Geography Portal (http://geoportal.statistics.gov.uk).

Sector Selection

The IDBR uses Standard Industrial Classification (SIC) codes[9] to record the sector each business operates within. Five digit codes are given in the IDBR, however taking the first four, three or two digits gives increasingly wider sector definitions. SIC codes can also be used to define bespoke sectors.

In order to provide sector definitions with enough local units to make the analysis meaningful we mostly chose 2-digit SIC code definitions. A full list of sector definitions is provided in the table below.

Table 1. SIC code definition of chosen sectors.

Sector	SIC Codes
Automotive	29
Ceramics	23
Creative – Advertising and Market Research	73
Creative – Broadcasting	60
Creative – Libraries	91
Creative – Movies	59
Creative – Performing Arts	90
Creative – Publishing	58
Electricity Generation	35.1
Maritime	30.1; 33.15
Oil and Gas	06
Pharmaceuticals	21
Rail Transport	49.1; 49.2

[9] https://www.gov.uk/government/publications/standard-industrial-classification-of-economic-activities-sic

Robotics	28.22; 28.99
Steel and Iron	24.1; 24.2; 24.3

The list in Table 1 is broadly linked to industries within the Industrial Strategy Green Paper[10]. This broad selection enabled the new analytical approach to the tested with sectors of varying size and distribution across the UK.

[10] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/611705/building-our-industrial-strategy-green-paper.pdf

Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

Density-Based Spatial Clustering of Applications with Noise[11] (DBSCAN) was the primary technique used in this analysis. Hahsler and Pienkenbrock[12] developed the implementation we used. The methodology is outlined briefly below as well as the rationale for using this approach.

Rationale

In order to overcome the limitations of previous cluster analysis (discussed above) the chosen methodology needed to identify high concentrations of points without relying on existing boundary definitions. DBSCAN uses locations of individual businesses to form clusters from the bottom up. The results are areas which fall within and across administrative boundaries.

Another advantage of DBSCAN over other methodologies is it does not restrict the shape of the resulting clusters. Some algorithms force the points into areas defined by convex boundaries which do not represent the natural growth of clusters.

The technique needed to be versatile to deal with a variety of sectors (outlined in the section above). An important feature was that the user does not need to specify the number of clusters in advance (as with k-means) as this restricts the results. Control over the clusters in DBSCAN is based on two parameters which is a more flexible approach (this is outlined in more detail below).

The final advantage of DBSCAN is that is has a robust approach to outliers, points which are not clustered. Unlike some clustering algorithms DBSCAN does not force every point into a cluster but allows points to be defined as 'noise' if they do not meet the density requirements.

Limitations of the DBSCAN approach

As with any technique there are limitations. It is important to understand these when looking at and interpreting the final results.

[11] Ester et al. (1996) A density-based algorithm for discovering clusters in large spatial databases with noise.

[12] Hahsler and Pienkenbrock. (2015) https://cran.r-project.org/web/packages/dbscan/vignettes/dbscan.pdf

The algorithm is not suitable for all sectors. Where there is a relatively even distribution of businesses across the country spatial clusters are unlikely to form and the results will be less meaningful. There are also problems with very large sectors as the technique requires large amounts of computer memory.

This implementation of the algorithm calculates the distances between points as though they lie on a flat surface. The Earth however is spherical therefore a certain level of distortion will occur when the distances are projected onto the UK. A circle defined on a flat surface will produce an oval area on a sphere. Given most areas defined are small this is unlikely to impact on the results but is worth bearing in mind.

As previously mentioned the user has to select two inputs (parameters) in advance which control the granularity of results and vary depending on the sector. The choice of these parameters is not fixed and whilst there are a few ‘rules of thumb’ it is ultimately a subjective decision. To ensure the same process was applied to all sectors a methodology was developed to reduce the number of potential pairs of parameters.

In addition, one of the parameters is defined in terms of degrees latitude/longitude, combined with the spatial distortion outlined above, this make this difficult to interpret.

Quality Assurance

The application of the DBSCAN technique to the IDBR data had not been used within the department before. As well quality assurance of the code the results were combined with another technique (Kernel Density Estimation – explained in the next section). This allowed us to sense check the results by checking the two methods produced similar outputs.

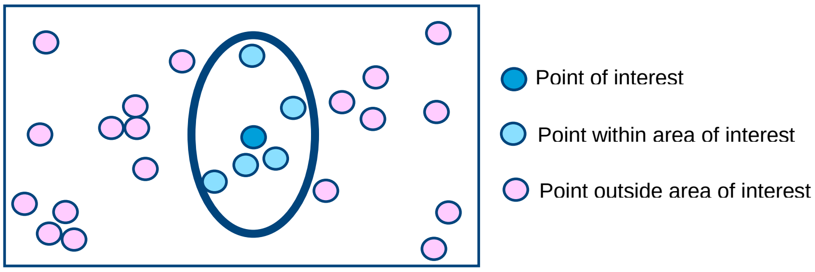
How the DBSCAN algorithm works

DBSCAN is a density based clustering algorithm, it looks for areas of highly concentrated data points and highlights those groups which are ‘suitably’ dense – as defined by the parameters. At the end of the algorithm every point will have been assigned to a cluster or identified as noise. This can be mapped which allows further analysis to be performed.

Parameters

The parameters (inputs) the user provides to the DBSCAN algorithm have an impact on the results. These will define the types (size, number) of cluster which are captured. The two values required for the algorithm are a ‘radius’ and a ‘minimum density threshold’.

The **radius**[13] defines the area of interest (shape, size) around each point and the **minimum density threshold** sets the minimum number of points which must fall within this area for it to be considered dense. They can be thought of as the maximum spread and minimum density associated with each point.



Point types

The parameters are applied to every point in the dataset. In the first instance points are assigned as either a **core** or a **boundary/noise point**.

Core points comply with both the thresholds set above, i.e. within the area of interest there are a greater number of other data points than the minimum points threshold. Clusters are built by grouping core points which fall within each other's areas of influence.

Boundary points do not meet the minimum density threshold but have at least one core point within their areas of influence. It is possible for boundary points to fall into two clusters, in these cases the algorithm assigns the final destination at random.

Noise points do not meet the minimum density threshold and do not fall sufficiently close to a core point.

A further graphical example is available in Annex B.

Weighting

In addition to looking at the density each point can be assigned a weight. The processes for determining clusters is the same as described above, however instead of counting the number of points within the area of influence the sum of the weights is compared to the minimum points threshold. For this analysis employment at each business premises was used to weight the points[14]. Essentially this creates clusters which are areas with high employment density. Disclosure rules mean that clusters are supressed if they do not contain sufficient local units, therefore the final definition for these groups of points is:

A geographic area with sufficient individual businesses and a high density of employment in a given sector.

[13] In this case the area will be elliptical because of the UK's position on the Earth.
[14] Local units with employment equal to zero were excluded from the analysis

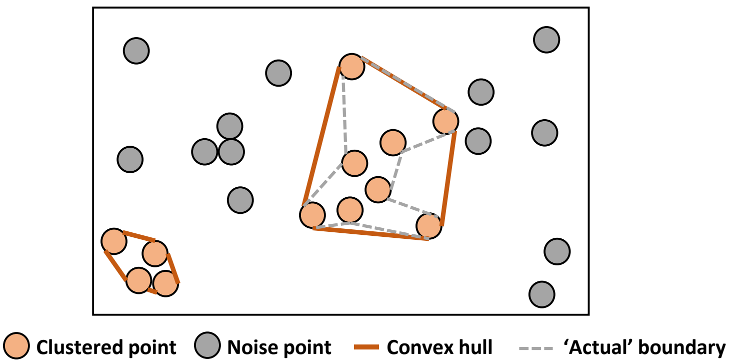
Final Presentation

Disclosure rules associated with the IDBR mean we are not able to show the location of individual businesses on a map. The results therefore show outlines of the clusters.

Convex Outline

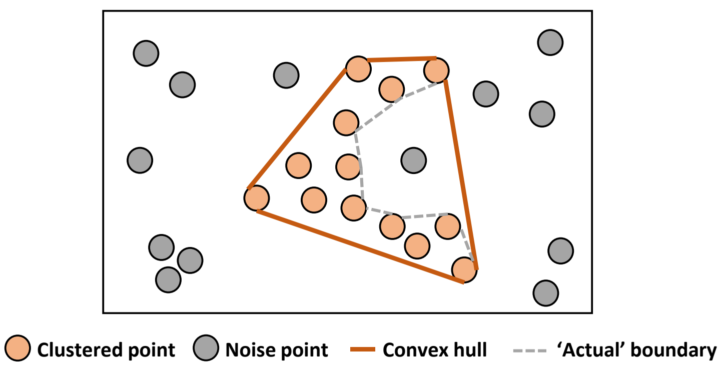
One of the advantages of the DBSCAN approach is the ability to develop more detailed cluster shapes (i.e. concave). In order to produce outlines for presentation purposes however we decided to produce the (minimum) convex outline due to the difficulty in extracting the boundary points from the algorithm.

An advantage of applying a convex outline is that it ensures all points within the cluster are included (see figure below). There are also only a limited number of boundaries which can be defined around each cluster.



Limitations

Applying a convex outline rather than the 'actual' boundary loses some of the precision of the output. It is also possible that the convex boundaries may include areas with noise points (see figure below) or give the appearance that they overlap. This will not affect the analysis except when looking at employment growth within clusters. All 2015 figures in the tables are based solely on the businesses which were in the original cluster, whereas the comparison year (2010) takes into account all points contained within the convex boundary.



Kernel Density Estimation

Kernel Density Estimation (KDE) was the second technique used in this analysis. The approach creates a heatmap which can be used to identify employment 'hotspots'. This methodology does not take into account the number of local units, only employment.

Rationale

The DBSCAN approach addressed many of the issues raised in the first section. The results however do not allow users to answer questions about the distribution of employment within clusters or outside them. KDE can provide this further context.

In general KDE is seen as less complex, better known and more widely tested than DBSCAN. There is also extensive literature available to support the choice of parameters (inputs). Another advantage is around quality assurance, combining the two approaches allows the results from the DBSCAN to be sense checked against employment 'hotspots' identified by the KDE.

A limitation of KDE is the difficulty in interpreting the 'density' output value, in particular converting this back to actual employment figures. In addition it does not allow you to take into account the number of local units, it is not suitable for creating clusters.

The colour range of the hotspots is produced based on the distribution of data for each sector therefore 'hotspots' should not be compared across different maps. This could give the impression that areas have similar employment in different sectors whereas in fact they may only have a similar level relative to the rest of the UK in those sectors.

How the algorithm works

Kernel Density Estimation produces a smooth image of the data indicating where there are high concentrations of data points. In this case these points relate to the amount of employment.

A grid is constructed which splits the whole area into cells. Each cell will be coloured a single colour therefore the size of each cell controls the 'smoothness' of the final result, smaller cells are more detailed.

The chosen 'kernel' function is applied to each point. The kernel function has a number of important features including its shape. This describes how we expect the influence of the point to decrease the further away from it we get. A normal distribution is a commonly used kernel. Another important feature is the bandwidth which helps define the area around each point that the kernel is applied to, similar to the radius parameter in DBSCAN. This has a strong influence over the resulting estimate.

For each cell in the grid the kernel functions are combined to produce a density estimate for that area. In this way KDE can also be used to interpolate values between the data points.

Parameters used in this analysis

The description above outlines three of the parameters which are needed for the KDE: **kernel shape**, **bandwidth** and **grid size**. In this analysis a square grid 750 cells high and wide was applied to the outline of the UK to produce a smooth image.

The kernel function chosen was the normal distribution. The associated bandwidth for this was selected based on a well supported rule-of-thumb according to the spread of the data. Venables and Ripley[15] offer a more detailed description on this and how this was first implemented in R.

Colours

The colours on the final maps were assigned to cells based on their relative density values, i.e. the highest density is associated with one end of the colour distribution and lowest the other. The remainder of the range was split linearly.

The majority of the cells are not coloured because they do not contain any data points (for example in areas of sea). There are also areas with much higher densities relative to the remainder of the map. These values stretch the colour range and make it harder to see finer details. A transformation was used which grouped the very high (and low) densities together, these values were assigned a single colour which allows the user to detect smaller changes in density.

This consolidated range meant high values were still marked but also ensured that the whole colour distribution was used for the rest of the map.

[15] Venables, W. N. and Ripley, B. D. (2002) *Modern Applied Statistics with S.* Springer, equation (5.5) on page 130.

Findings

A full set of results from this analysis is available in the tables which accompany this report however a guide to the output maps and some high level observations are set out below.

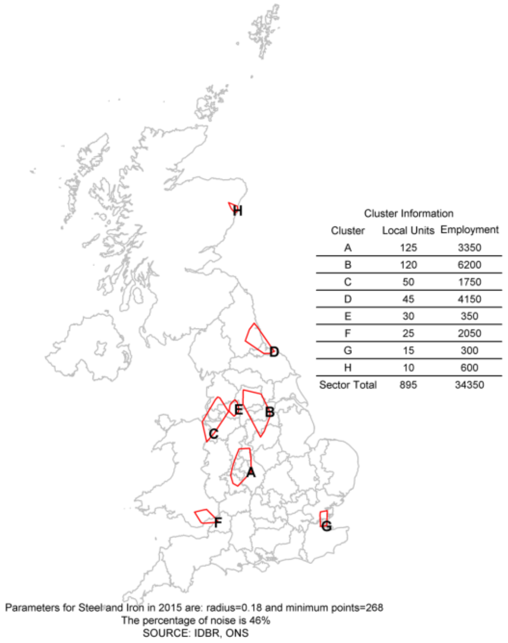
Map layout

Three different maps were produced for each sector in this analysis. These are explained below along with the rationale for why they were produced. The examples in this section are from the 'Steel and Iron' sector (SIC 24.1-3).

DBSCAN Clusters Map

The first type of output is a simple map showing outlines of the clusters produced by the DBSCAN algorithm. Instead of trying to name each cluster using city or area information they were labelled alphabetically based on the number of local units. This means that the labels vary between the maps, for example 'A' in steel and iron relates to the Birmingham area whereas for maritime cluster 'A' is around Southampton.

Another reason for the naming convention was that clusters did not often fall within existing administrative boundaries. To show this more clearly the boundaries for the Local Enterprise Partnerships are also displayed on the map.



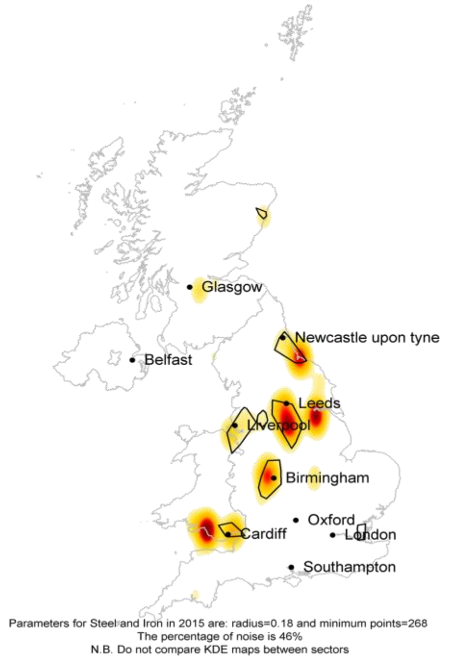
Each map has an accompanying table which gives details of the number of local units and employment in each cluster. The figures have been rounded in conjunction with ONS disclosure rules. These are important as they allow the user to identify different cluster 'types' within a sector as well as the scale of employment and number of businesses within a physical area.

KDE and DBSCAN Map

The second type of map is the result of overlaying the Kernel Density Estimation and DBSCAN cluster shapes.

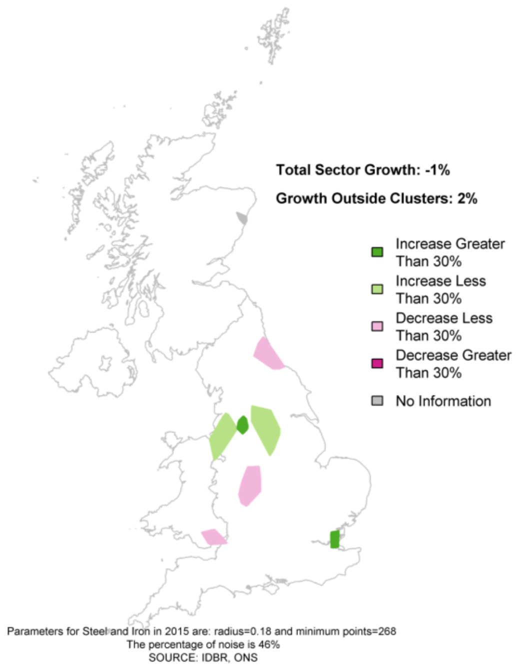
As previously noted combining these approaches allows the user to see the distribution of employment within the clusters and outside them. In most cases the red 'hotspots' are contained within a cluster detected by the DBSCAN. Where this is not the case (left of the cluster near Cardiff in the map below) it is because the KDE is picking out areas with high employment but not sufficient individual businesses to be a cluster.

An additional feature of these maps is the inclusion of major cities across the UK. This provides additional context for the clusters.



Employment Growth Map

The final map shows employment growth within the 2015 DBSCAN clusters as well as figures for the total growth in the sector and the change outside the clusters over the previous five years. Including the employment growth adds a longitudinal element to the analysis. It also enables the user to see how growth in the clusters compares with total sector growth. The table below suggests some scenarios and provides questions you may want to consider when looking at these maps.



To find the employment growth we take the outlines of the 2015 clusters and overlay these onto the 2010 data. Adding the number of local units and employment in 2010 which fall within the 2015 cluster boundaries means we can compare the change against a baseline.

The main limitation of this approach is the use of convex boundaries. As described above these may include areas which are not part of the original cluster. This does not affect the 2015 figures which are calculated based solely on the businesses identified as being part of a cluster however the 2010 data may contain points from outside these original shapes.

There is also the possibility that overlapping clusters are double counting some businesses. Therefore these statistics should be seen as indicative of the scale of growth or decline in an area.

		Total Sector	
		Growth	Decline
Outside Clusters	Growth	Are the clusters growing faster than the rest of the sector? Are all clusters growing at the same rate?	Is employment moving away from clusters? Are certain clusters becoming less concentrated?
	Decline	Is employment moving towards clusters? Are certain clusters becoming more concentrated?	Are the clusters declining faster than the rest of the sector? Are all clusters declining at the same rate?

This is only one longitudinal aspect; another is to look at where clusters disappear or emerge over time. An initial investigation of this showed that over the short time period considered there were little or no observable differences.

Conclusions

This section looks at some of the broad patterns which can be observed in the results for this small selection of sectors. Mostly these focus on the methodology and where it has worked best.

Areas

Clusters generally formed across existing administrative boundaries. This was expected and supports the view that looking at the statistics based on these boundaries can supress clusters.

In addition, clusters often captured major cities and urban areas, this is unsurprising given these areas have the largest population density.

Infrastructural versus service sectors

For sectors which rely on fixed infrastructure the results were clearer. For example, in the cases of oil and gas, maritime and iron and steel clusters are distinct and concentrated in particular parts of the country. In the case of maritime it is reassuring to note that all the clusters are by the coast.

By contrast creative industries and service sectors, such as libraries and electricity generation, are characterised by clusters covering a high proportion of the UK. In many cases it appears that the algorithm is picking out urban areas. Arguably these are not sectors which would be expected to cluster spatially however this does emphasise that this method is more suited to specific sectors.

Types of cluster

Even in sectors where the results do not show definitive clusters it can be possible to identify groups of similar areas in terms of local units and employment.

Annex A: Additional IDBR Notes

1. The employment information on the IDBR is drawn mainly from the Business Register Employment Survey (BRES). Because this is based on a sample of enterprises, estimates from previous returns and from other ONS surveys have also been used. For the smallest units, either PAYE jobs or employment imputed from VAT turnover is used. Employment is an auxiliary variable for the IDBR. The data is not all from the same point in time and so is not used to estimate national employment.

2. ONS excludes units solely VAT based or solely PAYE based where they estimate the employment to be 20 or more. Approximately 5,585 units are excluded pending checking.

3. Statistical disclosure control methodology is applied to IDBR data. This ensures that information attributable to an individual or individual organisation is not identifiable in any published outputs. The Code of Practice for Official Statistics, and specifically the Principle on Confidentiality set out practices for how we protect data from being disclosed. The Principle includes the statement that ONS outputs should “ensure that official statistics do not reveal the identity of an individual or organisation, or any private information relating to them, taking into account other relevant sources of information”. More information can be found in National Statistician’s Guidance: Confidentiality of Official Statistics and also on the Statistical Disclosure Control Methodology page of the ONS website.

4. Comparisons with earlier publications for the IDBR should be treated with caution due to the changes in criteria highlighted earlier. Historically there are differences between HM Revenue and Customs estimates for VAT registrations due to timing; the inclusion of solely PAYE based units (for 2008 onwards) and differences in definitions. The exclusion of Composite & Managed Services Companies and the treatment of divisional VAT registrations by the ONS will reduce the total, though the splitting of group registrations into separate enterprises will increase it.

5. When comparing the UK Business data with the Business Demography data published by ONS, a higher number of Active businesses will be reported by Business Demography. This is because the Business Demography methodology takes into account businesses that were active at any time during the reference year, whereas UK Business is based on a snapshot of the IDBR at a point in time in March. Additionally Business Demography includes unmatched non-corporate PAYE businesses, which are excluded from UK Business.

For more information on the underlying data please refer to the ONS website page on the annual publication UK Business Activity, Size and Location – see http://www.ons.gov.uk/ons/rel/bus-register/uk-business/index.html.

Annex B: Graphical Representation of DBSCAN

This builds on the section above describing how the DBSCAN algorithm works. The example below shows an example where the **minimum points threshold is four**.

A and **B** are core points: Each has four or more other points within the area of influence (including themselves)

C is a boundary point: It does not reach the minimum points threshold however it does have a core point within its area of influence.

D and **E** are noise points: They do not reach the minimum points threshold and do not have a core point within their area of influence.

The **grey line** shows the convex outline of the cluster. Point A and B are in the same cluster because they fall within each other's area of influence.