THE MODIFIABLE AREAL UNIT PHENOMENON : AN INVESTIGATION INTO THE SCALE EFFECT USING UK CENSUS DATA

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The Modifiable Areal Unit Phenomenon

An investigation into the Scale Effect using UK Census Data.

A thesis submitted to the University of St Andrews for the Degree of Doctor of Philosophy.

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Abstract

The Modifiable Areal Unit Phenomenon (MAUP) has traditionally been regarded as a problem in the analysis of spatial data organised in areal units. However, the approach adopted here is that the MAUP provides an opportunity to gain information about the data under investigation. Crucially, attempts to remove the MAUP from spatial data are regarded as an attempt to remove the geography. Therefore, the work seeks provide an insight to the causes of, and information behind, the MAUP.

The data used is from the 1991 Census of Great Britain. This was chosen over 2001 data due to the availability individual level data. These data are of key importance to the methods employed. The methods seek to provide evidence of the magnitude of the MAUP, and more specifically the scale effect in the GB Census. This evidence is built on using correlation analysis to demonstrate the statistical significance of the MAUP. Having established the relevance of the MAUP in the context of current geographical research, the factors that contribute to the incidence of the MAUP are considered, and it is noted that a wide range of influences are important. These include the population size and density of an area, along with proportion of a variable. This discussion also recognises the importance of homogeneity as an influential factor, something that is referenced throughout the work. Finally, a search is made for spatial processes. This uses spatial autocorrelation and multilevel modelling to investigate the impact spatial processes have in a range of SAR Districts, like Glasgow, Reigate and Huntingdonshire, on the scale effect.

The research is brought together, not to solve the MAUP but to provide an insight into the factors that cause the MAUP, and demonstrate the usefulness of the MAUP as a concept rather than a problem.

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Chapter 1

Introduction

1.1 Introduction

This thesis presents work that investigates the Modifiable Areal Unit Problem (MAUP), a problem that has vexed analysts of spatial information for many decades. One of the main purposes of this work is to challenge the notion, as seen in previous literature, that the MAUP should be considered as a problem *per se*. An alternative is proposed whereby it is suggested that the MAUP should more accurately stand for the Modifiable Areal Unit *Phenomenon*. In doing so, it is possible to promote a different approach to the MAUP, one that has already begun to be explored within the literature (see Steel and Holt (1996a) and Steel, and Holt, (1996b) for examples of the development of the approach). Thus, the MAUP is noted as a facet of areal data analysis, one that presents opportunities to derive further information about data, and not as something that needs to be 'engineered out' or solved. Indeed, one of the underlying themes of this thesis is that to engineer out the MAUP actually reduces the geographical content of the data and, in doing so, removes the geography from the analysis. Here geography is used as a very loose term simply denoting the patterns and processes that may occur within the data. In subsequent chapters these are dealt with more explicitly.

The MAUP is a theoretical problem that has clear impacts of the statistical results for the analysis of data arranged in spatial units. Although the MAUP was first identified by Gehkle and Beihl (1936), and has been investigated sporadically over the intervening 70 years, a solution or appropriate approach to deal with the changes in data analysis has not yet been identified. Today, spatial data are an increasingly important factor in everyday life. A, if not the, major source of spatial data in published in areal units is United Kingdom's decennial population Census. However, this is not the only source, as analysis on store card data, or other socio-economic data may also be analysed at a unit level. The advent of cheaper and faster computing power enabling a wider range of disciplines and activities to take advantage of statistical analysis packages (such as SPSS, STATA and SAS) along with the advent of desktop GIS (such as ESRI ArcGIS or MapInfo) has seen the further proliferation of spatial data analysis. Thus, a good understanding of issues, such as the MAUP, is highly relevant. However, the MAUP is not only a theoretical problem. In Chapter 2, two examples are given where the concepts of the MAUP can seriously contribute to the outcome of analyse that could affect real world policy decisions. These examples reference the discovery of childhood leukaemia clusters which are dependant of the units of analysis, not just in the traditional sense of the MAUP with spatial divisions, but also with time divisions which add an extra element of complexity to the problem (see Heasman *et al*., 1981 for more details). The second example comes from Boyle and Alvandies (2004) and provides evidence that deprivation scores of Local Authorities can be manipulated through the changing of boundaries either to exacerbate the problem or hide deprivation dependant on the objectives of a study. Thus, the MAUP and its analysis have a clear role in current geographical work.

1.2 Thesis Questions

The framework for the thesis is provided through the identification of four key questions that the analysis attempts to answer. Each chapter provides evidence to enable conclusions to be drawn in answer to the questions posed. These questions are:

1. Whether the MAUP scale effect really exists, and if so what evidence is there for the scale effect in UK Census data?
2. Are the changes in statistical measures significant? Statistical measures used include the Intra-Area Correlations and Aggregation Effects along with correlation coefficients. If no significant changes in coefficients are found then the concern over the scale effect may be overstated.
3. Is it possible to identify a suite of factors that contribute to the MAUP, and if so can they be used to understand the scale effect in more detail?
4. Is it possible to identify the factors contributing to the MAUP using spatial autocorrelation to visually define the spatial processes, and can these processes be likened similar to the factors identified in question 3?

The structure of the chapters and the topics that are considered in each of them are outlined below.

1.3 Overview

The original term, the MAUP, was first used by Openshaw and Taylor (1979), and has been investigated by many authors in geography and other social sciences since. It refers to a serious methodological issue that occurs in the analysis of data organised into areal units. There are two components to the MAUP, a scale effect and a zonation effect. These are both linked, although they refer to different elements of the phenomenon. The MAUP, along with the scale and zonation effects, are defined in chapter 2. A brief summary of previous important work relating to the MAUP is presented and critiqued to provide context and evidence of the MAUP. This literature can be considered in two different camps. The first seeks to investigate the different effects that could be observed in areal spatial data. Studies that have done this include Amrhein and Flowerdew (1989) and Fotheringham and Wong (1991), and all establish that it is possible to provide evidence of the MAUP in even simple statistical analysis. The second trend of investigation seeks to explain or eliminate the effects of the MAUP, and could include the work by Robinson (1956) as well as much of the zone design work by Openshaw (1977b) and Martin (2003). However, it has not been possible to establish a definitive answer that enables the elimination of the MAUP in areal unit data. Therefore, this review is used to provide context for the study. The work presented here does not continue along either of these themes, although it does draw on and exploit some of the concepts and findings made by both camps. Rather, an approach is taken whereby the investigation seeks to examine the effects of the MAUP in real Census data from the UK in order that the MAUP can actually be exploited in analysis to gain further information about the data. The purpose of this is to determine whether or not the MAUP is necessarily of concern to analyst as has been suggested in the literature. The literature review also provides a brief but important summary of the literature surrounding the usage of GIS in research. This provides a theoretical background for the thesis, and also a justification for the importance placed by the author on research investigating the manner in which statistical results of analyses are interpreted and the flaws that may exist within them.

In section 1.2 above, 4 questions were posed which determine the concerns of this thesis. In order that these questions may be answered it is necessary to provide a methodological framework within which this is possible. Thus, Chapter 3 discusses the methodology used to investigate the MAUP. The methodology is presented in sections that relate to each chapter, and as such each one can be seen as a standalone element, although through necessity there is a cross pollination of concepts throughout. As the data are specific to the methodology in their structure and composition a review of the data used is also incorporated in the methodology to aid understanding of the concepts presented. Thus, although the methodology can be applied to many different types of areal unit data, a discussion is necessary at this early point as the general concepts within the data are key to the understanding of the methodology. Furthermore, although the investigation uses relatively out of date census data, collected in 1991, the investigation is still highly pertinent. Firstly, the data from the 2001 Census has not been released at a sufficiently detailed level for individual record, where as there is a well documented set of individual records (the Sample of Anonymised Records or SARs) available for 1991 Census. After this the mathematical concepts are outlined, to describe theoretically the concepts that will be employed within the analysis.

One of the primary issues that a study investigating the scale effect of the MAUP needs to consider is whether or not evidence of the scale effect can be found within an areal unit dataset. Thus, the first investigation presented, therefore, considers evidence for the MAUP in the British Census. Previous investigations concerning the MAUP have focused on relatively small data sets. One notable exception to this is Amrhein and Flowerdew (1989) where a dataset for migration over Canada was analysed with respect to the MAUP. Other than this, however, investigations have focused on smaller areas, such as Census Districts, and only used a small selection of variables. This, therefore, means that a key starting point is to investigate the incidence of the MAUP for a far larger dataset than has previously been considered. This serves two purposes. Firstly, it enables the investigation of the MAUP as a pervasive problem that is observable within a large range of data in terms of variables, and also geographical location. This is necessary to provide evidence of the problem in current data and determine the seriousness of the problem. Furthermore, this thesis is set out around the premise that it is possible to obtain information from the incidence of the MAUP that can be used to inform analysis, and chapter 4 introduces a large scale analysis exploiting two concepts that are proposed by Tranmer and Steel (2001) to enable the quantification of the MAUP. These are aggregation effects and intra area correlations. The first of these provides a quick and easy value through which the impact of the MAUP can be quantified. However, as it is not controlled with respect to the population sizes of the areal units under analysis it is of limited use for comparative studies, as a high aggregation effect, suggesting more severe impacts of the MAUP can be achieved with a large population. The second measure, the intra-area correlation counters this, as they are population adjusted. Thus, a UK dataset of intra-area correlations is developed to present a picture of the incidence of the MAUP from the 1991 Census data. Conclusions are drawn from patterns that occur, such as the apparent differences between urban and rural areas, and the different processes that lead to the construction of areal units in England and Wales. It is notable that the data from Scotland requires separate conclusions, at least at the basic spatial unit scale. This is because the Scottish data units are smaller, and more compact, at least in terms of population size. The result of this is that the magnitude of the scale effect observed in many Scottish units is greater than observed in England and Wales. Overall, the observations from this chapter are used to lead the analysis in the remaining chapters.

The majority of this work is concerned with the incidence of the scale effect and the MAUP. However, as is outlined in chapter 5 there is a second component to the MAUP, which is the zonation effect. Thus, it is important to consider the zonation effect alongside the scale effect. This is done in chapter 5. Here, a number of concepts are drawn together for the analysis and discussion. A theme that has been developed in the literature as an important contributor to the MAUP is that of Spatial Autocorrelation, and internal areal unit homogeneity, (see Fotheringham and Wong 1991) for details on the relationships with spatial autocorrelation and Holt *et al* (1996a)) for discussions relating to the importance of homogeneity). Thus, it is pertinent to investigate the influence of these factors on the MAUP through the realisation of alternative areal unit geographies. There is a large literature concerned with zone design and this chapter does not attempt to critique it in detail. Rather it uses the concept that it is possible to re-engineer zonal geographies to investigate both the zonation and scale effect. Thus, the AZM program is used to produce alternative zonal geographies with the aim that they represent highly homogeneous zones. The different zonal geographies are discussed and correlation analysis is used to highlight the scale effect. The changes in the magnitude and direction of correlation coefficients are identified, and subjected to a significance test. This determines whether or not the differences in the magnitude of the coefficients resulting from the MAUP are significant. If not, then the seriousness of the MAUP can be questioned. However, if significant differences are identified then there is a clear statistical reasoning behind the investigation. This type of analysis has not been attempted previously.

Once the MAUP Scale effect has been identified as a statistically significant problem, it is logical that the next question that should be posed considers what factors contribute to the incidence of the MAUP. Thus, Chapter 6 discusses the results of Chapter 4, whilst focusing on the differences and similarities between areas with different magnitudes of the MAUP to attempt to determine the factors that may contribute to magnitude the MAUP. From this position, it is considered whether or not it is practical to provide a model through which the magnitude of the scale effect as measured by the Aggregation Effects and Intra-Area Correlations could be estimated. The factors presented are drawn out of the conclusions presented in chapter 6, and include factors such as the population density as a proxy measure for urbanization, and the magnitude of a given variable. The purpose of this is to determine if it is possible to predict the magnitude of the scale effect. If this were possible then it would be likely that further understanding would be gained into the factors that determine the magnitude of the scale effect. From this, it would then be able to determine if it were possible to understand why the scale effect occurred. However, previous attempts to gain such information have failed, primarily because the scale effect is largely unpredictable and does apparently operator uniformly across space. If this were the case then previous MAUP findings would be reinforced, and it would be apparent that the scale effect cannot be predicted, and represents factors in the analysis which are unknown, and potentially unquantifiable.

The questions considered above include a search for evidence of the scale effect, an investigation into the factors that contribute to the MAUP scale effect and an attempt to manipulate the results of the MAUP through zone design and analysis of the zonation effect that highlights significance differences in correlation coefficients. The final question that is posed considers these separate pieces of evidence together. The investigation focuses on areas that have varying levels of scale effect identified within them, ranging from high scale effect to lower level scale effect, measured using the Intra-Area Correlations. From this the question is posed is it possible to identify the processes that have been implicitly discussed in the previous chapters? Chapter 7 is the final analysis chapter and presents the results for this question. To do this it provides evidence that the scale effect occurs due to the inconsistency between the areal units and the publication boundaries and the spatial processes in terms of relationships between the low level areal units that are aggregated into high level coverages. This is discussed with a wide range of SAR Districts representing areas with higher magnitudes of the MAUP, and those with lower magnitudes used for comparisons. The methodology used to do this is unique to this work and provides an extension to the measures developed by Tranmer and Steel (2001). Furthermore it draws on a wide range of statistical concepts such as multilevel modelling to isolate processes that occur at different levels of aggregation, and well as concepts more commonly associated with the MAUP, including spatial autocorrelation. All these concepts are combined to provide a useful visualisation of the processes that occur between areal units at different scales.

The final Chapter, 8, presents the conclusions from each of the chapters and presents are series of considerations for the user of areal unit data. Firstly, it highlights that the MAUP and more specifically the scale effect are real, serious, issues about which the analyst of spatial areal data needs to be aware. Secondly, we are reminded that the MAUP is largely unpredictable, and that for a large data set such as the British Census there are likely to be a wide range of scale effects present. Although these scale effects are largely unpredictable, it is possible to make some generalisations about them. For instance, scale effects tend to be larger in the more urban areas in England and Wales. A comparison is also made between the English and Welsh data and the data from Scotland, as large differences are observed between these two supposedly comparable datasets. The MAUP scale effect on British Census data is shown to be significant, in statistical terms, as different realisations show that correlation coefficients do suffer significant change. This serves to reinforce the previous conjectures. These conclusions are made with respect to the construction of areal units and their ability to capture processes, both quantifiable and not quantifiable, which may contribute to the statistical variability of analyses.

1.4 Conclusions

As was stated at the top of this chapter, the aim of the thesis is to widen understanding of the MAUP scale effect. At no point does the discussion focus on methodologies that can provide a means to fully or partially remove the MAUP from spatial data. Thus, the work that is presented within this thesis is designed to develop better understanding of the MAUP can be made. It is this theme that runs through the work that is used to provide a means through which the chapters are tied together.

Chapter 2

Literature Review

2.1 Introduction

In the previous chapter, the concept of the Modifiable Areal Unit Problem (MAUP) was outlined. It was described as a problem that has vexed analysts of spatial data for many years, and in many different ways. This chapter seeks to examine the nature of the MAUP through the literature that has been written, to define the nature of the MAUP, and to describe the two elements of the MAUP, the scale and zonation effects. Justification will also be given for the importance of this research, in the context of past research outcomes, and as such this research is placed in a wider context.

There are two main approaches to MAUP research that are considered in this chapter. The first reflects on the MAUP as a pervasive problem that requires solutions to be found and claims that, without these solutions analysis of areal data is to a greater or lesser extent flawed. These attempts to provide solutions for the MAUP are presented, along with a critical appraisal of the methodologies. The second approach considers the MAUP as an opportunity to interrogate data as a means to uncover more information not only about the variables under analysis, but also as a means to better determine the areal characteristics of the population as a whole. The last section discusses the other, non-statistical, approaches that have been discussed with respect to the MAUP. Primarily this covers the issue of zone design as a way to 'control' or design out the MAUP, and a number of approaches that have been taken as a route to achieve zones that better describe the areal nature of the data are presented. Finally, data analysis techniques are briefly considered, outlining the Multilevel model concept detailing the usage and appropriateness of the application to MAUP analysis.

Before the MAUP is considered, it is necessary to present the theoretical standpoint of the thesis. This discusses the impact of Geographical Information Systems (GIS) on the discipline of Geography, and more specifically, looks briefly at the theoretical framework of Geographical Information Science (GISc), which can be considered as the supporting structure for the GIS software. This is important as it sets out why the

MAUP is still a relevant issue for researchers using, or contemplating using areal data despite the many attempts to resolve and understand the problem. This provides background for the remainder of the thesis.

2.2 Geographical Information Systems, and Analysis

This section is not intended as a full review of different GIS, or the theoretical concepts upon which they are built. However, it is not possible to consider the MAUP without first considering the motivation behind the investigation, beyond the satisfaction of scholarly pursuit. Therefore, the social context of GIS should be explored to provide context, to demonstrate that there is a very real need for users to be aware of the data and its potential pitfalls and what can be done, if anything, to overcome these pitfalls. Recognition of the MAUP as an element of geographical information analysis is, itself, an important element in increasing awareness. Thus, the discussion will focus largely on the debate surrounding GIS as either a tool or a science in its own right, and the discussion from the mid-1990s around the publication of *Ground Truth* (Pickles, 1995).

2.2.1 Definitions

GIS as a concept and a practice has been debated previously (see Pickles 1995, Openshaw 1991, Raper 2000 or Lake 1993). In general these texts have considered GIS as a member, or a child, of the positivist movement being in many ways at least related to the quantitative geography movement, if not the last stand of it (Lake 1993). The assertion that GIS is essentially positivist is not challenged here, and is in fact adopted. As Flowerdew (1998) states, positivism has in many ways become a “dirty word” as a philosophical approach. However, this need not be so, as the supposed value free approach (if ever achieved) to research seeking relationships and hypothesis testing is not necessarily a negative concept. It is true that not all facets of geographical phenomena can be borne in mind in research such as this, and that other more representative philosophical approaches need to be considered. Thus, the study of methods used within the positivist realm, and especially those of people ‘doing’ GIS is highly pertinent. It should also be noted that GIS is intrinsically linked to quantitative geography, at least in the contexts that are discussed here. This is not to state the GIS is *exclusively* the possession of quantitative geography, and that other geographers, or indeed other social scientists and researchers, are not able to employ a

GIS in their research, but in fact is recognised, in research on issues of data representation such as the MAUP, the literature and concepts that will be drawn on will largely result from quantitative work.

Before entering the debate concerning the practicalities of GISystems (herein referred to as GIS) and GIScience (herein referred to as GISc) it is necessary to provide distinction between these two ways of defining GIS can be considered to operate. The first definition is the more traditional, and the one taught in many undergraduate courses. GIS has been defined as a tool and that is a "system of hardware, software, data, people, organisations and institutional arrangements for collecting, storing, analysing and disseminating information about areas of the earth" (Dueker and Kjerne, 1989, pp7-8 quoted in Chrisman, 1997, p.5). This is a definition that will suffice for this discussion, as it describes GIS as a tool, or toolkit, for analysis, upon which researchers may draw. Goodchild (1992) first used the term GISc, and in doing so determined that its role was to "ensure that GIS … play their legitimate role in supporting those sciences for which geography is a significant key, or a significant source of insight, explanation and understanding" (p.32). Thus, he was attempting to provide a theoretical concept within which the development of the GIS (System) could take place. However, as Raper (2000) notes, this was not strictly a definition, and Goodchild has since provided a more specific definition for GISc. This states that Information Science "generally can be defined as the systematic study according to scientific principles of the nature and properties of information. GISc [is] the subset of information science that is about geographic information" (Goodchild 1999 p737, quoted in Raper, 2000). Thus, there is a strong definitional background within which GISc can be situated. This is further supported by Chrisman's (1999) assertion that "this 'science' is an attempt to reorient the energy created by the messy confluence of tool, practice, and competing disciplines" (p.182). Perhaps more importantly, the redefining of the discipline from GIS to GISc requires users within the academic community, at least, to begin to consider what they are doing with their GIS (*op. cit*).

2.2.2 The content of GISc

Once GISc has been defined, it is necessary to consider what research it will be concerned with, thus providing the content. There has been a long running debate concerning what is, and is not, GISc. The National Center for Geographic Information and Analysis (NCGIA) has provided a set of five areas within which GISc can be seen to be applicable. These are:

- Spatial analysis and spatial statistics;
- Spatial relations and database structures;
- Artificial intelligence and expert systems;
- Visualisation;
- Social, economic, and institutional issues. NCGIA (1989)

For the work presented within this thesis, the first, “Spatial analysis and spatial statistics” and the last “social, economic, and institutional issues” elements are perhaps the most relevant in the context of the work presented here. The first can be broken down into constituent parts, and in doing so enables the recognition of a number of important elements. These include Spatial Statistics, which Mark (2004) notes includes the properties of “spatial autocorrelation or spatial dependence”, a factor which will be demonstrated to be of key importance in increasing understanding of the MAUP. Building on this, Mark (2004) continues under the heading of Spatial Analysis that “several topics, especially the [MAUP] seem clearly to be of an important class of [GISc] research” (p.11). The final element is also relevant to MAUP research. Data and analysis from GIS and quantitative geography research is frequently presented as, if not absolute, having an intrinsically ‘correct’ quality within it. The existence of the MAUP shows that such research is scale-dependent

Finally, Schuurman (2000) further supports this assertion. GISc is defined here as bigger than just a subset of the GIS discipline. It is noted that Wright *et al* (1997) state that the discipline of GISc enables the fundamental analysis of the “issues raised by the *use* of GIS (p.358, quoted in Schuurman, 2000, p.584, emphasis in the original). Importantly, this *use* of GIS demonstrates the need to research and, crucially, further understand the MAUP as a major use of GIS is analysis and interpretation of data organised in areal units.

2.2.3 *Ground Truth*, and Critiques of GIS/GISc

The debate surrounding the widespread use of GIS in Geography has been ongoing for over a decade. One of the first exchanges that recognised GIS as a specific element of geography was between Openshaw (1991, 1992) and Taylor and Overton (1991). Whilst these articles exchange on the nature of GIS and what it means for Geography, they have a relevance to the work in this thesis as Openshaw states that GIS is part of "the new data-driven and computer based knowledge creating technologies" (Openshaw, 1991, p.622). This is highly contested by Taylor and Overton who highlight that this "implies that data are given" (p.1088). They relate this in a social context. However, it is not only the social context in which data are not given, as spatially the boundaries in which the data are published may also be open to different interpretations and adjustments, either for political or economic reasons (see Morrill 1973, or Boyle and Alvanides 2004). This last statement goes right to the heart of the MAUP, and it is precisely because the data are *not* a given, and that they may be contested in terms of the division and resolution of the space, that the MAUP exists. If GIS are data-driven then there is clearly a note of caution and a need to understand the MAUP to provide support to the wide range of users of GIS.

In the Ground Truth debate Pickles (1995), sought to promote the notion that users of GIS had a an obligation to society to use their systems responsibly. The researching and understanding of the MAUP is clearly implicated within the promotion of responsible use. This point is reinforced by Taylor and Johnston (1995) who state "[o]ne of the most disappointing features of the GIS is the failure to address this question seriously. Data are usually treated unproblematically except for technical concerns about errors". This refers not only to the need to acknowledge that the construction of the data is not necessarily a given, and the lack of serious consideration given by the GIS community to the promotion and consideration of responsible use of data in GIS. However, the GIS community reacted relatively negatively to *Ground Truth*. Raper (2000) summed it up as focusing "on the technologies rather than the underlying trends and theories requires a methodological and ethical self-awareness: without it the assumptions and commitments on which it is based remain unstated and unevaluated". It is clear that the investigation of the MAUP can be viewed as a small part of the increasing self-awareness of the methodological issues that researchers using areal data must be open to. Furthermore, there is also an ethical dimension to the MAUP, whereby researchers should not report data analysis results as absolute when a different set of zones might yield a different answer. It is not suggested that this frequently occurs, but nevertheless investigation into these issues is merited. Furthermore, Pickles (1995) calls for increased attention to ethical, economic and political issues within literature about and analysis by GIS. Again, it is suggested here, that through the recognition and discussion of the limitations of analysis, the debate is implicitly moved forward.

In a reaction to the Ground Truth debate, Flowerdew (1998) reviews the state of the GIS discipline alongside that of geography as a whole. One of the more pertinent points raised in the review is that in “quantitative geography in general, and GIS in particular is a perceived lack of critical attention to how data are constructed” (p.293). The MAUP is solely concerned (at an initial level) with the techniques used in the geographical construction of data, both with the delineation of the units used for collection and reporting, as well as the scale at which the units will exist. Thus, this research presented here, sets out partially to address this balance. Indeed Flowerdew (1998) concludes the section by stating “although some data sources may turn out to be effectively valueless once their provenance is investigated, others may still be usable once their limitations are known”. Again, although the *Ground* Truth debate centred largely around the social construction issues of GIS, there is an equally important geographical construction debate to be had alongside. Thus, providing techniques and information relating to the MAUP is part of the process of recognising the limitations of social science data as a whole, and specifically data that are released or analysed within areal units.

2.2.4 Conclusions: GIS, GISc and the MAUP

The MAUP has different implications for both GIS and GISc. It is, however, equally relevant to both GIS, the people “doing” GIS and the Science of GIS, GISc. It has clear implications for the practitioners of GIS, as the concept of the MAUP has practical implications for those people involved in the analysis of data contained within areal boundaries. These practitioners need to be aware of the potential sensitivity of results. It is, therefore, the responsibility of those who practice within the science of GIS (or GISc) to make awareness of the MAUP more widely known. Those practicing the science have an opportunity to increase awareness, through the presentation of case studies of the MAUP (like Openshaw and Taylor 1979 and 1981). The role of GISc should go further than that. There is also the need for investigation of the causes as well as the implications of the MAUP, both in terms of scale and zonation. Those researchers working in GISc have a unique opportunity to contribute to this debate, providing the stimulus to engage both members of the GISc community, and if the language is chosen appropriately, the GIS users. Furthermore, they can provide interaction points between the users of GIS, more traditional quantitative forms of geography, and the other disciplines involved in data analysis, such as statistics.

Although brief, this section clearly outlines the concepts of GIS and GISc and provides the distinction between them. Thus, research into the MAUP is important, not only because it obscures the interpretation of analytical results, but also it is conceptually important despite being a long standing, readily recognised, problem.

2.3 Introducing the MAUP

In order that the MAUP can be reviewed, it is necessary first to provide some definitions of the MAUP itself and the two component parts, the scale effect and the zonation effect. This is done below, and is followed by a discussion that relates the concepts of the MAUP to actual research examples demonstrating how the MAUP could actually alter the research findings in a number of key areas.

2.3.1 The MAUP

Spiekermann and Wegener (2000) state that the “limitations of zonal systems have led to serious methodological difficulties such as the ‘modifiable areal unit problem’” (p.45). Areal units are commonly used for the collection and reporting of data not only due to their significance and usefulness as administrative or political boundaries, but also because some aspects of society only occur at scales that can be observed through the analysis of data at an aggregate level. The boundaries are almost always imposed on to the underlying population structure(s) and so are, therefore, not only modifiable, but also have little or no fundamental relationship with the structure of the data that is being reported within them. This characteristic means that changes in the structure of areal units can result in the same data giving different results under many different types of analyses and as such can be considered as a serious methodological issue. However, this does not mean that areal data analysis should be thrown out. Rather, it is more appropriate, whilst acknowledging the seriousness of the MAUP to also consider it as a challenge to the spatial analyst, and a means through which more information can be obtained about the structure of the population processes of the data and people the areal unit represent.

If the notion that areal data are fraught with methodological difficulties is rejected, then it is necessary to propose an alternative framework within which we can consider the areal spatial data. In essence there are two types of data. Those that exist within non-modifiable units and those within modifiable units. A non-modifiable unit could be an individual who is clearly non-modifiable, as he or she cannot be sub-divided. For instance, the age of an individual is not divisible. Likewise, this principle can be applied to the production of goods, and as such, the production of a commodity within a single firm, as described by Arbia (1989), is not divisible into smaller units. Units that are modifiable are more commonly found in spatial data. Using the example from Kendall and Yule (1950) the argument of modifiable areas is made using the analogy of wheat and potato farming. “Since it is impossible, or at any rate impractical, to grow wheat and potatoes on the same piece of ground simultaneously we must, to give our investigation meaning, consider an area containing both wheat and potatoes; and this area is modifiable at choice” (p.312). For social scientists, a more practical example relates to the population Census, where many variables are only available at the aggregate level, such as migration. These data are in areal units and are intrinsically modifiable. Therefore, considerations of the implications of using modifiable data are highly relevant to the discipline of geography, as well as to the social sciences as a whole.

Evidence of the MAUP in geographical analysis is presented below (see section 2.3.2). However, before this it is necessary to define exactly what is meant by the term Modifiable Areal Unit Problem or MAUP. In general, the MAUP can be considered as the “sensitivity of analytical results to the definition of units for the data are [presented]”, (Fotheringham and Wong, 1991). This one, single, definition for the MAUP is not sufficient, however, as there are two separate, although interrelated, issues within the MAUP. These two components are known as the scale effect and the zonation effect. These are discussed in more detail below.

2.3.1.1 The Scale Effect

Arbia (1989) considers that the scale effect arises due to the nested hierarchies within which human society is arranged, and the resulting task of choosing the most appropriate scale for a given analysis. Essentially, the scale issue was defined by Openshaw and Taylor, (1979) as "the variation in results that may be obtained when the same areal data are combined into sets of increasingly larger areal units of analysis", (see figure 2.1). The UK population Census provides a practical example of the scale problem. For instance, data can be supplied in Enumeration District form as basic spatial units, which can then be aggregated into higher-level spatial units, such as Wards, Districts, or Counties. In each of these cases, it is possible to obtain different statistical relationships from analysis of the data. The primary focus of this thesis is with the scale problem. This is because the author believes this to be the greater of the two problems, as the discussion about boundary definition is preceded by the discussion concerning the scale at which the data are to be analysed. Moreover, it was this issue that Gehkle and Biehl (1934), and Yule and Kendall (1950) focused on when the statistical inconsistencies were highlighted through their initial investigations.

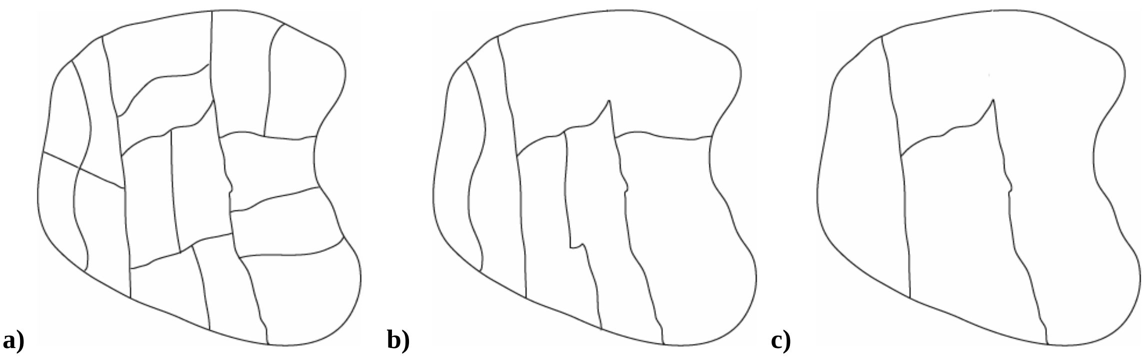


Figure 2.1: The Scale problem: The three different scales could represent a) Output areas; b) Pseudo Postcode areas c) Districts.

Kirby and Taylor (1976) present an analysis of voting in a referendum to illustrate the scale effect. They determine that it is possible to identify pockets of the population that vote differently to the overall measure for an area. They also highlight the inconsistency in the size of zonations at any given scale, and propose a framework for the construction of zones of similar population size, thus increasing the scale of the analysis. Kirby and Taylor also discuss the dilemma of choice of scale. At a scale that is too small, then it is not possible to compare data sources from different (modifiable) unit systems. However, with the scale too great, then much of the more local level detail within an analysis is lost through the aggregation process. Therefore, the scale effect may have a number of different elements, including the highlighting or smoothing of spatial processes and also a process similar to smoothing within the data. Overall, this can contribute together and result in the difficulty of obtaining definitive statistical results for data that are organised in areal units. The magnitude of the scale effect was highlighted further by Holt *et al* (1996b). They suggested that it was insufficient to reference the scale effect alone, as it was potentially possible to have a range of different scale effects, and the zonation and scale effects were so wide ranging they required a degree of qualification. Therefore, they suggest that it is necessary to refer to them in relation to what they act upon, for instance, as the "scale effect on the expectation of an estimator or the scale effect on the variance of the estimator" (*Op. cit.*).

2.3.1.2 The Zonation Effect

Once the scale has been determined then there is the additional issue of the definition of the boundaries to be used in the analysis. Openshaw, amongst others, has termed this the "aggregation problem" (1977a). However, the alternative description, the "zonation effect" (after Flowerdew and Green, 1994) is adopted here to prevent confusion between this element of the MAUP and the overall act of aggregation. Aggregation can be considered as the process whereby areal units are combined for the construction of larger units. This itself can result in instances of the scale effect. The zonation effect element of the aggregation process is concerned with the act of devising areal boundary definitions for a unit system. Moreover, the term aggregation effect is used (after Steel and Holt, 1994) for a quantitative measure of the scale effect in later chapters.

The zonation problem occurs where there are "any variations in results due to alternative units of analysis where *n*, the number of units, is constant" (Openshaw and Taylor 1979). Indeed, it is possible to argue that there are an infinite number of different ways in which a continuous space can be subdivided into discrete areal units. Figure 2.2 presents a diagrammatic interpretation of the zonation problem and demonstrates the arbitrary nature of the divisions of space that can be presented when there is no set division system.

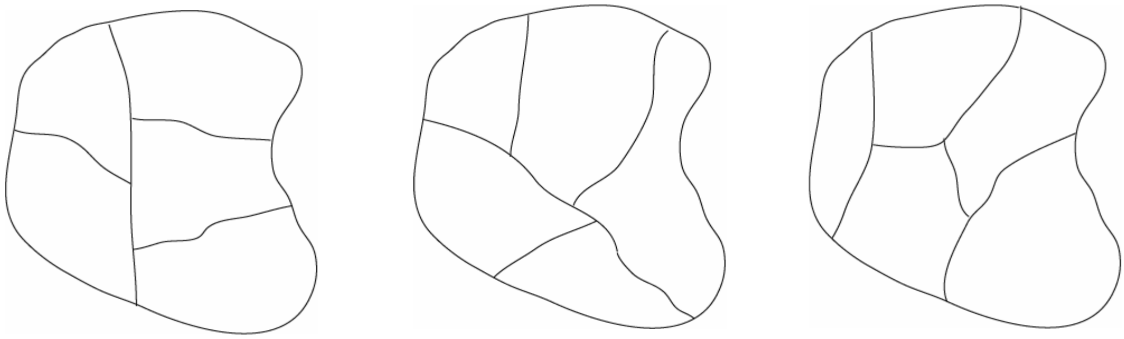


Figure 2.2: The zonation problem. Each of these diagrams demonstrates a division of a sample space into 5 distinct areal units, yet each could potentially yield different results.

Openshaw (1984) contends that the zonation effect is by far the greater of the two problems, as there is considerably more freedom choosing the delineation of boundaries than for choosing the number of zones that are required. However, whilst this view may be supported, it can still be suggested that until the scale for the study has been determined the zonation issue is largely academic, as the debate over what scale an analysis takes place, such as the number of units, or ideal population sizes, precedes the debate over how the analysis space is to be subdivided. Furthermore, the majority of areal data research, such as that conducted on the census provides the areal boundaries *a priori*, and as such the zonation problem is not an issue to an uncritical analyst. The real test is at which scale the analysis should take place, as was outlined above. Taylor and Goddard (1974, p.153) noted that there is no “spatial equivalent to the day, month, or year”. The consequence of this is that the process of zonation becomes susceptible to the whims of those involved in the overall aggregation process (Openshaw and Taylor, 1981, p.61). While this position may be extreme, it makes the point that there are serious problems with the arbitrary nature of the many areal units.

In practice the reality of the zonation problem can be outlined using an example of electoral redistricting. Morrill (1973) presents electoral redistricting for Washington State, and shows that with differing electoral boundaries it is possible to redistrict the State so that what Morrill terms “Toss-up” and “Lean” seats which are not assured to either of the Democrat or Republican political parties can be redrawn to make them more likely to fall to either one of the two parties. Furthermore, as Clark (1991) discusses, the MAUP as a geographical phenomenon has a place in everyday circumstances, be it the discussion and determination of the political boundaries post World War 1 at Versailles or the legal framework and contesting of voting rights and patterns and the complex social patterns that exist within areas that are defined for such purposes. Therefore, the zonation problem can have real implications, and real uses within a real world context.

2.3.1.3 Ecological Fallacy

The problem of the ecological fallacy is associated with the MAUP. “The ecological fallacy arises when spatially aggregated data are analysed and the results are assumed to apply to the relationships at the individual level” (Steel and Holt, 1994, p.3). In a similar manner to the MAUP, statistical results that are susceptible to the ecological fallacy may result in conclusions being drawn at an areal level different from those that would be drawn if unit level data were used instead. Clearly, therefore the ecological fallacy has a strong relationship with the MAUP as they both describe the potential pitfalls that are open to analysts of areal unit data. However, although the two problems are related and linked they are not complementary. This means that, solutions or methodologies that can control or understand the MAUP are not necessarily similar to those that can control or help to understand the ecological fallacy. For instance, it can be supposed that more homogeneous areas are appropriate to reduce the incidence of the ecological fallacy, as the greater the homogeneity of the areas the closer the areal data will be in structure to that of the unit level. It is not the case that the high levels of homogeneity desirable for this function would be desirable in limiting the impact of the MAUP. Indeed, it may cause the MAUP to be more pronounced. This thesis is not explicitly concerned with the implications of the ecological fallacy. However, it is undoubtedly linked, and therefore an awareness of it should be shown.

2.3.1.4 Conclusion

The MAUP can, therefore, be seen as a pervasive and real problem in areal spatial data. Openshaw (1984) presented three perspectives from which the MAUP could be viewed. These were:

- an insoluble problem;

- a problem that can be assumed away, and;
- a very powerful analytical device.

A further, fourth, perspective should be added, whereby the MAUP can be viewed as a problem endemic to all areal unit research, and that requires solutions to be found which will shed light on the spatial processes creating the data. This would entail the removal of the MAUP, which may reduce the usability and descriptive nature of the data under analysis. Thus, although many attempts have been presented to provide solutions to the MAUP none has been successful. So, from this perspective the MAUP could be viewed as insoluble. However, this perspective is rejected in the context of the work presented in the following chapters. The second of Openshaw's perspectives, a problem to be assumed away is highly naïve. Indeed, this approach could result in some serious data miscalculations and interpretations. Thus, this thesis regards the MAUP as a powerful analytical device. In fact, it goes further than this, and suggests that the MAUP should not be viewed simply as a problem. Rather it should be considered at most as a phenomenon, and one that could provide more information about the structures of the spatial data within the areal units. The very existence of the MAUP in areal data reinforces the notion that the data under analysis is inherently geographic, as there are relationship between individuals and areas that operate on numerous levels and in different spaces. Indeed, as Haggett (1981) stated, "a world without boundary or autocorrelation problems would be one with little geographic interest".

2.3.2 Evidence of the MAUP

Gehlke and Biehl (1934) published the first evidence that aggregation resulted in changing statistical results when applied to areal data. They noted that the correlation coefficient tended to increase as the number of areal units representing the census data decreased. They investigated this effect using census data, random tosses of a coin, and the experimental groups of rural counties. With the census areas, as the number of areal units in the study fell, so the correlation coefficients increased (see table 2.1). The coin tosses demonstrated that, even with randomly generated data, when the data were aggregated, the correlation coefficients were prone to change. In the case described by Gehlke and Biehl (1934) the coefficients of the correlation analysis were seen to increase. Their last example, using the value of farm products, demonstrated for the third time that changing the scale of analysis resulted in increasing correlation coefficients. They concluded by questioning whether or not “a geographical area is an entity possessing traits, or merely one characteristic of a trait itself”, (p.170). In essence, they highlighted the notion that data from areal units should be treated with caution and “that variations in the size of the correlation coefficient seemed conditioned on the changes in the size of the unit used” (*op.cit.*).

Number of Areal Units	Correlation coefficient (r)
252	-0.502
200	-0.569
175	-0.580
150	-0.606
125	-0.662
100	-0.667
50	-0.685
25	-0.763

Table 2.1: Correlation coefficients under aggregation using juvenile delinquency and monthly rentals. (taken from Gehlke and Biehl, 1934, p169).

Yule and Kendall (1950) furthered the investigation using UK agricultural data organised into county level areal units. They pose the question that, although they are able to identify relationships between variables, these relationships may not still exist in the same manner when the areal divisions chosen were changed. They sought to assess this by aggregating existing areal units together, and as such provide a study that investigates the scale effect (see below). They found correlations ranging from 0.22 to 0.99, which led them to question whether or not any of the correlations are actually “real” (p.311). They established that the results are only applicable “for the specified units chosen for the work”, (p.312), and lack validity once removed from the zonal context. In conclusion, they presented 5 summary findings from the paper, the first of which is the most relevant in the context of this thesis: “Units may be modifiable or non-modifiable. For modifiable units the values of correlations depend on the size of the units and must be interpreted accordingly”.

Blalock (1964) considers the impact on correlation coefficients between the percentage of non-white residents in the population and the differential between white and non-white income. Four different aggregation models are used in the study: random grouping; grouping by independent variables; grouping by a dependent variable, and; grouping by proximity. Each of the aggregation methodologies are used to produce aggregations of 75, 30, 15 and 10 areal units. The results are presented in table 2.2.

Method / Units	Initial	75	30	15	10
Random	0.54	0.67	0.61	0.62	0.26
Maximum variation in X	0.54	0.67	0.84	0.88	0.95
Maximum variation in Y	0.54	0.67	0.87	0.91	0.95
By proximity	0.54	0.63	0.70	0.84	0.81

Table 2.2: Results of Blalock's aggregation study.

From these results it is established that using the random method, there is little pattern to the MAUP effects in correlation analysis, (with the exception of the 10 unit system). This demonstrates that data which are aggregated not according to spatial location are not as susceptible to the MAUP. From this it is possible to suggest that the MAUP scale effect occurs due to the non-random nature of data aggregation. With independent variables coefficients increase with aggregation, but without systematic pattern. Where aggregation is undertaken using dependent variables, results similar to those described by Yule and Kendall (1950) and Gehkle and Beihl (1936) are observed. The proximity model also generates increases in coefficient, although to a lesser extent. Again, this concurs with the results of Gehlke and Beihl, as well as those presented below observing that the increasing correlation coefficients are present in data that are aggregated according to the values of *X* or *Y*. The effect of proximity is the same, but to a lesser degree, because areas close to each other tend to have similar variable values.

Clark and Avery (1976) presented further evidence supporting the Gehlke and Biehl (1934) and Yule and Kendall (1950) studies. Clark and Avery investigated the MAUP and the effects of changing scale using data from Los Angeles Metropolitan Area Survey (LAMAS). They considered the mean income of a household against the median number of school years completed by the head of the household. This data was organised into census tracts, which could then be hierarchically aggregated into the 952 LAMAS areas, 1556 Census tracts, the 134 units of the Welfare Planning Council and the 34 units of the Regional Planning Commission. They then compared the results of correlation analysis, the coefficients of which are replicated in table 2.3.

	Method of Generalisation	Correlation coefficient
952 LAMAS	Not Applicable	0.4028
1556 Census Tracts	Tract Mean	0.6434
	Tract Mean (log income)	0.6707
134 Units	Group Mean	0.7606
	Group Mean (log income)	0.8285
35 Units	Group Mean	0.8503
	Group Mean (log income)	0.8811

Table 2.3: Results of Correlation Analysis from Clark and Avery (1976 p.432).

As with the previous two examples, under aggregation it was observable that variation in the results increased as the level of aggregation increased. Their conclusion noted that is "incorrect to assume that relationships existing at one level of analysis will necessarily demonstrate the same strength at another level" (p.311), and that the results "measure ... not only the variation of the quantities under consideration, but the properties of the unit mesh which have been imposed in order to measure it" (p.312). This is one of the first investigations within the literature that recognises that the "unit mesh" or specification of the areal units and processes that they may reflect can be of influence on the statistical results and the observation of the MAUP. This, as is discussed throughout the thesis, is of prime importance. However, another theme that Clark and Avery highlight is the notion that "the ideal aggregation procedure would yield groups which are homogeneous with respect to all of the variables in the model" (p.430). However, it must be acknowledge that this is neither practical nor possible. Nevertheless, it is a useful proposition, and does serve to highlight the importance of homogeneity in relation to the MAUP, a theme which is expanded below with respect to spatial autocorrelation.

With increased computing power in the late 1970s, it has been possible for the wider social sciences to become interested in large-scale data sets of aggregated data. Therefore, issues such as the MAUP were becoming of more interest to practitioners of the social sciences, and specifically geographers. Openshaw and Taylor (1979, 1981) first referred to the statistical sensitivity as the Modifiable Areal Unit Problem, and presented it to the wider geographical audience. They did this by posing a series of questions to geographers that are still as relevant today. They asked two questions: “what is the nature of the modifiable areal unit problem?”, and; “Why is it so important to geographical analysis that it cannot be ignored?” (1981 p.60). They propose answers to these questions, although these are not discussed at this stage as they are discussed below in chapters 4 and 5. This thesis will attempt to demonstrate the answer to these questions, with reference to real examples of research where the MAUP could have made a difference to the outcomes of a study. Their questions were posed in the introduction of one of the largest studies of the MAUP (Openshaw and Taylor, 1979, and 1981). They used correlation analysis, and assessed the impact that the MAUP could have on correlation coefficients. In the first instance, they correlated the proportion of republican voters against the percentage of the population above 65, from the 1970 US Census. To assess the impact of the zonation effect, Openshaw and Taylor produced correlation coefficients for different arrangements of counties in Iowa into six counties, and demonstrated changing correlation coefficients (see table 2.4).

Number of Areal Units	Correlation coefficient (r)
6 Republican-proposed	0.4823
6 Democratic-proposed	0.6274
6 Congressional districts	0.2651
6 Urban/rural regional types	0.8624
6 Functional regions	0.7128
99 Iowa counties	0.3466

Table 2.4: Correlation coefficients from Openshaw and Taylor (1979 p.129) showing zonation and scale effect.

Therefore, Openshaw and Taylor provided further proof that the MAUP is pervasive in spatial data. Using this dataset they demonstrated that is was possible to obtain highly changeable correlation coefficients for a single set of data. They went further than this in the article by attempting to describe the universe of correlation coefficients that were possible to achieve using the different scales of zonation. For many of the scales, they claim that the range was from –0.999 to 0.999. However, this is not the case for all scales. For instance, for a scale of 72 zones the minimum found was –0.579, and the maximum was 0.927. This demonstrates the impact of the aggregation effect as differing boundary choices change the correlation coefficient values. However, it is also clear that the range of coefficient values is not limitless, as the coefficients could not achieve any value between –0.999 and 0.999 as in some cases they were bounded by much lower limits. A further criticism of the work by Openshaw and Taylor would be that, although they demonstrated that a wide range of correlation coefficients were available through both the aggregation and scale effects, they did not seek to validate the realism of the aggregations that they used. Thus, it is possible that a number of the extreme correlation coefficients were identified using aggregations that would not be permissible in a real world context, either because of shape or population constraints. This dimension is clearly important in the construction of aggregated data systems, as they are required to reflect their potential use. Nevertheless, this did raise an important conclusion, that scale and zonation were real issues, achievable with real data, highlighting the necessity of study of the MAUP. Moreover, they demonstrate that each aggregation system, both in terms of scale and boundary placement, should be treated as individual problems, and that the complexity of the MAUP prevented quick generalisations being made.

Fotheringham and Wong (1991) demonstrate results that include support for much of the work that has already been documented above, such as the fact that there was a "general increase in correlation coefficients as the level of data aggregation increases". They liken this to a smoothing effect, a notion first introduced by Kirby and Taylor (1976), which sees decreasing variation as aggregation increases (p.1026). Fotheringham and Wong (1991) suggest that an important aspect of the MAUP that had been neglected is that of multivariate statistical analysis. As they recognise, much has already been written on the relatively simple problems of univariate and bivariate statistics. To do this, they use a number of aggregations at different scales, using the 871 Census Tracts, and then new aggregations of 800, 400, 200, 100, 50 and 25 units, with 20 different realisations at each of these scales. Thus, each parameter had 121 estimates. The aggregations are carried out on a wide range of variables including a large number of census variables, such as ethnicity and house ownership. Fotheringham and Wong contend that if the MAUP did not exist then as scale changed the parameter estimates would show little or no variation. This is not the case with their results, which do show variation at different scales. For instance, with the proportion of elderly people, and the proportion of blue-collar workers, they note that the variation is systematic, and a decrease in the number of areal units result in a higher negative parameter from the regression. For the other variables, the ethnic proportion of the population, and the proportion of owner occupied households, they conclude that there is little systematic variation (p.1033). There were also aggregation effects present at the same scale with different zonation systems (p.1040).

Fotheringham and Wong (1991) also propose a framework which extends the univariate model to incorporate spatial dependence, thus highlighting the issues surrounding spatial autocorrelation. They developed two models to investigate the MAUP;

1. a linear regression model relating to the mean family income in dollars, and;
2. logit regression model relating the mean logit transformation of the proportion of owner-occupied housing within an areal unit to the proportion who are blue-collar workers.

Their analysis also considered the levels of spatial autocorrelation present in the data using Moran's *I* statistic. Their results show that although there is spatial autocorrelation present in the data it occurs at differing magnitudes depending upon the variable and level of aggregation. Fotheringham and Wong suggest the results of this test demonstrate that in general the data "exhibit local differences which diminish as the data are aggregated", (p.1037).

Fotheringham and Wong conclude that the MAUP effects in multivariate analysis are essentially similar to those found in studies of univariate and bivariate methods, although they are more unpredictable. Among their recommendations is the need for a solution that uses GIS and links this with strong statistical capabilities that allow parameter estimation to overcome these problems. Furthermore, changes in variance and covariance would need to be calculated prior to the prediction of the sensitivity of the scale and zonation changes. It is also important to realise that the scale and zoning problems need to be treated as separate problems, while also recognising that they are interrelated. Most importantly, they show that spatial autocorrelation has a role determining the rate at which the variances of X and Y decrease (p.1027). This leads to the conclusion that spatial autocorrelation has a key role to play in MAUP. The potential impact of spatial autocorrelation is discussed in greater detail below, and is exploited with reference to the scale effect in chapter 7.

Openshaw (1984) explicitly defined the MAUP as being largely attributable to the fact that a study region over which data is collected will be continuous, and it "follows that there will be a tremendously large number of different ways by which it can be divided into non-over-lapping areal units" (p.3). The effect of the MAUP is to cast uncertainty over the validity of a set of given results in relation to their ability to demonstrate undisputable relationship between an aggregation system and analysis results. For instance, as the level of aggregation increases, then generally, the level of correlation tends to increase. This could be demonstrated using Census data, where a correlation is usually stronger at the Ward level than at the Enumeration District level. Openshaw discusses this in the context of a general example for the MAUP. This considers the Tyne and Wear County, where approximately 1.1 million lived in 300,000 households. The basic spatial units in the 1981 census divided this area into around 2800 enumeration districts. Firstly, there is a large number of different ways in which these 2800 zones could have been constructed (zonation effect). Secondly, "there are other huge combinatorial explosions whenever a zoning system of 2800 zones are re-aggregated to form other zoning systems with fewer zones; for example the 258 zones used for transportation modelling and planning. There are, therefore a tremendously large number of alternative 258 zone aggregations that could be used, most (if not all) of which will yield different results" (p.4).

Amrhein (1995) identifies three unanswered questions in relation to the aggregation effects. Firstly, it is noted that some of the so-called aggregation effects are to some extent due to methodological considerations. Therefore, they exist as a consequence of the inappropriateness of the statistics used in an analysis, and represent a mis-specified model. As has already been noted, frequently statistical measures such as correlation coefficients are based on the assumptions that data are normally distributed and that each case in the correlation is of equal importance. Data of interest to social scientists frequently breaks these assumptions. Therefore, in many cases it can be suggested that the statistical models used are incorrectly specified. Secondly, given the shortcomings in the datasets, in that they do not and cannot measure every facet of a population, is it realistically possible to identify the aggregation effects? That is to say, the MAUP may also be compounded by missing variable effects, effects caused by variables that have been left out of the analysis. This thesis will contend that this is the case, and that it is possible to identify different correlation coefficients MAUP through statistical measures. Thirdly, the spatial processes may not necessarily occur at the level of the analysis, and may occur differently at different levels. This is explored more explicitly in chapter 7. Amrhein's paper searches for the aggregation effect in a computer generated idealised population. However, the results provide "no evidence of any scale effects in the mean values of the population versus various aggregations, or among the various aggregations", (p.110). This leads Amrhein to note that for the mean at least, there is no reason for the analyst to be afraid to use aggregated data. When using the variance statistic, this conclusion is repeated, so that whilst there are differences between different levels of aggregation, there is no "substantial scale effect beyond that expected given the change in the number of zones" (p.113).

Amrhein investigates this using a set of simulated data that, importantly, contains "no useful process-based information". This means that Amrhein's investigation is not hindered by the spatial processes that occur in real socio-economic data. This enables the study to assess the aggregation effects. In conclusion, Amrhein develops what are termed 'aggregation rules', which relate both to the scale and zonation effects. These rules are.

1. "The mean does not display any pronounced aggregation effects (scale and zonation) at any level of aggregation used in this study.
2. The variance does not display any pronounced scale effects beyond those expected form the decrease in the number of observations. However, it must be noted that scale-specific variance values cannot be imputed to other scales without adjusting fir the change in the number of reporting units.
3. Populations with high variances tend to exhibit more pronounced zonation effects than do populations with smaller variances.

4. The regression coefficient does not display scale effects that increase systematically with decreasing numbers of zones (that is increasing levels of aggregation).
5. The standard deviations of the coefficients display pronounced zonation effects. As in the correlation coefficient, the standard deviation of the coefficient increases to a point at which the coefficient fails to provide reliable information (based on the expectation). An additional problem is encountered in sign reversals of the coefficient. In this case, reversals are evident in the first step of aggregating [using 100 zones in this case].
6. The Pearson correlation coefficient exhibits systematically increasing aggregation effects as the number of [zones] decreases. The range and standard deviation of coefficients calculated in these experiments ultimately span the range of the statistic."

These rules are useful as, although they do not seek to provide a solution to the MAUP, they do serve to aid the further understanding of the MAUP. Indeed, this thesis is built around the premise that a solution is not required for the MAUP, and more consistent statistical analysis will be achieved with greater understanding of the MAUP. Finally, Amrhein concludes that, unlike previous assumptions aggregation effects, by which both the scale and zonation effect are meant, are not pervasive and unpredictable, occurring in all data, at all levels.

2.3.3 Real Implications of the MAUP

The examples discussed above are mostly theoretical although based around real world data, and illustrate the MAUP and the effects it *could* have on data. In response to this, Marble (2000) questioned the validity of the many investigations into the MAUP by wondering if "anyone [could] produce a real-world example, couched within a significant operational context, that clearly demonstrated that if ignored the MAUP represents a costly but correctable mistake?" With reference to two studies, presented below, it is possible to reject this claim.

The first study investigated the effects of the Dounreay Nuclear Power Plant in relation to instances of Childhood Leukaemia for an application to introduce reprocessing facilities (Heasman *et al*., 1981). Here it is noted that the importance of their findings is difficult to evaluate as the choice of radii and time periods for their study area "are arbitrary" (p.266). As a consequence, clusters of cases in one area and time period may, or may not be significant, and could be eliminated by a different choice of radii and time periods. Therefore, the choice of aggregation was very important, as depending on the choice a finding could be reported as significant, whilst with a different aggregation the same data could appear insignificant.

The second example is provided by Boyle and Alvanides (2004) and demonstrated both the scale and zonation issues of the MAUP. Using a case study involving the City of Leeds, and measures of deprivation they demonstrate that it is possible to change the ranking of Leeds relative to other Cities across the UK by using different boundary systems. This is of particular importance, as the European Commission was offering what are termed structural funds to aid the reduction of inequalities at a local level within member countries. Using the 1998 Index of Local Deprivation (ILD) based on the 1991 Census it was possible to rank Leeds against the other Cities of the UK. In an initial ranking Leeds appeared 56th. However, this could be improved to 11th if the boundaries were redrawn, using a smaller population threshold. Applying different criteria for the aggregation, whereby the scores were taken for Wards not LADs, enabled a further improvement in the ranking, with third being the best achieved for Leeds. Clearly, there is a substantial and significant difference between a ranking of 56th in the country and 3rd in the country in terms of the most deprived areas. This difference was also sufficient to determine whether or not an area got Objective 2 funding from the structural funds. Overall, the work by Boyle and Alvanides serves to highlight the potential difficulties opportunities and concerns that research using aggregated data should address. Although not observed in such an applied context, Green and Flowerdew (1996) also show how an apparent positive relationship between ethnicity and unemployment looks very different when MAUP effects are taken into account.

Although the focus of this thesis and much of the MAUP research has focused on the MAUP as a statistical issue, it is also worth noting that the MAUP is a far wider issue than this. The MAUP also has influences on the visualization of data, and so "any numbers collected over … areas … that are displayed as … maps, will depend greatly on the precise boundary definitions used", (Dykes and Unwin, 1998). Thus, when presenting areal data in cartographic map form, even within a study based around the

MAUP, it is necessary to keep in mind that the visual pattern perceived on the map space, is itself also a function of the division of the data into areal units.

2.3.4 Conclusions

Clearly, the MAUP has relevance to almost all sections of quantitative analysis, and as such must be considered. Whilst this thesis rejects Spiekermann and Wegener's (2000) notion of a "tyranny of zones" as a "spatial modelling in the straightjacket of zones", it does not suggest that the quantitative analyst can ignore it. As was discussed above, the approach taken reflects that suggested by Openshaw (1984), where it is possible to view the MAUP as a challenge to understand, but ultimately one which, when better understood, will be something that can be used as an analytical tool. Nevertheless, it must be remembered that analysis of zonal data relies on the assumption that the spatial units used are determined *a priori*, an assumption which in many cases can be considered inappropriate. Therefore, it is possible to see that if the notion of the MAUP is not at least adhered to, it is possible that an analysis could have potentially very different results, and as a consequence serious analytical outcomes could be changed. There is therefore, justification for further study into the factors that can influence the MAUP, and the way in which the structure of areal units can influence the data upon which they are imposed.

2.4 Statistical Explanations for the MAUP

Above, it was outlined that there have been two basic directions of research into the MAUP. The first of these directions is considered below, and reflects work that has attempted to provide statistical methods that seek to 'solve' the MAUP. These are ways in which data can be analysed or manipulated in order that the effects of the MAUP are removed or at least understood more easily, so that the resulting analysis can occur on the 'true' data. The second section reviews work that has sought to use the MAUP as a method to explain processes with the data.

2.4.1. Attempting to control the MAUP

One of the first solutions for the MAUP was proposed by Robinson (1956) and used areal weighting. The starting point was the supposition that the standard correlation equation is incorrect for the analysis of areal unit data as correlations require characteristics to be distributed within units of equal importance (as was highlighted above in the discussion around the work by Amrhein, 1995). When these units are not of equal importance, through size or population issues as is frequently the case in areal unit data (such as data from the Census), then what Robinson has termed significant discrepancies occur. To overcome this problem, each areal unit can be given appropriate importance through the process of applying a weighting term related to the varying sizes of the areal units in question. Robinson (1956) uses an example with data organised in a hypothetical state that was subdivided into two different arrangements of counties. If traditional analysis is applied to the data, then the correlation coefficients differ, as the MAUP theory would suggest (see table 2.5). However, if the data are weighted by the "areal units to which they refer" prior to the analysis, then in each case the correlation coefficient is 0.715 (p.234).

State	Correlation Coefficient (*r*)
1	0.715
2	0.687*
3	0.500

Table 2.5: Correlation coefficients changing under different aggregation systems (from Robinson, 1956, p.234). *The value shown by Robinson of 0.875 is incorrect, after Thomas and Anderson (1965).

Thomas and Anderson (1965) critique the methodology presented by Robinson, and note that the technique of data weighting is specific to the example Robinson presented and does not, therefore, offer a general solution. Indeed, they state that there are only two cases where Robinson's technique will work. Firstly, when the spatial distributions of an *X* and *Y* variable have exactly the same total distributions in both the initial data state and the subsequent aggregations. The second occurrence is when the values for the linear equation and the *r* are equal in the subsequent re-aggregations. Thus, Thomas and Anderson reject Robinson's theory as a special solution occurring in circumstances rarely present in real world data.

This thesis does not seek to provide a solution to remove the MAUP from data contained in areal units, as Robinson (1956) sought to achieve. In fact, the theme developed in this thesis suggests that if this goal were achieved, analysis would actually be poorer. The analytical sections of the thesis seek to demonstrate that the existence of the MAUP, exhibited through the changes in correlation coefficients actually serve to describe the nature of spatial interactions and processes within the data. If areal data existed where it was impossible to observe the MAUP, either in terms of the scale effect or the zonation effect, then the spatial arrangement individuals within that data would not have any relevance. Thus, the MAUP is a function of the complex relationships that occur within society. Consequently, the attempt by Robinson to remove the MAUP is critically viewed as an inappropriate response to the problem of the MAUP.

2.4.2 Spatial Autocorrelation and the MAUP

The conclusions of the critique of Robinson's areal weighting lead to the recognition that spatial autocorrelation is important in any statistical understanding of the MAUP. Goodchild (1986) presents a general review of spatial autocorrelation, where he introduces the subject as being concerned with the "degree with which objects or activities in some place on the earth's surface are similar to objects that are located nearby" (p.3). Indeed, Goodchild (1986) recognises the link between spatial autocorrelation and MAUP, albeit indirectly, by stating that the "concept of scale is implicit in any measure of spatial autocorrelation, and that spatial patterns may possess quite different forms of autocorrelation at different scales". Spatial autocorrelation is closely related to Tobler's "First Law of Geography", (1970, p.236), whereby similarity is related to distance. Spatial autocorrelation itself appears to have multiple definitions. One was presented by Upton and Fingleton (1985), where they described it as an organized spatial pattern. This reinforced the definition from Cliff and Ord (1981, p.105), who refer to spatial autocorrelation as "systematic spatial variation". Furthermore, they extend their definition in relation to the MAUP, and note that the size of the cells in the areal unit system are important in the strength of the spatial autocorrelation, or in their terms, spatial dependence. In essence, "the larger the areas, the weaker the dependence will be". This suggests that there are interactions and dependencies that occur at certain levels, and if the areal units are at a different level than those interactions then the level of dependence will fall.

Arbia (1989) builds on the work by Cliff and Ord (1981) by providing a more formal framework within which the discussion can take place. Arbia presents an example using Cliff and Ord's discussion considering settlement patterns first presented by Matui (1932). Here data relating to the location of the homes of a population were divided on a lattice of 32 by 32 cells. These were aggregated further into combinations of 16 by 16, 8 by 8, 4 by 4 and 2 by 2 (Arbia 1989). The results of the investigation demonstrate that with aggregation there is increase in the level of variance, and that as the level of aggregation increases the estimates of the variance of the data become more unreliable as the number of observations diminishes with fewer degrees of freedom. There is clearly, therefore, evidence of the MAUP, and it is possible to conclude that areal units are likely to contain a level of homogeneity, as people with similar characteristics tend to group together. Arbia termed this 'systematic spatial variation'. Fotheringham and Wong (1991) in their work presented above concluded of spatial autocorrelation that it has a "role determining the rate at which the variances of X and Y decrease as the level of aggregation increases".

Amrhein and Flowerdew (1989) investigate the effects of MAUP in relation to Poisson regression, and conclude that the choice of model with which MAUP effects are measured or presented is just as critical as the aggregation process itself. They are able to conclude this because their results show that within their Poisson model there is little aggregation effect to be found, not because it doesn't exist, but as a result of the data and techniques used in the analysis. A paper that develops from this research is that of Amrhein (1995), in which he presents a set of conclusions that suggest that the world of the spatial analyst dealing with spatial data is not as bleak as previously presented by, among others, Fotheringham and Wong (1991, see page 21 above). He summarises this in six points, which suggest that certain statistics and results (for instance the standard deviation of coefficients, or the Pearson correlation coefficient) exhibit greater changes due to MAUP (scale) than other statistical methods (for instance, mean or the variance). However, this does not mean that the MAUP is close to being understood, or that aggregation effects can be "easily purged from the data" (Amrhein, 1995).

The importance of spatial autocorrelation has been further developed by a number of authors such as Green and Flowerdew (1996). They note that "correlations between variables tended to increase when zones were grouped together", an effect that is clearly related to spatial autocorrelation. Their study provided statistical evidence that correlation coefficients will always suffer from MAUP in the presence of spatial autocorrelation. Green and Flowerdew employed simulated data to assess the impact of the MAUP as they could build in a known pattern of spatial autocorrelation into a variable. The basic grid of raw simulated data was aggregated (a) randomly, (b) systematically based on the value of one of the simulated variables, and (c) spatially into contiguous blocks.

In conclusion Green and Flowerdew (1996) argue that the effects of spatial autocorrelation may "result from contiguous processes affecting the distribution of one or more of the variables being analysed, or the spatial distribution of other variables which have effects on these". This is a very important conclusion, as it explicitly expresses the realisation that the variables of areal units may display linked characteristics. To explain this phenomenon Green and Flowerdew present three possible causes of spatial clusters:

1. "A tendency for people with similar attributes to choose to live near each other;
2. Effects of other characteristics of the area (which may or may not be available for analysis);
3. A tendency for people living nearby to interact and as a result to develop common characteristics".

Of these, the first and last are relatively straightforward, while the second point is the one that will present more difficulty due to its nature and the fact it is largely unquantifiable. In the future it is likely to be these types of unknown or unmeasurable variables that prevent or hinder fuller 'explanation' of MAUP.

2.4.2.2 Conclusion

It is considered here that the purging of MAUP from the data would not be beneficial to areal data analysis as the effects that different aggregations can have on data could provide additional information about the structure of the data and the processes that occur within groupings, which are of inherent interest to geographers as well ass social scientists as a while. Furthermore, spatial autocorrelation has been important in the understanding of the MAUP and it is a link that is explored in more detail in the following sections.

2.4.3 Using the MAUP to analyse data

Instead of removing the statistical effects of the MAUP, the second research theme has been to analyse the MAUP itself, in order to obtain more information about the data. There are two main research schools working on this theme. The first considered is that of the Green and Flowerdew research. The second considers the work from the Holt, Steel and Tranmer research group. Both themes look to deconstruct the data, and use structures similar to those proposed by the multilevel modelling approach.

2.4.3.1 Green and Flowerdew

It has been stated previously that the MAUP can be viewed as a problem that relates to the differences between the spatial processes generating data and the units within which they are reported. Green and Flowerdew (1996) present an argument that proposes that it is possible to understand the MAUP in terms of interactions between data objects that occur at the local level and at the regional level. This is presented as cross-correlation. Consider the relationship between two variables, denoted by X and Y. It is possible that the relationship is not simply Y_i to X_i, but also Y_i to X_j, where X_j is the X variable for a neighbouring zone. Green and Flowerdew (1996) define this as cross-correlation, which occurs when the response variable is affected by the explanatory variable both at the same place *and* at surrounding locations. This could be seen in an example using house prices, where the price of one house is a function of not only its own condition, but also of the upkeep of the houses in the immediate area.

It is apparent that this is related to the concept of spatial autocorrelation. They define this to be part of the range of processes that can influence the results of statistical analysis on areal data. Green and Flowerdew (2001) explore this notion further and express it as where "Y is a function of X and there is a cross-correlation effect, then statistical measure, in this case a regression, of Y at the most local level should include as explanatory variables both a *local effect,* i.e. the value of X at that local level, and a *regional effect,* i.e. the values of X in the surrounding area" (p.91, emphasis in original). This is clearly a useful contribution to the literature. It also reflects the approach taken in this thesis, whereby the MAUP is seen as an opportunity to gain a greater understanding of the data that is being analysed. Chapter 7 takes the concepts of the local and regional effects and attempts to determine if it is possible to view these effects through the concepts of multilevel modelling and local association statistics. The concept of the local and regional effects can be seen as a similar concept to that of multilevel modelling as it clearly identified that there are levels at which processes may operate within the data. Thus, the concepts developed by Green and Flowerdew (2001) are referred to in the forthcoming chapters.

2.4.3.2 Information from the Areal Units

The Green and Flowerdew work set out concepts through which the MAUP could be better understood. However, further attempts have been made to understand the MAUP and rather than control or remove it, use it to gain extra information from the areal unit structure. Much of the research presented here develops from the theoretical standpoint that the process of aggregation and, perhaps more importantly, the structure of the population under analysis are not the result of processes occurring randomly. Rather, the processes that operate on and around the population under analysis are highly structured. So, for instance, people tend to choose where to live not through random chance but through careful decision making taking into account a host of factors such as the type of area, the type of housing, and the location of amenities to name just three factors. This contributes to the processes that occur within society, in the location of the population. Consequently there is a requirement that these processes are identified as these processes are likely to be, at least one of the causes of, areal homogeneity. Much of the work here is derived from investigations into the ecological fallacy and not, directly, the MAUP. However, it is clear that the techniques initially developed to understand and resolve the ecological fallacy are highly applicable to the MAUP.

Steel and Holt (1994) start by stating "whilst aggregation effects have been studied empirically in many studies, the lack of a clearly specified statistical model has limited the interpretation of these [MAUP] studies". A key proposition within the work discussed below is that when data are aggregated into areal units the combinations of the population do not represent a random distribution. Thus, to start to consider how statistical models can be better specified, Steel and Holt (1996a) sought to explain the ways in which the population interacts in terms of the different processes (grouping effects in Steel and Holt's terminology), and the ways in which the areal units in which individuals live are developed. These were first discussed in

Steel and Holt (1994) and published for the wider academic community by Steel and Holt (1996a). There are three different models for the processes that could be used to describe the way in which populations were structured so that their distribution was non-random. Thus, the groups were:

1. Grouping models, where some process operates so that the combination of units is not random, either at the stage of group formation or potentially in migration
2. Group dependent models, where the population of a group is subject to the same influences. Steel and Holt suggest that this may include contextual variables, which may be unobservable. If this is the case, then they suggest that this is a random effects model, and crucially will lead to "positive intra-class correlation", which areal unit homogeneity.
3. Feedback models, where "units interact with each other and the frequency and/or strength of this interaction is greater between units in the same group than between units in different groups" (p.40).

Of these models, Steel and Holt discuss the first two, leaving the third one as a description. They determine that the way in which the population forms groups is crucial in the determination of the magnitude of the aggregation effect, a term that is used to define both scale and zonation effects. The first model is clearly a reflection of the aggregation process in areal data, where units may only be aggregated with adjacent units. The second reflects the desire of people to live in similar areas and with similar people. Both of these provide a casual relationship that can be seen in the spatial autocorrelation that occurs within spatial data.

In practice, Steel and Holt (1996a) discuss the implications of the different types of groups by identifying the homogeneity and heterogeneity in the variables, which was highlighted in group 2 with the term "intra-class correlation" (p.40). Again, the argument can be directly linked to the spatial autocorrelation argument and can be understood by the following example. They propose a study that investigates the relation between some health variables, which have values that are correlated across different individuals within an ED. The analysis based on the ED means of the health variables will produce different results to a similar analysis that used individual data. "In a grouping model, the similarity of people within an ED with respect to the health variables is due to their similarity in terms of … age, income and occupation. The similarity, in turn, is due to people of similar age, income and occupation choosing to live in the same ED and will depend on the characteristics of the ED such as the type and cost of housing, access to work and other facilities" (Steel and Holt, 1996b, pp.40 – 41).

Individuals who live in the same area exhibit a positive association for a wide variety of socio-economic characteristics, (Holt *et al* 1996). It is, therefore, not necessarily appropriate that the solution of the MAUP is based around the assumption that data aggregations are random. By their nature, geographical areas are not equivalent to randomly formed areas, as individuals in the same area tend to be more alike than individuals from other areas (Tranmer and Steel, 2001). Therefore, once random aggregation has been understood the models can, theoretically, be advanced to include examples of non-random aggregation. The initial three models are summarised in two statements by Steel and Holt (1996b) who state that within-area homogeneity may arise because of:

1. Individuals who live in the same area are exposed to common influences, and;
2. Individuals with similar characteristics 'choose' to live in the same area.

"Essentially, the between-area differences, and hence the within-area homogeneity, is drawn in to the area-level analysis and confounded with the individual-level effects" (Steel and Holt, 1996b). This implies that the homogeneity is a cause of both the individual level and area level effects. Holt *et al* (1996a) clarify this and state "zoning effects occur because one choice of areal boundaries may create areas which are relatively homogeneous whereas another choice may result in areas that are less homogeneous". However, it is not necessarily true that the levels of homogeneity will be consistent between zones, in a larger area. Indeed, frequently the opposite is true, confounding the effects still further. Holt *et al* (1996a) therefore state that a "key issue is how any grouping affects the within area homogeneity in terms of variances and covariances".

Holt *et al* (1996b) demonstrate that it is possible to quantify the aggregation effects considering census data from Australia. Using graphical plots, they depict expected relationships that would be observed if there were no aggregation effects present within the data. That the analysis of the Australian census data does not conform to the idealised line demonstrates clearly not only that the MAUP is present in the data, but also the magnitude and deviation of the data away from the idealised position. Indeed, from this analysis Holt *et al* (1996b) state that there is “considerable variation in the effect of the aggregation for different pairs of variables” (p.182), thus illustrating the scale effect. The results found in this paper demonstrate that one of the most important issues in MAUP research is the determination of how grouping affects what this group have defined as within-area homogeneity. This is the level of similarity found between individuals who have been combined to construct higher level areal units. The opposite of within-area homogeneity is between-area homogeneity, and this defines the degree of similarity between individuals that occupy different areal units. When within-area homogeneity is high, then between-area homogeneity is low and vice versa. This concept is crucial to the understanding of this literature. The practical application of the concept of within-area homogeneity is outlined below. The conclusion of this work, however, is that the “effects of using aggregated data are complex” and that the “population structure … and the level of aggregation … are interlinked” (p.197) and, therefore, understanding of the MAUP will be increased through better representations of these. If the data were aggregated randomly, then the results of higher level analyses would “recover the individual relationships” (p.198). Thus, the differences of the analyses at different levels of aggregations has to be a result of non-random processes within the population, as identified by Steel 1994 and 1996(a), and reported above. The concept of within-area homogeneity enables these processes to be highlighted to a greater extent, and thus their role identified. If the areal units are designed in a manner that the within-area homogeneity is low, then the resulting aggregation effect will also be low. If the areal units contained elements of the population “who were essentially random subsets of the population …, then there is no aggregation effect” (p.199). Therefore, the conclusion is that the existence of within-area homogeneity is a contributor to the incidence and existence of the MAUP in aggregated data analysis.

It would, therefore, be useful to be able to identify the levels of within-area homogeneity, and quantify the processes that have been discussed. Such a method has been proposed by Tranmer and Steel (2001). The model suggests that variance of specific variables at the Enumeration District Level and the Ward Level when divided by the variance of the same variable at the individual level can provide a numerical answer that allows the quantification of the so-called aggregation effect, which summarises the scale effect for each of the chosen variables. The specification of the model is not given here, as it is reviewed in detail in the next chapter (chapter 3). Their explanation for this is that the variance changes due to variations in the level of homogeneity in the data at the different levels. The ability to estimate the homogeneity at different levels of aggregation allows an assessment of the scale effects in different statistics at the different levels of aggregation. The importance of this method is that it allows the identification of the individual level effects, and the area level effects as separate processes. The results presented by this model conform to the assertion made by Holt *et al* (1996a), whereby there is "empirical evidence from the sample survey literature that as the areas defined become larger so they become less homogeneous”. One limitation of the method proposed is that the boundary definitions are defined as fixed, which is not the case in many geographical analyses. Therefore, further analysis needs to take into account the assumption that the geographical boundaries may not be considered as fixed entities and the coefficients of the individual and area based effects could be used to demonstrate the sensitivity of the data to differing boundary definitions (Tranmer and Steel, 2001).

2.4.3.3 Conclusions

The discussion above has presented work from two different disciplines, that of geography and statistics. However, they have clear similarities, in that they both seek to increase understanding of the MAUP. This is not through the removal of the MAUP from statistical analysis of areal unit data. Rather, it is through the recognition that the data organised in areal units are frequently the result of a data hierarchy that exists at a number of different levels, not necessarily restricted to those described in the data. Green and Flowerdew present concepts that examine the nature of the interactions, and these concepts are taken forward in Chapter 7 of the thesis, where a technique to identify the local and regional effects within the data is considered. The work of Steel, Holt and Tranmer is also key to this thesis. Their techniques to identify within-area homogeneity are applied on a greater scale than has previously been undertaken, and their ability to describe the magnitude and incidence of the MAUP is investigated. The ability of this work to provide a technique to negotiate the MAUP is significant, although it was over emphasised by Wrigley (1995) who suggested that it would provide not only a way to gain information about the areal units and the MAUP but also more a solution than has been shown so far. Nevertheless, this thesis also adopts the position reflected in these papers that the MAUP is a phenomenon that could provide useful information about the data under analysis, rather than a problem that needs to be removed from analysis.

2.5 Zonation Solutions

As was outlined in the introduction, there are two aspects to the MAUP, and as such research around the MAUP is not solely concerned with the scale effect. However, much of the statistical work reviewed here suggests that the scale effect has been the primary focus of research, and that the zonation effect has been neglected. This is not the case, and in order than a fuller understanding of the MAUP is reached, it is necessary to consider the zonation effect as well. This issue has been tackled more successfully than the scale issue, and rather than provide statistical solutions for the zonation problem, the focus has been on the provision of methods to make zonations and zonal systems that are appropriate to the data analysis task (see Cockings and Martin, 2005). Moreover, the ability to provide multiple realisations of zonal systems within one analysis space enables the scale effect to be investigated further, as many different zonations can be derived as scale changes.

If zoning systems, as presented, are problematic, then it may be useful to reconsider why and how zoning systems may be redesigned. The rationale behind this has been summed up by Openshaw and Rao (1995), who state that "[t]he new opportunity provided by [the increasing availability of digital] boundaries is not to demonstrate the universality of MAUP effects, or to manipulate results by gerrymandering the spatial aggregation used, but it is to design new zoning systems that may help users recover from MAUP". Much of the early work in this field was carried out by Openshaw (1976, 1977b and 1978). It is useful to consider why re-aggregation is a useful tool prior to reviewing the methods and possibilities of implementation procedures. To demonstrate this, Openshaw (1976) has presented the following considerations to determine where and when re-aggregation should take place:

- If it can improve consistency of spatial representations by aggregating out anomalous areas thus reducing spatially lumpiness;
- If it can help display hidden geographic patterns by removing or reducing aggregation distortion whilst amplifying interest patterns;

- If it can improve the quality of the data by removing small number and unreliable data effects;
- If it can be used as a visualization tool to enable geographically representations of the data in particularly purposeful new ways
- If it can help simplify subsequent analysis and modelling tasks by removing the aspects of spatial data that cause the greatest statistical problems; and
- If it can help as a visual spatial analysis tool.

Openshaw (1978) developed the zone design theme further, and questions the validity of a number of the traditional methods used for such problems. He presents two extremes. A conventional statistical approach within which spatially aggregated data can be viewed as fixed, or a model that assumes that the "undefined parameters [are] fixed, and the identification of an appropriate zoning system has to be made in some optimal manner". The first view is unacceptable due to the interdependence between the choice of zone and results achieved. From a statistical standpoint the second solution is as poor as the first one was from a geographic perspective, as it could serve to remove the comparability between studies. Whilst there is undoubtedly an argument that zonal systems can be designed to reflect the data that they represent (Cockings 2005), it is also the case that if multiple zonal solutions are realised for an area, totally dependent upon the data under analysis then the arbitrary nature of the zones used will only be exacerbated. Moreover, to enable effective zone design to be implemented for the data, as prescribed in the second approach the "undefined parameters" would need to be defined, but as Green and Flowerdew (2001) and other have shown the processes occurring within social spatial data are not easily identified.

Thus, zone design may be deliberate, and can present a compromise, by designing a zonal system that satisfies multiple criteria, and assessing whether this model performs satisfactorily. Openshaw's final observation is that frequently zonal design systems are applied in a deterministic and naïve fashion. To avoid this, Openshaw (1977b) has proposed a number of criteria within which a zonal system can be drawn, where the criteria are known as objective functions. In order that this could be facilitated he constructed the Automatic Zoning Procedure, which was implemented through the Automatic Zoning Program (AZP). This grew into the ZDES (Zone

Design System), which is discussed later. Zone design is always geared toward the maximising of at least one objective function. There is a vast array of objectives that may be considered Not least amongst these, are the objectives of equal population; equal area; equal population density, and; compactness (Openshaw 1978). It is worth outlining the six points of Openshaw's heuristic that was implemented through AZP:

1. Decide how many regions are required in the final aggregation;
2. Generate a random zoning system with this number of regions;
3. Randomly select one of the regions and proceed around its boundary measuring the effects on the objective function of moving zones from the bordering region into it;
4. Once an improvement is recorded for the objective function which is being optimised, then check whether the move is possible; that is, it must not destroy the internal contiguity of the region from which a zone is being moved; either accept or reject the move;
5. Once all the members of a region have been examined return to step 3 to process another region. If all regions have been examined then go to step six;
6. If one or more moves have been made then return to step 3, otherwise stop.

An important aspect of this is that there may not necessarily be a unique solution that AZP finds.

More recent research has revisited the requirements for zone design and integrated this need with the more general 'field' of GIS. It can be argued that there is a real need for zone design systems. Openshaw and Alvanides (1999) present a series of reasons behind the renewed interest, including the maturity of GIS; increasing use of electronic census data; increasing computing power; the increasing need to link and compete with competing data sources linked to postcode geography; and the final goal of allowing users to define their own zonal units. To facilitate such a goal, the AZP presented above was extended to become the ZDES package. ZDES starts with the proposition that it is important to consider alternatives to the 'as is' spatial representation and allow the development of zone design as a spatial engineering tool. However, whilst this is a useful tool for the redesign of zonal geographies it does not in itself offer a way forward to determine the causes or influences of the MAUP. It is acknowledged that the production of alternative zonal systems is a goal that can help understand the MAUP. It does not, however, provide a guide to likely levels of the

MAUP. For instance, research has shown (see Holt *et al* 1996a) that the level of homogeneity in a zonal system is an important determinant of the magnitude of the MAUP. Zone design could enable the manipulation of the level of homogeneity, but it cannot provide a methodology by which the understanding of the MAUP can be increased.

Much of this section has, so far, concentrated on the work of Openshaw. However, there are other systems that have been developed specifically for zonal data analysis and redesign. An alternative to ZDES, is AZM (<u>A</u>utomated <u>Z</u>one <u>M</u>atching). This is a tool for automated zone design. It "implements zone design on a set of zones described by polygon and arc attribute tables exported from Arc/Info or generated by users' own programs. [The program is designed to optimise] the match between two zonal systems, or the aggregation of a set of building block zones into output areas with a range of user-controlled design parameters" (Martin, 2003). The AZM program uses the AZP procedure outlined by Openshaw (1978) and is therefore conceptually similar. However, unlike the ZDES and the systems that developed from it (see for instance the ZoDE program developed from the principles of ZDES, Alvanides 2002) the AZM program was not designed specifically for the purpose of zone design. Rather, the primary function of the program is to provide a means to enable two incompatible zone coverages to be aggregated into a higher-level zone system that enables comparison (Martin, 2003). However, through the input of two identical coverages it can be used to perform an aggregation function. Martin (2000), Martin *et al* (2001). Although aggregation was not the primary purpose of the program, the ability provided by AZM to enable the aggregation process to regard shape, homogeneity and population size as restricting factors in the aggregation process means that it is more suited to the design of analytically appropriate zonal systems. That is to say, zonal systems that better reflect the required uses of data, as purely random aggregations where there is little or no control over one or all of these factors is not relevant in the context of research where desired scales of aggregation are required. Thus, AZM is used in the aggregation of data for analysis in chapter 6 and as such a more detailed discussion is presented in Chapter 3.

The last major piece of software considered here is the SAGE program (<u>S</u>patial <u>A</u>nalysis in a <u>G</u>IS <u>E</u>nvironment). This differs from the previous two as it is not specifically aimed at the zone design problem. Rather, it is aimed at the lack of statistical capability in the GIS packages to allow the GIS user to make intellectual sense of the patterns and processes they can visualize within the zonal systems. Haining *et al* (1996) argue that there is a need for strong spatial statistical analysis (SSA) within the GIS packages. SSA comprises of "numerous specialist techniques that, whilst well established in the academic literature are not routinely available in most statistical packages" (p.449). These will integrate into GIS and complement the current functions (of map based analysis and modelling). The SSA within SAGE are concerned with what has been termed lattice data, that is to say, data that are "already partitioned into zones with vectors attached that describe that zone" (Wise, *et al*, 1997). SSA grew out from the Exploratory Data Analysis (EDA) literature (see Tukey 1977 for examples) and the associated Exploratory Spatial Data Analysis (ESDA). The ESDA literature enabled the recognition of the problem that in "area-based analyses … the results of the analysis may be sensitive to the choice of spatial unit" something which has already been demonstrated above. SSA is designed as a set of tools that can help overcome, or at least account for some of this variation. Consequently, the importance of programs such as SAGE should not be underestimated. They perform relevant and vital operations on zonal spatial data that enable analysis in the GIS environment to an extent that previously was not possible. This is extremely relevant for MAUP, as MAUP is an inherently spatial problem. Furthermore, programs that are usable within the GIS environment will be more likely to enable increased user understanding of issues such as MAUP, especially within an era where users are increasingly at liberty to choose their own zonal design, or produce what Openshaw (1996) termed, User MAUP (UMUAP). Thus, although Openshaw enabled the development of a wide range of zonal solutions for a single dataset, he also noted that "unfortunately, allowing users to choose their own zonal representations, a task that GIS trivialises, merely emphasises the importance of the MAUP. The **user** Modifiable Areal Unit Problem (UMAUP) has … an even greater propensity to generate an even wider range of results than before" (emphasis in original, Openshaw 1996), as users have easier access to the basic building blocks, and therefore the freedom to deign their own geographies.

2.6 Multilevel Modelling

"Many kinds of data, including observational data collected in the human and biological sciences, have a hierarchical, nested, or clustered structure", Goldstein (2003a). It is logical therefore, that models are developed to exploit this structure of the data for analysis. A full discussion concerning multilevel modelling is not included here, as it is well covered in the literature (Gould *et al* 1997; Goldstein 1987; Rasbash *et al* 2000; and Courgeau, 1998). The mathematical formulae behind the multilevel model are discussed in chapter 3, where its uses are discussed. However, the basic concepts are covered, to demonstrate that a multilevel model can provide a useful statistical methodology within which it is possible to further understand aggregated data. Indeed, Goldstein (1987) states that "the failure to account for hierarchies [within data] may lead us into trouble" meaning that ignoring the hierarchical structure of a dataset could result in mis-specified analysis, or analysis that simply does not reflect the nature of the data.

Much of the initial work with hierarchical structures has used educational data, as the school is clearly a hierarchical institution. Therefore, it is useful to use the example of the school to outline the concept of a multilevel model. Consider a set of students, who are grouped together into a class, which itself is a part of a school. Thus there a three levels: level 1 (the lowest) the student; level 2 the class, and; level 3 (the highest) the school. Using a more specific example, if a researcher is interested in modelling the attainment of a class, then it is not unreasonable to suggest some of the factors influencing achievement will be highlighted by a multilevel model. The achievement of a given pupil is due, in part, to the characteristics of that pupil. However, some of the level of achievement will also be ascribed to the group level effects, such as the class and therefore the teacher, and also the school itself. The multilevel model enables this to be identified explicitly, and crucially enables the researcher to determinate how much variation in achievement scores is likely to be due to the different components.

The example provided above deals with school achievement. However, it is clear that the multilevel model may be applied to other data. Specifically, it has a relevance to aggregate level data, such as that from the Census, as it also has a clear hierarchical structure, not only in terms of the areal units (Output Areas, Pseudo Postcode Sectors, Districts) into which it is aggregated, but also in terms of the interactions that exist between people, something already alluded to by Green and Flowerdew (1996). As Goldstein (2003a) notes, the existence of these hierarchies and groups is not accidental. In a school pupils are frequently grouped together by ability, and likewise in the general population people will tend to live near other people of similar characteristics, as the distribution of the population is not random. Indeed, within a multilevel model, the structure of the population is, itself, of interest (Goldstein, 2003a).

Goldstein (2003a) implicitly links the multilevel model to the MAUP, as he states that "when studying relationships among variables, there has often been controversy about the appropriate 'unit of analysis'". Furthermore, Goldstein cites Robinson (1950) who noted that aggregate-level relationships were not always reliable as estimates of the corresponding individual-level relationship. However, the multilevel model is not without problems. First and foremost it requires clearly definable levels to exist prior to analysis. It may be the case, especially in social science data that the levels are not always definable prior to analysis. Furthermore, a multilevel model requires the levels to exist at the same scale over the whole of the analysis space. Again, this may not be the case with much social science data. These issues may result in misspecification of levels within the model, thus reducing the usefulness of the model. However, a mis-specified model that acknowledges that there are potentially different levels at which interactions may occur within the data is a step forward from a traditional statistical model that does not recognise that there are different levels at which interactions may occur within the data. Whilst this is not discussed explicitly in the thesis, the concept of multilevel modelling and the presence of hierarchies at different levels are considered, and the techniques associated with Multilevel Modelling are implemented in Chapter 7. Therefore, it is important to realise the potential strength of the multilevel model as a tool for identifying relationship at a number of different levels within the data.

2.7 Direction of the Thesis

This review of the literature has served a number of purposes. First and foremost, it has provided a background framework through which the work that follows can be understood and viewed. It provides a justification for the research, defining the

MAUP as a long-standing complex problem that is as relevant to analysts today as it was in 1934 when first identified by Gehlke and Biehl (1934). Indeed, with the advent of increasingly powerful and cheap computer processes power, and with the proliferation of GIS technology the potential for analysis of data published in areal units has increased. Therefore, the need to research, understand and utilise the MAUP has, perhaps, never been greater than at this point in time. The work that follows seeks not only to build upon the literature that has been presented, discussed and critically examined, but also to extend the debate and increase the understanding of the MAUP. However, as has been a theme running through the whole of the preceding chapter, the work that follows treats the MAUP not as a problem, but as a phenomenon. It seeks not to determine a solution to the MAUP, but to increase the understanding of the concept. Finally, it attempts to seek ways in which the MAUP can be harnessed to increase the analysts understanding, not of a problem with the data, but of the complexity of the social world within which all data are positioned.

Using the literature as a basis for investigation it appears pertinent that a full investigation of British Census data is made. Previous literature has either provided a large amount of variables in a small area, (see for instance Tranmer and Steel 2001 who used 8 Census variables for one SAR District) or a large extent of data for a smaller amount of variables (see for instance Amrhein and Flowerdew, 1989 who used Canadian migration data). Therefore there is a clear need for an investigation using the British section of the 1991 UK population Census. This seeks to identify the presence of the MAUP through a dataset of far greater size than has previously been done. Once identified a commentary on the state of the MAUP, specifically the scale effect will be presented. This analysis will also provide the background for a large scale test of the statistical measures of Aggregation Effects and Intra-Area Correlations developed by Tranmer and Steel (2001) to assess their appropriateness for commentary on the incidence of the MAUP in large dataset (for a more extensive discussion of the statistical measures see Chapter 3).

The work presented by Openshaw and Taylor (1979) was highly relevant in the determination of the pervasiveness and complexity of the MAUP. Thus, attempts to engineer high levels of MAUP, using the 1991 data are presented, partly to replicate this work, but also to determine how different variable act under aggregation in different places. This moves beyond the Openshaw and Taylor work, as it seeks to present the results only for aggregations that could be considered realistically appropriate to the data. Therefore, issues such as compactness of the zones will not be ignored. To increase the understanding of the MAUP, a range of variables that could determine the underlying pattern of the data will be considered. It has already been identified and discussed that spatial autocorrelation is important in the incidence of the MAUP. However, little discussion has taken place to determine what conditions in the underlying data need to be present to result in the processes that give rise to the varying levels of spatial autocorrelation. Finally, attempts are made to visually identify the spatial processes. This is important, as their existence will give visual proof to the concepts discussed by Green and Flowerdew (2001) and demonstrate the importance of data structure in the recognition of the causes for the MAUP. Overall, this series of analyses seeks to provide a greater understanding of the likely causes that contribute to the MAUP. They will not provide a solution, nor do they seek to. As with the literature by Holt *et al* (1996a), Holt *et al* (1996b), and Tranmer and Steel (2001) they seek to provide a better understanding of the data.

Chapter 3

Methodology

3.1. Introduction

The purpose of this work is to seek a greater understanding of the Modifiable Areal Unit Problem, or Phenomenon (MAUP), specifically to investigate the nature and potential causes of the scale effect. Tranmer and Steel (2001) outline a methodology that enables investigation of the scale effect. Their methodology is adopted and tested here, in order to investigate the scale effect in British Census data, and to provide a starting point for a further, more detailed investigation. This investigates how areal units are composed in terms of the smaller level units from which they are constructed. This is designed to increase understanding of the MAUP through the factors that may contribute to incidence. The methodology that Tranmer and Steel suggest is outlined below. Three specific types of analysis are explained relating to the work by Tranmer and Steel. This is then supplemented by a fourth section, which extends their work. The three analyses are: a consideration of the scale effect for the whole of GB using the 1991 Census data; a discussion proposing the factors that might be used to predict the level of the scale effect, without needing to fully calculate the range of measures set out by Tranmer and Steel, and an investigation using known levels of homogeneity to investigate the performance of the methodology. The final section considers the composition of the Districts within which the above analysis takes place. This is done through an extension of the multilevel model**,** which is explored in theoretical and mathematical detail below. However, it is necessary to outline the data that are to be used, as the methodology is dependent on an understanding of the data.

3.2. Data

The data used throughout are derived from the 1991 UK Population Census and are drawn from the Small Area Statistics (SAS) and the Sample of Anonymised Records (SAR). The data are organised into the 278 SAR Districts, which form a complete coverage over Great Britain. The SAR Districts are relatively large spatial areas, consisting of a minimum of 120000 people (Marsh, 1993 p.305). In practice, the population sizes of the SAR Districts are greater than 120,000 people, which is similar to the population of Local Authority Districts. There are two datasets within the SAR set providing individual level data records. These are the 1% household and 2% individual datasets, where the percentage refers to the proportion of the population included in the sample. The 2% individual sample is used in the analysis performed below. Although the 1991 data have been superseded by the 2001 Census data, there were a number of advantages to using the 1991 datasets. Primarily this is due to the lack of an individual level dataset in 2001. This is present in the 1991 data, in the Sample of Anonymised Records, and therefore makes the 1991 data more appropriate than the 2001 data. Even when the 2001 SAR data are released, although the sample will be at 3% rather than 2%, there will be no geographical identifiers below the government office region for the population (Dale and Teague, 2002). The means that this work could not be carried out using the 2001 SAR release as it currently stand.

The variables used for the study are as used in Tranmer and Steel (2001) and are outlined descriptively in table 3.1, whilst table 3.2 provides definitions of the variables from the Census tables (obtained via CASWEB, the Census Dissemination Unit run for the academic community funded by ESRC and JISC see Harris *et al.* 2002 for more information). This set of variables was chosen for a number of reasons. Firstly, it enables comparison with the Tranmer and Steel (2001) results. Secondly, tenure variables (RLA and OO) have been shown to be variables that exhibit high levels of scale effect. They are, therefore, of particular interest. Conversely, the employment variables (EMP and UNEMP) have been shown to exhibit relatively low scale effect. The other variables such as NONW and CAR0 were chosen as they are thought to be variables that tend to have high levels of spatial concentration, and therefore could be useful in investigating the spatial processes that contribute to the scale effect (see Tranmer and Steel, 2001 for a breakdown demonstrating how the different variables react under aggregation).

There are some important differences between the English and Welsh data, and the Scottish data. The basic spatial unit (BSU) for the Scottish data, the Output Area, is smaller than the BSU for the English and Welsh data, the Enumeration District, with an average of 147.5 people versus an average of 487.5 people. However, these different areal units are frequently analysed together, a fact which has major

Variable	Description
A60P	Proportion of the population aged sixty years or over
NONW	Proportion of the population that are not white
EMP	Proportion of the population employed from the total considered as economically active
UNEMP	Proportion of the population unemployed
LLTI	Proportion of the population with limiting long-term illness
CAR0	Proportion of households with no car
OO	Proportion of households owning their house
RLA	Proportion of households living in accommodation rented from the local authorities.

Table 3.1: Description of the variables to be used.

<table>
<tr><th>Variable</th><th colspan="2">Census element</th></tr>
<tr><td>A60P</td><td colspan="2">(S350106 + S350113 + S350120 + S350127 + S350134 + S350141 + S350148) /S350001</td></tr>
<tr><td>NONW</td><td colspan="2">(S06003 + S06004 + S06005 + S06006 + S06007 + S06008 + S06009 + S06010 + S06011) / S06001</td></tr>
<tr><td>EMP</td><td colspan="2">(S340007 - S340043) / S010065</td></tr>
<tr><td>UNEMP</td><td colspan="2">S340043 / S010065</td></tr>
<tr><td>LLTI</td><td colspan="2">S120001 / S010065</td></tr>
<tr><td>CAR0</td><td colspan="2">S210045 / S210044</td></tr>
<tr><td rowspan="2">OO</td><td>In England and Wales</td><td>((S200142 + S200143) / S200141)</td></tr>
<tr><td>In Scotland:</td><td>((S200156 + S200157) / S200155)</td></tr>
<tr><td rowspan="2">RLA</td><td>In England and Wales:</td><td>(S200148 / S200141)</td></tr>
<tr><td>In Scotland:</td><td>(S200162 / S200155)</td></tr>
</table>

Table 3.2: The variables defined through the Census tables from which they are constructed.

consequences, outlined below. For simplification, both will be referred to as Enumeration Districts (EDs). Moreover, the second level of aggregation for Scotland is known as the Pseudo Postcode Sector, while in England and Wales it is known as the Ward. These areal units are more similar in size and will be referred to as Wards for simplification. The number of areal units in each District can vary considerably, from 150 to 5000 EDs, and between 13 and 139 Wards. In England and Wales there are 113,196 EDs, with a further 38,255 EDs in Scotland (Dale and Marsh, 1993, p.55).

A further difference between data from England and Wales and data from Scotland is observed in the construction of the tenure variables. Although the variable names used in the construction of the OO variable are different, the data which they select are the same as they both represent a set of data recording houses that are owner occupiers, which can be divided into outright owners, or buying owners. The RLA variable is not constructed in a similar manner. In England and Wales the RLA variable is composed of the percentage of households who rent their property from a Local Authority, or a New Town. However, for the Scottish data these two groups are separate categories, with the New Town homes combined in a variable with households renting from Scottish Homes. Therefore, there needs to be a further note of caution when comparing data between the two areas, as not only are the boundary definitions different, but in the case of RLA, the data definition is also different.

Those zones that had their population suppressed for confidentiality reasons, such as a population below the disclosure threshold, were excluded from the study as they would not record a realistic level of homogeneity relative to those zones with which they were contiguous. Each variable was calculated as a proportion of the resident population, all those people resident in a household on the day of the Census. Consequently, members of the population who were recorded as visitors, and those recorded as not being members of a household (such as those living in Residential Homes) were excluded from the analysis.

These definitions relate to the aggregate level data that were used in this investigation. However, there was also a requirement for individual level, or a sample of individual level data. This came from the 1991 UK Census Sample of Anonymised Records (SARs) using the 2% individual data. The variables are recoded into Boolean responses, determined by whether or not a given individual in the data matches a given criterion. These were then treated in the same way as the aggregate level data, and proportions and weighted variances calculated for each SAR District. Herein, each SAR District will be referred to as a District, and when a SAR District is constructed from more than one Census District then the SAR District will be referred to by the name of the first District listed. Thus, the SAR District of Reigate and Banstead with Tandridge is known as Reigate, as in Tranmer and Steel (2001).

3.3. Tranmer and Steel

Tranmer and Steel propose two measures to investigate the scale effect. These are known as the Aggregation Effect (AE) and the Intra-Area Correlation (IAC). Although both the AE and IAC provide information relevant to the MAUP, there are important differences between the two measures. The key difference is that the IAC is adjusted for the average population size of the areal units in the District in question. Therefore, the results are comparable for a range of different zones with different population sizes, and can be used to compare different scales or districts. For example two districts may have different aggregation effects but the same IAC value. The aggregation effect is not adjusted for population and may, therefore, vary widely. Because of this, it is also possible to have a small IAC associated with a high AE for a big District. Furthermore, the IAC also provides a quantification of the within-area homogeneity. This enables the investigation of the relationship between the magnitude of the scale effect and the level of homogeneity

3.3.1 Weighted Variances and Covariances

Initially the variables are calculated as proportions. From these, mean proportions can be obtained for each of the areal unit systems under investigation. The weighted variances and covariances are used in the calculation of the AEs and IACs. These are distinguished from normal variances as they are explicitly weighted by the size of the population of the areal unit for each case. The weighted variances are calculated using the formula below.

$$S_{11} = \frac{\sum w(x-\bar{x})^2}{n-1} \qquad (1)$$

Where: S_{11} is the weighted variance for variable 1;

w is the population size of each areal unit;

x is the proportion of variable 1 in the areal unit;

$\bar{x}$ is the mean proportion of the variable 1 for the District, and;

n is the number of observations (areal units).

The covariances require an adjustment to the formula, and this is shown below.

$$S_{12} = \frac{\sum w(x-\bar{x})(y-\bar{y})}{n-1} \qquad (2)$$

Where: S_{12} is the covariance for variables 1 and 2;

w is the population size of each areal unit;

x is the proportion of variable 1 in the areal unit;

$\bar{x}$ is the mean proportion of variable 1 for the District;

y is the proportion of variable 2 in the areal unit;

$\bar{y}$ is the mean proportion of variable 2 for the areal units, and;

n is the number of observations (areal units).

The individual level data are similar, as each record represents a single person, so the weight would be one. Therefore, the individual variances can be calculated using the standard formula.

SAR ID	Zone ID	Population	Proportion	Weighted Variance component
23	1	450	0.60	4.303
23	2	350	0.46	0.657
23	3	400	0.45	1.137

Table 3.3: Sample data for the calculation of the weighted variance of a SAR District.

Table 3.3 presents data from two hypothetical areal units in a hypothetical District. The weighted variance is calculated by subtracting the mean for the SAR Districts from the individual Zone proportions. Thus for Zone ID 1, the calculation is

$$0.60 - ((0.60 + 0.46 + 0.45) / 3) = 0.0966$$

This is squared to give the result of 0.00934, which is then multiplied by the population weighting term, in this case the calculation is

$$0.00934 * 450 = 4.303$$

The weighted variance for this is then the summation of the zones both of which are in SAR ID 23. The summation is divided by the number of observations, minus 1. Therefore, the weighted variance for this example is 6.097.

Once completed for all data, a set of weighted variances and weighted covariances are available for the variables in question. These provide a first indication of the potential scale effect, as those areas with high weighted variance or covariances tend to exhibit greater differences between different levels of aggregation. As will be demonstrated, (see chapter 4) higher within-area homogeneity results in increased scale effect. These weighted variances and covariances may then be used to calculate the two measures below.

3.3.2 Aggregation Effects

The AE is a quantitative measure that characterises the scale effect for a particular variable in a particular geographical location. The greater the AE, the greater the likely magnitude of the scale effect on the variables under analysis, and thus, the greater the likely instability of the results of statistical analysis, such as correlation coefficients.

The AE requires the use of at least two levels of data. These two levels can either be an individual and an areal unit level, or two areal unit levels (such as the ED and Ward). In the case of this investigation, the areal units are either EDs or Wards. Thus, denoting the individual level as 1 and the aggregate levels as *k* for EDs and *l* for Ward then the calculation is as follows.

For the individual level:

$$\text{AE} = \frac{S_{11}^{(k)}}{S_{11}^{(i)}} \qquad (3)$$

Where: S_{11}^{i} is the weighted variance for variable 1 at the individual level (*i*), and;

S_{11}^{k} is the weighted variance for variable 1 at level k (ED in this case).

Note that the subscript of 11 implies that in the case of these AEs we are only discussing a case that considers and aggregation within one variable, and not across variables. At the aggregate level, the equation is essentially the same. However, the denominator changes:

$$\text{AE} = \frac{S_{11}^{(l)}}{S_{11}^{(k)}} \qquad (4)$$

Where: $S_{11}^{(k)}$ denotes the lower, areal level weighted variance (ED in this case), and;

$S_{11}^{(l)}$ denotes the higher, areal level weighted variance for the variable (Ward in this case).

The aggregation effect can be regarded as a measure of the differences between zonal proportions at that level. For instance, if people with a certain characteristic are dispersed fairly evenly between zones, the aggregation effect will be fairly small. At any given level, the aggregation effect will increase as concentrations of a characteristic increase. Importantly, it must be noted that the aggregation effect is a relative measure, and therefore the increase in concentration is relative to the magnitude of the concentration at the level of aggregation used in the comparison. The higher the value of the aggregation effect, the stronger the impact of the MAUP scale effect on the data in question.

Tranmer and Steel (2001) described the aggregation effect as a "simple way of summarising the scale effect for each variable separately" (p.116). By dividing by the lower level variance a measure is produced that can be compared for a range of variables even though they measure different quantities. A value of zero would indicate that there is no within-area homogeneity for a variable. This corresponds to the case where the variation within areal units is the same as the variation across the entire district and hence the population in the areal units are effectively random subsamples of the population in the district. In this case, there would be no scale or zonation effect as wherever the areal unit boundaries were drawn there would not be any differences between the levels of homogeneity in the variables as aggregation occurred. Likewise, if there were no within-area homogeneity present in the data at any scale, and so no similarity between individuals in an area, then the aggregation effect would be 1, as the weighted variances would be the same. In practice, values greater than one are frequently found, indicating evidence of the scale effect. Values below 1 are theoretically possible, but they are uncommon in practice.

3.3.3 Intra-Area Correlations

The IACs are measures that relate to just one variable at two different scales. The method investigates whether or not the variance of a variable is composed of individual-level, ED-level and Ward-level effects. These effects, together with some 'unknown' effect(s), can account for the variation seen in an analysis. Therefore, the term IAC refers to the proportion of the individual-level variance that can be ascribed to the area in question. In the case presented here where it is assumed that there are three levels (Individual, ED and Ward), we can estimate intra-ED correlations and intra-Ward correlations for each variable. For example, the intra-ED correlation for the variable A60P is the proportion or concentration of the individual-level variance in that variable which is attributable to ED-level effects. According to Tranmer and Steel (2001), the IAC for this variable in Reigate had values of 0.0288 for the ED level and 0.0032 for the Ward level. In terms of analysis, these results allow the following two statements to be made: at the ED level, 2.88% of the variation in the population can be attributed to the areas, and; that only 0.32% of the variance can be attributed to the areas at the Ward level. This enables a far better understanding of the data structure to be formed. The values for IAC are usually small. As Tranmer and Steel note, small IAC relationships can be associated with big aggregation effects as the latter is a function of population size, which can frequently be over 1000 people.

The IAC is a direct measure of within-area homogeneity. For areal units of the same scale it is the correlation between different people living in the same areal unit, for a given variable. The resulting value gives an indication of the level of homogeneity for this areal unit system. Two techniques are suggested for calculating intra-area correlations. The first of these techniques is called the moments approach and the second approach is known as iterative generalized least-squares (IGLS). Tranmer and Steel show that the results obtained from the two approaches are very similar, and hence the simpler moments approach is used in this discussion. Details of IGLS can be found in Tranmer and Steel (2001) while Tranmer (1999) presents a comparison.

Using the moments approach, the IAC is calculated using:

$$\lambda^{(k)} = \frac{S_{11}^{(k)} - S_{11}^{(1)}}{(\bar{N}-1) * S_{11}^{(1)}} \qquad (5)$$

Where: $\lambda^{(k)}$ represents the IAC (for the level *k*);

$S_{11}^{(1)}$ is the individual level variance for the variable;

$S_{11}^{(k)}$ is the area level weighted variance for level *k* calculated using the area populations as weights, and;

$\bar{N}$ is the average population size per areal unit at level *k*.

When $S_{11}^{(k)} = S_{11}^{(1)}$, $\lambda^{(k)}=0$ and this corresponds to the case of no within-area homogeneity. The maximum possible value of $\lambda^{(k)}$ is $\frac{M}{M-1} \approx 1$, where M is the number of areal units, and corresponds to the case where each areal unit is perfectly homogeneous, for example when the proportion in each areal unit is 0 or 1. The minimum possible value is $-1/(\bar{N}-1)$ which occurs when all the areal units have the same mean and so $S_{11}^{(k)}=0$. Small negative values may occur for characteristics that are more variable within areal units than in the whole population. In practice values much less than 1 but larger than 0 are usually obtained.

The relationship between the aggregation effect and the IAC is

$$\frac{S_{11}^{(k)}}{S_{11}^{(l)}} = 1 + (\bar{N}-1)\lambda^{(k)} \qquad (6)$$

From this relationship we might expect that the aggregation effect is a linear function of $\bar{N}$. An IAC of 0 gives an Aggregation Effect of 1 and an IAC of 1 gives an Aggregation Effect of $\bar{N}$. However $\lambda^{(k)}$ will vary for different scales and zonings and may also be related to $\overline{N}$ and other features of the district. Thus, the relationship may not be strictly linear. This is discussed in later chapters.

3.4. Analyses

The Tranmer and Steel methodology will be used in three different analyses, as was outlined in the introduction. These analyses are discussed below, to present the motivation behind them and implications of the investigations.

3.4.1 Scale effects in Great Britain

Previous investigations into the MAUP (see for instance Fotheringham and Wong 1991, or Flowerdew and Amrhein 1989 for examples) have proposed methodologies to understand or control for the MAUP. However, the methodologies are frequently implemented with small datasets that provide illustrations rather than full analyses. Thus, the Tranmer and Steel methodology is used to analyse the scale effect over the whole of Great Britain for the 1991 Census data. This is useful for a number of reasons. Firstly, it will provide a full and robust test of Tranmer and Steel's methodology. Secondly, no investigation of the MAUP, and specifically the scale effect, has been published on such a wide scale. Thirdly, a large-scale test of a dataset as extensive and diverse as the whole of Great Britain census will enable conclusions to be drawn concerning the relative importance of the scale effect, and MAUP in general, for social science research. Whilst it is undoubted that the scale effect exists, it is still a matter of considerable debate whether or not it is an issue that has wide ranging or serious data analysis impacts.

In order that the scale effects can be analysed, the AEs and IACs of Great Britain are analysed using distribution statistics including the maxima, minima, median and means, along with the coefficients of variation. These are reported in Chapter 4. The data are also plotted on histograms to determine the shape of the distribution. Finally, outliers are identified for both the AE and IAC distributions at both the ED and Ward levels. The outliers are defined as occurring three or more standard deviations above or below the mean value of the distribution. These outliers will describe Districts that have high or low AEs and IACs in comparison to the rest of Great Britain, and they will be used for further analysis to identify elements within the structure of the areal units within the District to determine common influences or rules within the scale effect.

3.4.2 Testing the Measures Using Reaggregation

The analyses outlined above made use of the publication geography for the 1991 Census, and provided comparisons across space. However, it is also potentially useful to produce different aggregations of the same data, aggregating using criteria to produce areal units similar to those published for the Census of Great Britain. An investigation for the scale effect has already been outlined. The aggregation of data when scale is kept constant will enable the investigation and realisation of the second element in the MAUP, the zonation effect. This is necessary as it will assist the identification of the zonation effect in real world data, something that has not been discussed in the previous sections, and highlight that it has the potential to disrupt analysis in the same way as the scale effect. Furthermore, it will aid the investigation of influence of differing levels of homogeneity on the MAUP, as each realisation of the aggregation process will have a different level of within-area homogeneity.

For the investigation, two areas have been chosen. The first is Reigate, chosen as it was the District that Tranmer and Steel used in their brief analysis, and also as it is a District within the GB dataset that does not exhibit relatively high levels of scale effect. To provide contrast, the second District is Bradford. This District has relatively high levels of scale effect for a number of variables, most noticeably the proportion of non-white residents (see table 3.4 for details). Therefore, it is proposed that there will be clear spatial processes present in the data, and that these could be used through the maximisation of homogeneity in the construction of alternative aggregations to compare with the publication geography. Thus, the most important criterion will be the maximisation of within-area homogeneity, as the purpose of the investigation is to determine the effects of high homogeneity on the scale effect. The second criterion required relates to the number of areal units in each realisation. In order that the aggregated data can be compared with Census data, the aggregations must have the same number of areal units. A third criterion ensures that the areal units are relatively compact. However, for the purpose of this investigation, this is not essential, and the homogeneity criteria will overrule this if there is conflict between them.

		NONW
Aggregation Effect	Enumeration District	309.4
	Ward	4336.4
Intra-Area Correlation	Enumeration District	0.567
	Ward	0.288

Table 3.4: Aggregation Effects and Intra-Area Correlations for the NONW variable in Bradford.

There are a number of programs that enable the aggregation of areal units into higher level areal units. There is insufficient space here to present a detailed discussion of all the programs. However, it is sufficient to note that each of the different programs has advantages and disadvantages. Two current programs are ZDES (now known as ZoDE, see Openshaw and Alvanides, 1996 for more details) and AZM (Martin, 2003). The ZoDE program is currently insufficiently flexible for this investigation, as it is possible only to work with one criterion at a time. Thus, the multi-criteria requirements of this investigation of homogeneity, population size and shape are not possible in ZoDE. Therefore, the AZM program is used to create the zonal systems in this study. AZM was originally designed as a zone matching program, whereby two different zonal systems were input and the program would produce a third zonal system that was compatible with both coverages. However, it can be adapted to zone design by inputting the same coverage twice. It has options for the specification of minimum population of zones, a target population of zones, the ability to specify the importance of the compactness of the zone and whether or not homogeneity is to be used in the aggregation process. It is also possible to specify that simulated annealing will be used as a method for reaching a good solution. These issues are dealt with in more detail below.

3.4.2.1 AZM Details

The Automated Zone Matching program (AZM) is designed to produce areal units that enable the transition between two incompatible base zone systems. However, as it employs Openshaw's AZP algorithm (1977, 1978) it is possible to input two identical coverages and use it to produce higher level aggregations. There is quite a high degree of flexibility with AZM, as there are a number of optional arguments that can be entered if required (see figure 1 for details of the interface).

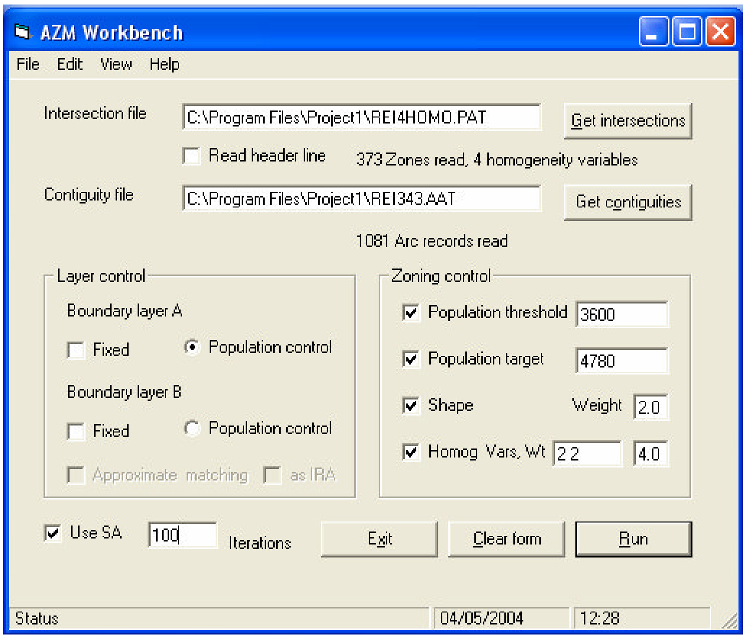


Figure 3.1: AZM Workbench interface.

Two files are required, which are built using ArcInfo. These files replicate the topology details found within an ESRI coverage file. Thus, the first output file reports the intersections of the line arcs from which the polygons are made and is know as the Polygon Attribute Table (PAT). The second reports the contiguity of the polygons to enable to aggregation process to use polygons that neighbour each other and is known as the Arc Attribute Table (AAT), (for further details see Martin, 1995). The layer control area is redundant for the process of zone design as there is no need to fix a base layer because this is set as Layer A by default. For the purposes of the zone design here, both Layer A and Layer B are identical. The zoning control enables the aggregation to be constructed in accordance with user specifications. In the case of figure 3.1 all 4 controls have been selected.

In order to make the new zonal system as comparable as possible with the publication geography at the ward level, both the Population Threshold control and the Population Target control were used. This enabled the specification of a lower limit below which the population of a given zone was not permitted to fall (the population threshold function). The target enabled the ideal size of the zones to be specified through the use of population. These controls were used as a proxy to determine the number of areal units in each aggregation as AZM does not have an explicit option to determine the number of areal units required. Whenever a solution occurred with either more or less than the necessary number of zones it was rejected. The population variables are automatically given a weight value of 1, which is the default for all the criteria. The third optional criterion used is that of shape. This is related to the compactness of the zones in the output coverage. For data publication, the results are required to be as 'realistic' as possible and compact shapes are desired. However, in this case, shape was not used, as the greater the number of criteria, the greater the conflict between them in the solutions. If a greater number of criteria are used, then achieving a suitable solution will be less likely as the criteria may conflict. For instance, the most compact shape is a circle. However, homogeneity may be influenced by features such as road networks or physical features like lakes and mountains, all of which may prevent the compact circle shape being achieved. Therefore, as the study was concerned with the levels of homogeneity, and not shape it was decided that shape could be dropped. The fourth criterion available, homogeneity, is the most important for this study. The program is designed to match the homogeneity levels between the 2 input zone systems. However, as both the input geographies were the same in this case, the homogeneity function maximised the homogeneity within the zones of the new aggregations. The specification of the homogeneity is made in the last box in "Zoning Control". There are two boxes to be populated. The first deals with the specification of the variables, and the values are set up to describe the number of pairs of variables in each of the coverages. As the coverages input in this investigation are identical, the specification reads 2, 2. The second box details the weight that the homogeneity variable is given. The two population elements are weighted as 1. Thus, the homogeneity (and shape) may be weighted relative to these. Values greater than 1 will increase their relative importance, whilst values below one will result in the population criteria taking precedence. This specification can then be run to produce alternative aggregations.

The other specification details for the construction of the new zonal geographies required the selection of the number of restarts (iterations) the program uses to attempt to improve the solution, and the use of simulated annealing. The iteration process runs as follows: "At each iteration, [a number of building blocks are] chosen at random, and the effects on the selected statistical measures of swapping it into a neighbouring tract are considered" (Martin, 2003). Simulated annealing, in the case of

AZM enables the program to accept swaps during the first half of the run that can reduce the overall reduction in the suitability of the solution. While reductions to the suitability are not generally useful, they can enable an overall improvement in the final solution and are, therefore, a method through which non-optimal, local, solutions can be escaped (Martin, 2003, Openshaw and Rao, 1995 and Openshaw and Alvanides 2000 provide more information on simulated annealing). A final operational point that needs to be made, is that if the inputs to the AZM program are kept consistent (such as the input coverages and the aggregation criteria) through a number of trials then the same result will be achieved. This can be avoided by changing the “random seed initialisation value” within the program options, which results in different combinations of pseudo random aggregation decisions being made by the software. Consequently it is possible to generate unique aggregations, (Martin, 2003). When the random seeds are changed, then 16 aggregations had to be attempted to achieve a set of 10 unique results. No single aggregation was consistently occurring as a result.

AZM was run until 10 suitable new zonal systems (Pseudo Wards) had been created. After the AZM runs, the results were input into ArcMap, where the aggregation process was carried out using the Geoprocessing tool. The AZM output, joined to the original publication OA geographies enabled graphical representations of the zones to be created, and the raw data for the eight variables at the OA level were included in the aggregation process to enable weighted variances, the AEs and the IACs to be calculated at the Pseudo Ward level. The suitability of the zonal systems was assessed in ArcGIS (ArcMap) primarily using the number of new zones and secondly the realism of the shape as criteria. The number of zones was a hard objective criterion. If there were fewer or more zones than in the publication geography, then the solution was rejected. However, as the objective of the investigation is to consider maximised levels of homogeneity, not the creation of realistic geographies for Census dissemination, the shape of the areal units was considered less important, and therefore solutions with boundaries that would normally be rejected on the grounds of unrealistic boundaries were accepted. The aggregation process is conducted without replacement.

3.4.2.2 Assessment of the Aggregations

The assessment of the scale effect in the realisations will be carried out using correlation analysis. Correlation analysis is relatively simple, but has long been known to suffer from incidence of the scale effect (see Gehlke and Biehl 1934 for details). The incidence of the scale effect will be taken as the difference between correlation coefficients for a pair of variables at two different levels of analysis. However, for inference purposes the standard correlation coefficients are not used directly, as they are transformed first using the Fisher transformation (Fisher, 1921). The Fisher transformation takes the form of:

$$Z_k = \frac{1}{2}\ln(\frac{(1-r_k)}{(1+r_k)}) \qquad (7)$$

Where: r_k is the actual correlation coefficient observed from the data, and;
Z_k is the transformed coefficient that is to be calculated.

The transformation is used because the distribution of r is non-normal, and constrained within the range -1 to 1. The transformed coefficient is treated as having an approximately normal distribution with standard deviation equal to $\sqrt{\frac{1}{m_k - 3}}$, where m_k is the number of observations used to calculate the correlation coefficient. Essentially, the greater the difference between the correlation coefficients at the different scales, the greater the incidence of the scale effect. It is possible to approximately test if the difference between two transformed correlation coefficients is significant. This will be carried out, enabling conclusions to be drawn relating to the importance of the scale effect. Clearly, the more significant differences there are, the more important the scale effect is in relation to the potential of obtaining unreliable statistical results. This has not previously been explicitly explored. Significance is tested at both the 5% and 1% level using the difference between the transformed correlation coefficients for the different levels of analysis Thus, for the 5% level significance occurs where:

$$(Z_k - Z_l) > 1.96 * \sqrt{\frac{1}{m_k - 3} + \frac{1}{m_l - 3}} \qquad (8)$$

whilst at the 1% level significance occurs at the:

$$(Z_k - Z_l) > 2.58 * \sqrt{\frac{1}{m_k - 3} + \frac{1}{m_l - 3}} \qquad (9)$$

Where: m_k is the number of observations (areal units) in the higher aggregation, and;

m_l is the number of observations in the lower aggregation, or the individual level data.

Thus, the difference between the correlation coefficients will be said to be significant if the difference is greater than the values given in the above equation.

The second analysis considers the dataset of weighted variances, AEs and IACs and investigates the links between these measures and factors that are thought to contribute to the distribution and dispersal of the population within a given District. These factors include: the population density, as a measure of rurality; the proportion of a given variable; the size of the average population of the units of which the District is composed, and the relationship between the AEs and IACs and the weighted variance. Using regression techniques, the relationships will be measured for magnitude, direction and significance.

3.4.3 Factors influencing the Scale Effect

The relationships that will be assessed are:

- AE and the weighted variance;
- AE and the average proportion of a variable;
- AE and the average population size of the areal units;
- AE and the population density;
- IAC and the weighted variance;
- IAC and the average proportion of the variables;
- IAC and the average population size of the areal units, and;
- IAC and the population density.

It is highly likely that none of these factors will adequately explain the incidence of the scale effect. However, it is proposed that they will, at least, provide an insight into the complex nature of the scale effect within the MAUP.

3.5. Searching for Spatial Processes

The presence of the scale effect in the British Census data will be established through the use of a number of examples. The above analysis seeks to establish that the AEs and IACs can be used effectively in geographic analysis to identify variables that suffer from more severe incidences of the scale effect. However, whilst it is necessary to identify incidences of the scale effect the techniques discussed so far do not provide sufficient insight into the potential causes of the scale effect. Therefore, a number of well known concepts from the geographical and MAUP literature are brought together to provide an analytical technique with which to identify contributions to the incidence of the scale effect. After the discussion of techniques, the concept and description of what is meant by a process is outlined. The steps required for a practical implementation are then described.

The first concept is spatial autocorrelation. Spatial Autocorrelation has been identified as a highly relevant concept that requires consideration when analysing spatial data, and especially data that are aggregated in areal units (see for instance Cliff and Ord, 1973). The role of spatial autocorrelation has been included in the debate concerning the MAUP, (see Openshaw and Taylor 1979). At its simplest spatial autocorrelation can be defined as the correlation of a variable against other instances of itself through space. It is related to Tobler's first law of geography where "everything is related to everything else, but near things are more related than distant things" (1970, p.236). A more detailed treatment is given by Goodchild (1986). Spatial autocorrelation can inform analysts about the structures and processes occurring in areal data.

A second technique that has also been prominent in the geographical literature recently is the Multilevel Model (or MLM). Indeed, it is logical that spatial autocorrelation and multilevel modelling should be analysed together. Jones (1991, p8) states, "the degree of auto-correlation in MLM can loosely be conceived as the ratio of 'variation at the higher level' to the 'total variation of all levels'. A value of zero in a spatial autocorrelation coefficient signifies no auto-correlation, indicating that there is no variation at the higher level”. The MLM enables the construction of an analysis that acknowledges that traditional statistical concepts, which give a single result regardless of scale, are inadequate for many forms of analysis. Thus, the MLM can be used to obtain describe processes that operate at, for instance, the individual person level, and also one or more grouped level (e.g. EDs or Wards). The technique for analysis presented here builds on this, and seeks to identify the spatial processes in the data under analysis, using a combination of adapted multilevel modelling and spatial autocorrelation techniques. These two concepts are explored with reference to their implications for analysis of the MAUP. This method also aims to provide conclusions about these processes for informed analysis.

These two concepts are brought together in an attempt to identify the local and regional effects that contribute to data structure in areal units, initially identified by Green and Flowerdew (1996), and which is outlined in greater detail below.

3.5.1. Conceptual Basis

The concept that is developed in this method draws on the local and regional effects identified by Green and Flowerdew (1996). They saw that the structure of data in areal units was highly complex. However, many of the processes within areal unit data may be difficult not only to recognise, but also to quantify and have not, therefore, been quantified beyond the descriptive. Nevertheless, they have been recognised, and it is these effects that the methods presented in the following sections seek to clarify further.

3.5.1.1. Local and Regional Effects

One view of the MAUP is as a problem that relates to the differences between the spatial processes generating data and the units within which they are reported. Green and Flowerdew (1996) present an argument that considers that it is possible to understand the MAUP with respect to interactions between data that occur at the local level and at the regional level. This is presented in relation to cross-correlation. Considering the relationship between two variables, denoted by X and Y, it is possible that the relationship is not simply Y_i to X_i, but also Y_i to X_j, where X_j is the X variable for a neighbouring zone. Green and Flowerdew (1996) define this as cross-correlation, which occurs when the response variable is affected by the explanatory variable(s) not just at the same place but also at surrounding locations. This could be seen in an example using house prices, where the price of one house was a function of not its own condition, but also of the upkeep of the houses in the immediate area. It is apparent that this is related to the concept of spatial autocorrelation. They define this to be part of the range of processes that can influence the results of statistical analysis on areal data. Green and Flowerdew (2001) explore this notion further and express it as where "*Y* is a function of *X* and there is a cross-correlation effect, then statistical measure, in this case a regression, of *Y* at the most local level should include as explanatory variables both a *local effect*, i.e. the value of *X* at that local level, and a *regional effect,* i.e. the values of *X* in the surrounding area" (p.91, emphasis in original). However, in neither Green and Flowerdew (1996) nor Flowerdew *et al* (2001) are the local and regional effects explicitly defined beyond this abstract concept, and they do not define the extent of a surrounding area. If this concept is to be used, then this is clearly a question that needs to be addressed.

3.5.1.2 Areal units and spatial processes

This method is based on the assumption that the variance of a particular variable may be understood in terms of processes operating at several different spatial scales. There may be individual-level and aggregate-level effects, as is assumed in multi-level modelling. The aggregate-level effects may occur at two scales, as in the discussion by Green and Flowerdew (1996) on local and regional effects, or at more than two scales. However, there are no theoretical reasons to suppose that these effects happen to coincide with the scales at which data are released, such as EDs and wards in the British census. Indeed, it is highly likely that they will not coincide with the areal unit definitions. Therefore, the most likely case for Census data is that data consist of at least one hierarchical structure but are being analysed within a different, imposed, hierarchical structure (the EDs or Ward boundaries). This is further complicated by the fact that the effects occur at one scale in part of the study area and can occur at a different scale elsewhere in the same study area.

For certain variables, it may be possible to conceptually identify the spatial processes causing local and regional effects. A good example is housing rented from the local authority; in many places (Glasgow is a good example), such housing is found in large estates. Even where much of the local authority housing has been sold off under

Britain's right-to-buy legislation, there may be local spatial patterns in the distribution of which houses have and have not been sold, perhaps influenced by construction type, council housing allocation policy or social stigmatisation. Other spatial processes may include the impacts of local housing markets or job markets on the economic status of residents, patterns of ethnic concentration, suburbanisation, gentrification and urban decline. The geographies of these processes will all be reflected in geographical space and their coincidence or otherwise with areal unit boundaries will affect the magnitude of the MAUP.

The methodology explored here cannot be used to investigate the impact of the sizes and shapes of the basic spatial units (EDs in the case of census data). Instead, it is possible to investigate the relative effects of zones of larger sizes. For example, the success of the system of ward boundaries in reflecting the extent of spatial processes operating to affect variable values in the study area can be assessed, by judging the similarity of the spatial structures to the Census boundaries.

It should be noted that this analysis deals with only one variable at a time. Further work would be necessary to extend it to analyse the correlation and regression coefficients that usually dominate discussion of MAUP effects. It is also the case that zones appropriate for one variable may not be appropriate for another, and also that the spatial processes operative in one study area may show up at a different scale in another.

3.5.1.3 Identifying individual and areal effects for spatial processes

It is possible to identify elements of correlations and covariances that are influenced by areal processes, which can be considered in terms of the local and regional effects, that were discussed above. Usefully, it is also possible to isolate these elements and statistical measures that reflect only the processes occurring at the given level of analysis, do not involve processes occurring at other areal levels and the individual level. This follows the line of argument within MAUP research that does not seek to provide an overall solution to the problem. Rather it seeks to provide better statistical measures, which enable the isolation of MAUP effects, and therefore a better understanding of the processes behind the MAUP. A methodology for this is given in Tranmer and Steel (2001), and is the culmination of a set of research ideas discussed by Steel and Holt (1994), Steel *et al* (1996) and Tranmer (1999). The concepts they discuss were presented in section 3.

These effects can vary over the study area and it is unlikely that they will be reflected by a predetermined geography of the areal unit divisions. Hence, it is not expected that they will be completely captured using the standard geography of publication. In the case of the Census, for instance, this means using the ED or Ward boundaries. Therefore, it may be that the effects will not only be identifiable at the levels of the ED and Ward, but they may also exist at an undetermined level between these two scales. Moreover, we consider that it is possible that scale effects are stronger in one part of the entire study area than another. These issues are discussed further below

3.5.2 Extending the Multilevel Model

Standard MLMs require at least two levels of data, an individual level and a group level. With the decennial Census of the United Kingdom full individual records are not available due to confidentiality requirements. However, it is possible to access a 2% individual sample at a coarse geographical level, although these are of limited use for traditional multilevel modelling, as they do not contain identifiers for an individual's location below the coarse SAR district level. It is not possible, for instance, to assign individuals to the ED within the SAR district that they live. Consequently, it is not practical to use the standard MLM techniques to analyse the Census data, areal units below the SAR level. However, Tranmer and Steel, (2001) have shown that it is possible to estimate these structures without the full individual level, and not lose significant efficiency, by making use of additional ED level data.

It is possible to express the traditional multilevel model in the following manner:

$$y_{ig} = \mu + u_g + \varepsilon_{ig} \tag{10}$$

Where: y_{ig} is the value of the variable of interest for the i^{th} individual in the g^{th} area (ED in the case taken here);

μ is the overall population mean, in the SAR;

u_g is the area level component, and;

ε_{ig} is the individual level component.

In terms of understanding the spatial processes that occur within geographical data, the u_g term is the most useful as it reflects these processes. As the area effects will represent the interactions between people living in an area, it is likely that they would not be fully identifiable if an analysis were conducted purely at the individual level. Within this model, there are a number of important assumptions that must be taken into account. One assumption is that the processes that occur within the data occur solely at the levels available for analysis. When using real world data, such as the Census, it is unlikely that this assumption will remain valid. Thus, it would be useful to be able to provide an estimate of the areal level variance component that is free from such constraints. This can, through further analysis, enable the estimation of the higher level processes within the data.

3.5.2.1 Local Multilevel analysis

We will consider an example, which uses the SAR districts as the regions in which our analysis will be contained. The individual level data necessary will be taken from the 2% SAR, while the areal units are EDs.

The estimator of u_g will be denoted as $\hat{u}_g$, and is an estimate of ED level effects. Mathematically, it can be defined as:

$$\hat{u}_g = w_g(\bar{y}_g - \bar{y}) \qquad (11)$$

Where: w_g is a weighting term;

$\bar{y}_g$ is the observed mean of the variable in the ED in question, and;

$\bar{y}$ is the overall observed mean of the variable for the whole (SAR) district.

The weight (w_g) can be calculated by the following equation:

$$w_g = n_g(\lambda^{(2)}/(1+(n_g-1)\lambda^{(2)})) \qquad (12)$$

Where: n_g is the number of observations in the g^{th} group (in this case, ED), and;

$\lambda^{(2)}$ is intra-area correlation of the ED for the variable, as defined in the previous section (Pers. Com. Steel 2002)

These estimated group effects attempt to allow for the variation between group means that could come from purely individual level random variation. Application of the weights w_g shrink the deviations of the chosen areal means from the overall mean to allow for the likely impact of individual level variation, thus controlling for potential outlier values.

3.5.2.2 Identifying and Using Spatial Autocorrelation

Analysis of the $\hat{u}_g$ can be used to determine the processes occurring in the data *between* the areal units (in this case EDs), as each $\hat{u}_g$ value is an indication of the group level effect within that unit. Therefore, $\hat{u}_g$ values that are similar can be said to be the result of similar processes operating at the areal unit level. Measures of spatial autocorrelation of the group level effects can be used to determine the geography of the processes. Consequently, these analyses will be able to show whether or not the spatial processes operate at the same scales as the standard Census units. Such occurrences can be identified as clustering at a different level to that use in the level of analysis, through the setting of limits on the range of potential Local Moran's *I* values observed. This is explored in greater detail below. In the discussion that follows, the basic units used will be at the ED level of aggregation. Instances of spatial autocorrelations of $\hat{u}_g$ will point to the existence of larger scale processes. If, as is supposed from the research of Tranmer and Steel (2001) the greater the level of spatial autocorrelation, the greater the effects of the MAUP (scale) on potential statistical analysis, then this will be identifiable from this analysis. Moreover, this technique could identify processes that operate between the standard Census levels, such as at a level of aggregation that was half way between the ED and Ward level. If it were possible to recognise this, then it would be possible to better inform Census users as to how to perform their analysis. Once the scale processes have been defined, the $\hat{u}_g$ values can then be interpreted and used to suggest a definition of a higher aggregation level for the data. If the analysis were carried out on British Census data, at the individual (SAR) and ED levels, then the subsequent analysis could suggest a more appropriate construction for the higher level of aggregation for the Census data, given the data structure of the variable under investigation. Furthermore, it would also be able to demonstrate how well the current Ward structure matched the autocorrelation (which indicates the extent of any spatial processes) apparent within the data. This would enable users to develop their expectations of the level of MAUP effect that occurs within their analysis of a given data structure.

The pattern of the processes within the data can be explored using the concepts of spatial autocorrelation. There are a number of measures of spatial autocorrelation, the most common of which are Geary's G statistic and the Moran's *I* test. These measures are similar, and the analysis below uses a version of Moran's *I*. This measurement is "analogous to a covariance between the values of a pair of objects", (Goodchild, 1986, p.17), measuring the differences between the values for attributes that, in this case, exist within a given spatial proximity. Figure 3.2 presents the three extreme cases of spatial autocorrelation, against which the results in Chapter 7 can be compared.

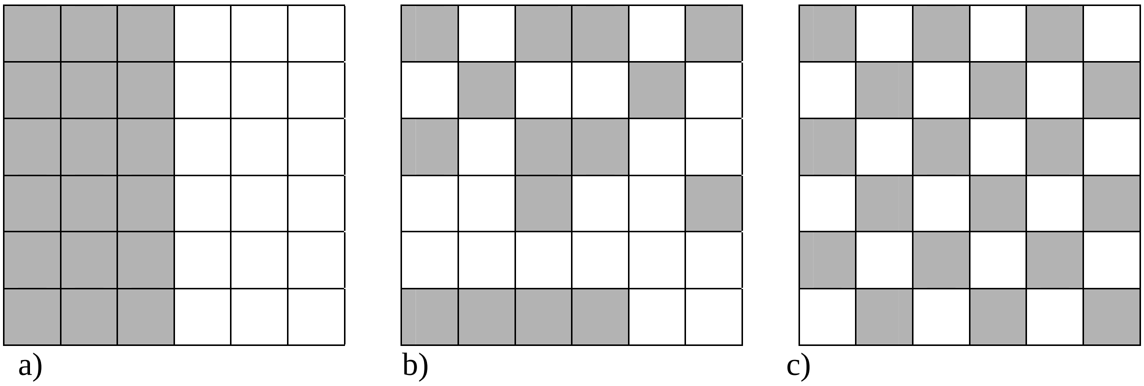


Figure 3.2: The three types of spatial autocorrelation a) Positive spatial autocorrelation; b) no spatial autocorrelation, and; c) negative spatial autocorrelation (from O'Sullivan and Unwin, 2003).

However, to determine a spatial pattern, and therefore process, *within* a given dataset the standard measures of spatial autocorrelation are inadequate, as in some of the SAR districts there could be as many as 5000 EDs. There is no guarantee that the extent of the spatial autocorrelation will be constant within the study area. Consequently a measure that can be defined within the suite of tools known as Local Indicators of Spatial Association (or LISA) is required (Anselin, 1995). One of these tools is the Local Moran's *I* which is a variant of the Global Moran's *I*. In the Local Moran's *I* individual values are determined for all of the units in an analysis area. The form of the Local Moran's *I* is as follows:

$$I_g = \frac{\hat{u}_g - \bar{\hat{u}}}{S_Z^2} * \sum_{h \neq g} [W_{gh} * (\hat{u}_h - \bar{\hat{u}})] \qquad (13)$$

Where: I_g is the Local Moran's value;

$\bar{\hat{u}}$ is the mean value of all observations;

$\hat{u}_h$ estimated area-level effect for unit *h*;

$\hat{u}_g$ area estimate of the variable for unit *g*;

S_Z^2 is the variance over all observations, and;

W_{gh} is a distance weight that can be defined by $W_{gh} = \frac{1}{d_{gh}}$ (14)

from CrimeStat (2003, p.288) and Levine (1996)

Hence a value for the Local Moran's I can be computed for each areal unit in the region. To enable comparison, it is possible to calculate a 'standardised' version of the Local Moran's *I* that takes into account its sampling error, and it is this that is referred to in the following analysis. The standardisation is carried out using the following function:

$$Z(I_i) = [I_i - E(I_i)] / S(I_i) \qquad (15)$$

Where: $Z(I_i)$ is the value of the standardised Local Moran's *I;*

I_i is the Local Moran's *I* value for the variable under analysis of areal unit *i* at the ED level;

$E(I_i)$ is the mean Local Moran's value of areal unit *I*, and;

$S(I_i)$ is the standard deviation of areal unit *i.*

These standardised results are presented in map form, along with the estimates of area effects in the following section. The range of values for the Local Moran's *I* is far greater than for the global Moran's *I* measure. However, after standardisation, the Local Moran's *I* range falls between the –1 and 1 limits. A negative value indicates negative spatial autocorrelation, where geographically 'close' values are less similar than would be expected than if there were no spatial autocorrelation, while a value of zero indicates complete spatial independence. Strong spatial autocorrelation is denoted by high positive values. In practice it is unlikely that high positive or negative will be observed. Because the Local Moran's *I* is standardised the results between different districts can be compared. Moreover, we take any values of standardised Local Moran's *I* that are either below –3 or above +3 to indicate significant spatial processes between the areal units. These bounds were chosen, as it is likely that all significant clustering would be identified using these limits as they approximately correspond to the 99% confidence intervals of standard deviations.

3.5.3. Implementation for the spatial process methodology

Above the theoretical methodology for the analysis was described. It is useful to outline the practical implementation of the method, as it used a number of different programs to calculate and visualise the results. Much of the raw data calculation and preparation was carried out in SPSS, where the SAR District level mean of the variable is subtracted from each ED instance of the variable, as in equation 11. The result of this is then weighted by the weighting term, calculated from equation 12. CrimeStat is designed for point data, not polygon data, which is the native form of Census data. Therefore, it is necessary to calculate the centroids for each of the areal units within the system. The centroids are obtained from within ArcGIS where a Visual Basic script is run to obtain the centroids of the areal units. This is joined with the results for the SPSS calculations to form a file that has centroid *X* and *Y* values, and a $\hat{u}_g$ value for each of the areal units.

The Moran's *I* and Local Moran's *I* value was calculated using the CrimeStat program (2003). The Local Moran's *I* is then calculated for the centroids of the areal units, with the distances between the centroids being used as the distances between the areal units. This is not ideal, as the areal units form a continuous coverage over the study space. Figure 3.3 shows the interface of the Crimestat program for file selection, and demonstrates that for any analysis at least three variables are required: X position, Y position and a Z value (intensity). Figure 3.4 demonstrates the Local Moran's *I* interface, as used to obtain the results. The output from the Crimestat program is saved to a *.dbf file, which can be opened in ArcGIS. The output file is joined to the original data file in ArcGIS, where the values of the Local Moran's *I* analysis are applied to the areal units. This produces the visual output demonstrating the areas of spatial association and dissociation. The results are also visualised using histograms to better understand the spread of the distribution.

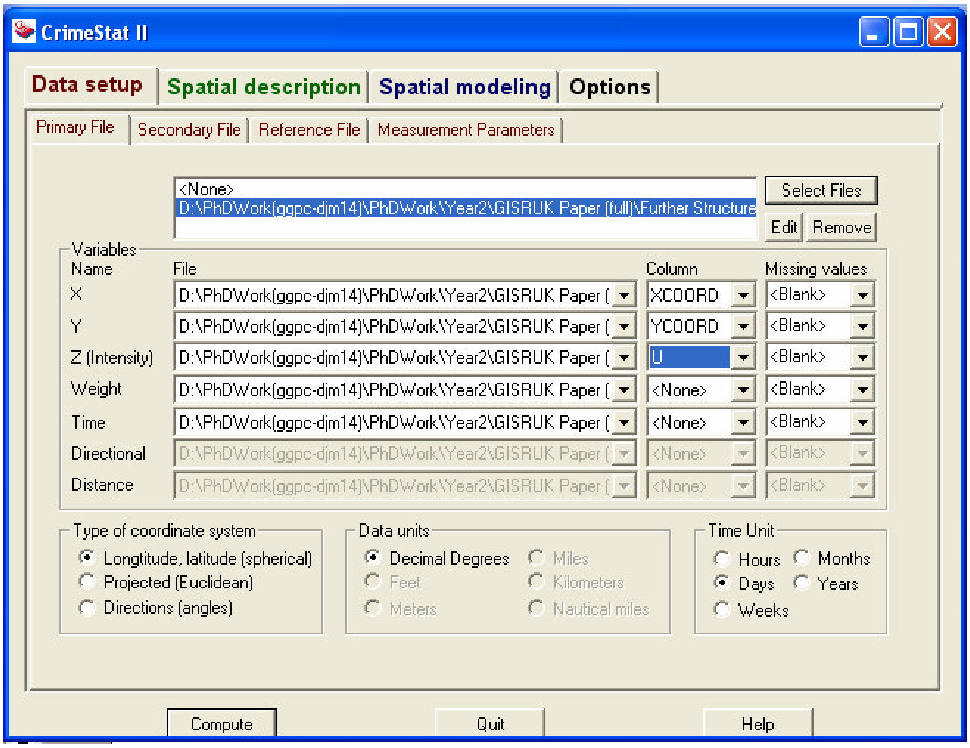


Figure 3.3: The Crimestat file selection interface, with X (XCOORD), Y (YCOORD) and Z (U, representing the $\hat{u}_g$) elements specified.

Note from figure 3.4 that the 'Adjust for small distances' option is selected. This is because the weight index for distances does not work for distances under 1 (as is clear in equation 6). When the distance is less than one, then the weighting increases towards infinity. The adjustment mechanism imposes a maximum possible weight of 1 to control for this. As it is theoretically possible for the distances to be less than 1 unit for the centroids of the areal units, the small distance adjustment has to be used in this analysis. It was not possible to change the units for the distances without requiring the program implantation to be changed.

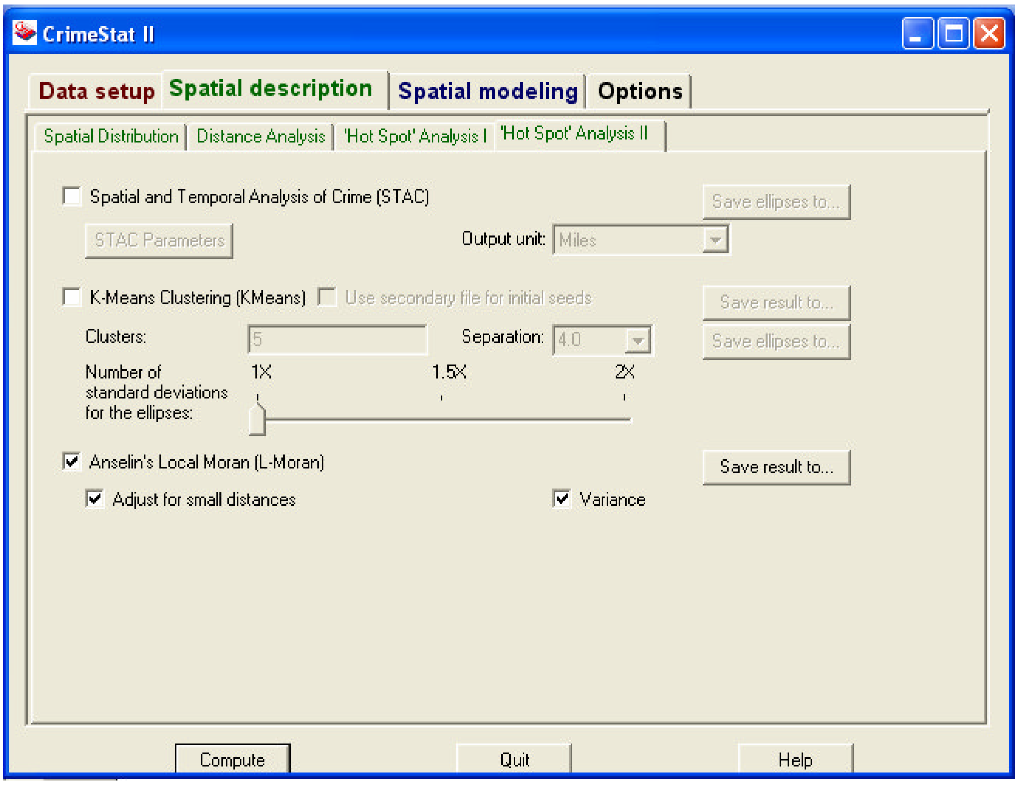


Figure 3.4: Local Moran's I interface, with adjustment for small distances selected.

Chapter 4

The Scale Effect in the 1991 UK Census

4.1 Introduction

The data used throughout this work are derived from the 1991 UK Population Census. The basic variables used are as outlined in Chapter 3.1. The results of the investigation of the scale effect for the whole of the UK are outlined, presenting the Aggregation Effects (AEs) and Intra-Area Correlations (IACs) for each of the eight variables, at both the ED and Ward scale. This is necessary, as it provides the framework from which the later investigations into the nature of the scale effect in the UK Census takes place. Moreover, it considers the scale effect in relation to a dataset far larger than has been analysed to date, and provides a discussion concerning the scale effect in the UK using the AEs and IACs.

4.1.1 Theories behind the incidence of the scale effect

It is likely that there will be trends identified in the work described above. Below, two theories are examined which seek to provide explanations for the potential trends in the analysis. Both of the theories relate to the impact that the areal units have on the data, given the type of area in which they are located.

Firstly, it is supposed that there will be a difference between the magnitude of the scale effect in urban areas and the scale effect in more rural areas. Urban areas are more likely to have higher within-area homogeneity. Although urban areas tend to have higher populations, the spatial extent of the areal units is frequently smaller than those in rural areas, thus decreasing the area over which they extend. This, combined with the greater population density of the areal units in urban areas, is likely to lead to an increase in similarity between individuals within an areal unit. By their nature, urban areas tend to be more structured and, as such, attract similar people to specific places. In contrast, rural areas will often have a wider diversity of people living within them. For instance, a small village could comprise only one or two EDs in which the full population for that village would be grouped. This population could include a very wide range of people, from commuters, local workers and farm workers, thus exhibiting a high level of diversity in the population. Consequently, this is likely to be a more diverse grouping than in an ED in an urban area.

Another explanation for this phenomenon is that there are processes occurring within the population at many different scales, in many different places. In particular, there may be areal segregation within settlements of all sizes. The composition of rural basic spatial units results in a geography that, even at the lowest level, is too large to enable the identification of these processes, because of the lower populations. Conversely, in urban areas the population is much greater, and it is likely that the processes will operate at greater spatial extents and can, therefore, be identified by the basic areal units. For instance, a basic areal unit in an urban area could be a similar size to a housing estate, where similar people would be likely to cluster. Thus, the change in homogeneity levels between different scales of aggregation will be greater as the changes in areal unit composition will be greater. Two areal units that have high within-area homogeneity are likely to have lower between-area homogeneity; the result of a combination of these two units will be greater scale effects. In a rural area, similar processes of segregation will be at a scale too small to be picked out by the census geography, so there will be less within-area homogeneity and higher between-area homogeneity, thus resulting in a lower scale effect.

4.2 Introduction to the Analysis

The AEs and IACs act differently for each of the variables in different districts and at the different scales. This reinforces the notion that the MAUP is largely an unpredictable phenomenon. Rather than attempt to provide outright solutions to the MAUP, for example by finding analyses that are not affected by the MAUP (see for example, Robinson, 1956), it is suggested here that it is more productive to increase our understanding of the processes that result in instances of the MAUP. This chapter sets out to examine the AEs and IACs for the whole of the UK using a range of visual and statistical measures, to attempt to characterise the extent of the scale effect in normal census analysis. The basic structure of the data is considered using tabular analysis presenting the means, ranges, and coefficients of variance to establish the relative magnitudes of the measures for the different variables. This enables basic description of the measures to be outlined. The Aggregation Effects and the IACs for the 278 SAR Districts were mapped for the 8 variables using Enumeration Districts and Wards as the areal units. This enabled patterns and clustering to be identified within the data, and supported the statistical analysis. For each variable the IAC and AE are presented together, to demonstrate the patterns of the scale effect for each variable, and also the similarities and differences between the two measures. Moreover, it will be possible to identify patterns between urban and rural areas. Lastly, the IACs and AEs data will be examined using histograms, and compared against the normal distribution. This will enable statistical analysis later, such as correlation to be used. Each variable is considered separately, using all the analysis information described above. Distinction is also made between the two spatial scales of ED and Ward.

4.3 Describing the Distributions

The results of the analysis are divided into two sections. The first section deals with the effects of changes in scale between the individual and the ED level. The second section deals with the effects a change in scale has between the ED and Ward level. In each case, the variables are dealt with in turn, and a table describing the range and mean of the distribution is presented along with histograms to show the full distribution and a map of the distribution over the UK to demonstrate the spatial differences.

Below, the distribution of the measures is discussed relative to the indicated levels of homogeneity, the incidence of the scale effect, and the location of the districts relative to their population and place types. It is worth noting at this point that all the discussions about the measures imply a level of relativity. There is no absolute scale for the AEs, and as such, an AE that appears relatively high for one variable, could be relatively low in another variable. However, the greater the magnitude of the AE, the greater the extent of the scale effect. The IAC ranges between 0 and 1 and, therefore, the magnitude of the IAC is less relative to the AE as there are upper and lower limits against which the IACs of a given area may be judged. However, the fact remains that all discussions are constructed considering the scale effect values relative to the other scale effect values for that variable.

4.3.1 AEs and IACs at the ED level

Below, the distributions for the AEs and IACs at the ED level are discussed. In each case an overview of the scale effects is given, using tabular data, histograms of the distribution and mapped results.

The variables addressed are:

- A60P – percentage of the population aged over 60 years old;
- NONW – the proportion of the population coded as non-white in the Census;
- EMP – the proportion of the population employed;
- UNEMP – the proportion of the population unemployed;
- LLTI – the proportion of the population with a limiting long term illness;
- CAR0 – the proportion of the population without access to a car;
- OO – the proportion of the population owning the house in which they live, and;
- RLA- the proportion of the population renting a house from the local authority.

4.3.1.1. A60P

Table 4.1 and Figure 4.1 provide exploratory statistics to describe the distribution of the scale effect measures at the ED level for the A60P variable. It is clear from the graphs that both the AE and IAC are positively skewed, although the skew of the AE is less severe as the histogram displays a more progressive spread towards the high values. However, once population size is controlled for, as in the IAC histogram, the spread of values reduces, and is more concentrated at the low end of the scale. Using the Kolmogorov-Smirnov test it is possible to determine that neither of the distributions shown in figure 4.1 is normally distributed. Table 4.1 demonstrates the key statistical values relating to the distribution of the AE and IAC. The relative tightness of the distributions is apparent, as the mean of the AE is closer to the mid-point value of the AE distribution than the mean of the IAC, which is relatively close to the low-point of the IAC distribution. It is interesting to note that, although the histogram spread for the AE is greater than for the IAC, the Coefficient of Variation demonstrates that the more concentrated spread of the IAC measure is more unstable than the spread of the AE measure.

Measure	AE	IAC
Mean	20.733	0.0457
Coefficient of Variation	0.3557	0.5410
Minimum	7.1100	0.0177
Maximum	56.2726	0.3133

Table 4.1: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on A60P at the ED level.

The outliers for the AE distribution are the Districts of Kingston-upon-Hull and Poole, both in England and with District populations of 250,820 and 130,666 respectively. Renfrew (in Scotland) is also an AE outlier. The two highest Districts for the IAC distribution are again Renfrew (population 194,732), and Dundee City (population 163,071). These are both within Scotland. Renfrew is on the outskirts of Glasgow and contains Paisley, a former textile area, whilst Dundee City is on the Eastern coast of Scotland. The areas identified as outliers for the AE measure come 5th (Kingston-upon-Hull) and 155th (Poole) highest in the IAC distribution. This demonstrates that the adjustment for population in the IAC is important, as it enables zones of different sizes to be compared. It also demonstrates the influence that population size has on the magnitude of the scale effect, as measured by the AE, as larger populations in general have large AEs.

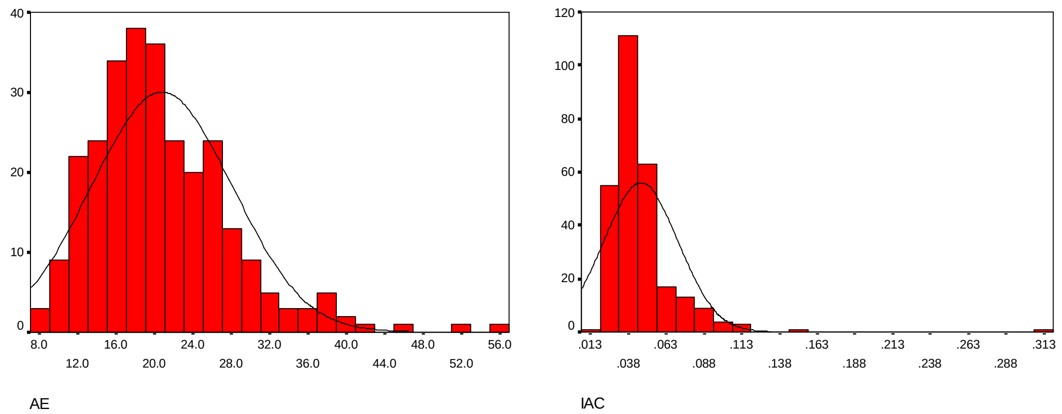


Figure 4.1: Histogram of A60P at the ED level, with normal curve fitted.

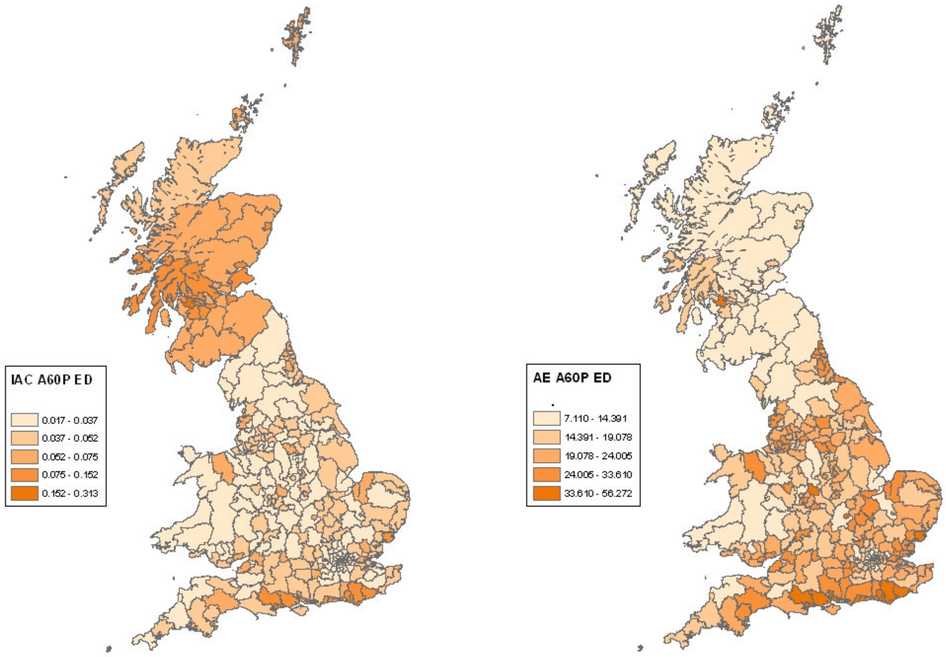


Figure 4.2: AE and IAC for A60P over the UK aggregating between Individual and ED level.

Figure 4.2 presents the A60P variable at the ED level. Although both measures present information about the scale effect, there are clear differences between the spatial patterns presented. The most notable difference is the shift in relatively high values for the IACs in Scotland to the relatively low values observed in the Scottish AEs. This is a pattern that is present in much of the data, and will be observed in many of the figures below. This difference can be explained through the population adjustment that occurs for the IACs. The population of each of the Scottish ED units is approximately one quarter to one half the size of the ED areal units in England and Wales. Therefore although the AE values are low, when compared to the English and Welsh areal units without population adjustment, the AE values for Scotland are relatively high given the low sizes of the Scottish ED units. Once the measure is adjusted for population size differences, as with the IACs, then the relatively higher levels of homogeneity in the smaller Scottish areal units is apparent. Therefore, considering the Scottish data and the A60P variable, it would be possible to conclude that the MAUP scale effect is relatively high, as demonstrated by the IAC measure. For instance, the highest Aggregation Effect in Scotland for this variable is 46, (Renfrew SAR, ED level); while in England and Wales the highest is 56 (Kingston upon Hull, ED level). Although the areal units do not change, using the IAC measures, the relative magnitude does. Thus, the highest IAC for Scotland, in the A60P variable is 0.3 (Renfrew SAR District, ED level), while in England and Wales, the highest IAC is 0.11 (Kingston upon Hull SAR, ED level).

In England and Wales, there are a number of areas that exhibit relatively high magnitudes for both measures. For instance, Newcastle and surrounding areas, such as Durham, in the North East of England exhibit high IACs and AEs for the A60P variable. This is also the case for the South and South East of England and the coastal Districts of East Anglia, and the coastal Districts on the South coast, such as Southampton and Portsmouth. There is also a reasonably clear urban to rural split. As noted above, the urban areas of Newcastle and Durham have relatively high incidences using both measures. This is also the case for the urban districts around London, Manchester, and Birmingham. The more rural Districts, such as in the South West of England, in the Counties of Devon and Cornwall, the Districts in the area of the Lake District and Wales, with the exception of Swansea and Cardiff all exhibit relatively low AEs and IACs. This is a general pattern that will be discussed with the other variables below.

4.3.1.2. NONW

The NONW variable has a wide range of IAC values, with both very low IACs and high IACs above 0.5. Within-area homogeneity is therefore dependent on the District under investigation, and it is not possible to generalise. As was described previously, although the values of the IACs are expected to be bounded by 0 and 1, it is possible for them to fall at either side of these extremes. However, this is not to be commonly expected. The SAR District of Knowsley, Merseyside has an IAC of -0.001 at the ED level. At the Ward level, Knowsley is still the most homogeneous SAR District for the NONW variable, although the IAC has risen to 0.0001 (see discussion below for the Ward level NONW measures). The highest IACs for the NONW data are 0.59 for the ED level, in the SAR District of Bradford, West Yorkshire. From the other statistics presented in table 4.2, it can be seen that the measures are greater than for the A60P variable, and that there are areas at the two extremes of relatively low scale effect and relatively high scale effect. The histograms in figure 4.3 demonstrate this to be the case. Again both histograms are positively skewed, and neither fit the normal distribution. In the case of NONW the distribution of the AE and IAC appear to be relatively similar to each other, suggesting that population size is less of an important factor for the scale effect in this variable. This is confirmed by figure 4.2 where the spatial nature of the distributions is also similar. However, unlike the A60P variable, both Coefficients of Variation are relatively high for the NONW variable, and both are relatively similar. The fact that they are above 1 demonstrates that the standard deviation of the NONW measures are greater than the means of the measures, which enables the conclusion to be drawn that the distributions of the AE and IAC for NONW are highly variable. The outliers for the histograms are Birmingham, Calderdale, Kirklees, Leicester, Rochdale, Bradford, Oldham and Blackburn for both the AE and IAC. Therefore, these places are highly segregated at the ED level. This is the only variable where the AE and IAC outliers not only remain the same Districts, but also remain in the same order of magnitude.

Table 4.2 presents the IACs and AE at the ED level for the NONW variable. The overall range of the measures is much greater for the A60P variable. There are

Measure	AE	IAC
Mean	32.2311	0.0648
Coefficient of Variation	1.5061	1.4607
Minimum	0.3922	-0.0011
Maximum	309.4031	0.5970

Table 4.2: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on NONW at the ED level.

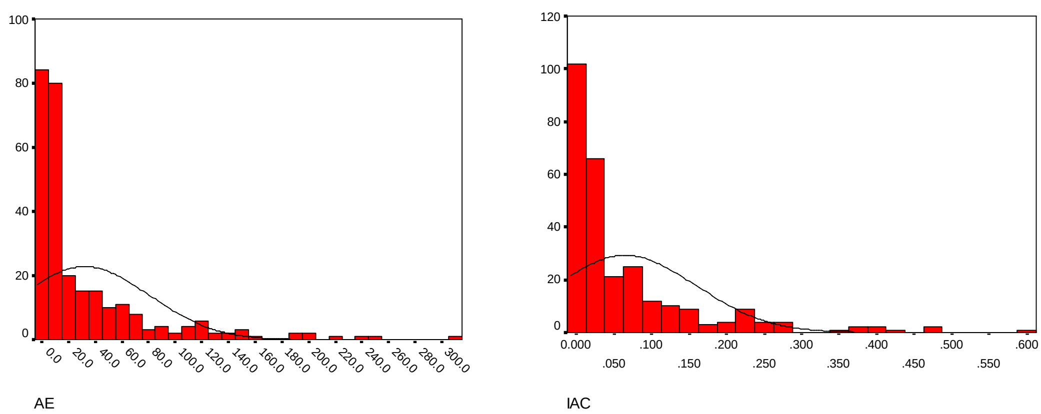


Figure 4.3: Histogram of NONW at the ED level, with normal curve fitted.

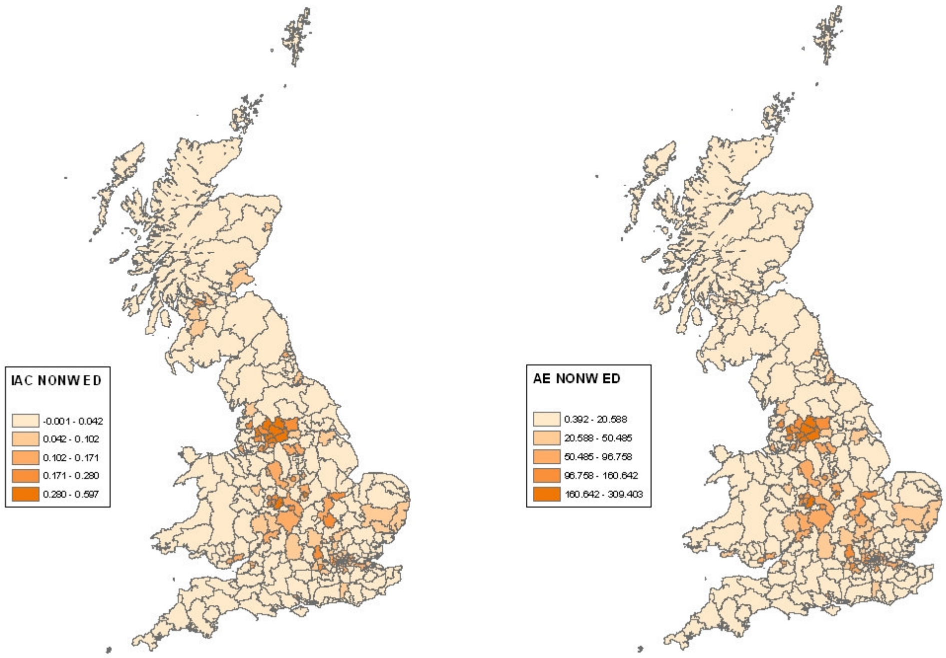


Figure 4.4: AEs and IACs for NONW over the UK aggregating between Individual and ED level.

extreme outliers showing high levels of the scale effect (in the AEs) and of within-area homogeneity (in the IACs). Unlike the other variables presented here, there is a higher degree of similarity between the AE and IAC measures and their mapped distribution (see figure 4.4), The AE mapped distribution reflects that of the IAC. With the exception of a few Districts, such as Fife, Dundee City and Aberdeen in Scotland, the distribution of the two measures remains same. These Districts in Scotland demonstrate relatively higher IACs than AEs largely due to the population adjustment, and are the major differences between the two distributions. This difference could be related to the lower levels of ethnic populations in Scotland in 1991 in comparison with the rest of the UK. Moreover, those ethnic groups that do live in Scotland may well be more concentrated in their locations than the groups in England and Wales, thus producing higher levels of homogeneity, observed in the IACs. Reference to the spatial plots also reveals that there is a concentration of high IACs in the North of England around the Manchester District. This is consistent with previous results, as the outliers identified previously were all located in the North. However, it is notable that although only three Districts were identified as outliers, a large group of Districts in the North West all demonstrate high levels of scale effect and within-area homogeneity in the non-white population using the AE and IAC measures respectively.

There is a clear urban to rural divide again within the measures. The highest values for both of the measures occur within the urban Districts such as those in the Cities of London, Manchester and Birmingham. Glasgow in Scotland also exhibits relatively high values for both measures. The Districts that are in areas considered more rural have values for both measures that occur in the lower two categories within the map distributions, as can be seen for instance, in East Anglia, and Wales.

4.3.1.3. EMP

Table 4.3 describes the main statistics for the AE and IAC measure of the EMP variable. In comparison with the NONW variable, the measures are relatively low. However, they are greater than for the A60P variable. The major difference between the AE and the IAC can be observed in the Coefficient of Variation for the IAC measure, which is double that of the AE measure. In both cases, the means of the distributions are closer to the minimum values of the distribution, rather than the midpoints, whilst the range is relatively large for both of the measures. Again this is reflected in the Coefficients of Variation, and is shown by the histograms (see figure 4.5). As with the other variables discussed, the histograms demonstrate that the distributions of the measures are skewed positively, and neither of the measures has a distribution that reflects the normal curve. Furthermore, the majority of the AE measure is more evenly spread within the histogram range, thus explaining the higher coefficients of variation that are observed for the IAC than the AE. For both the AE and the IAC, the outlier District is Renfrew, Scotland.

Measure	AE	IAC
Mean	11.4339	0.0249
Coefficient of Variation	0.7327	1.8487
Minimum	2.5736	0.0037
Maximum	112.7468	0.7663

Table 4.3: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on EMP at the ED level.

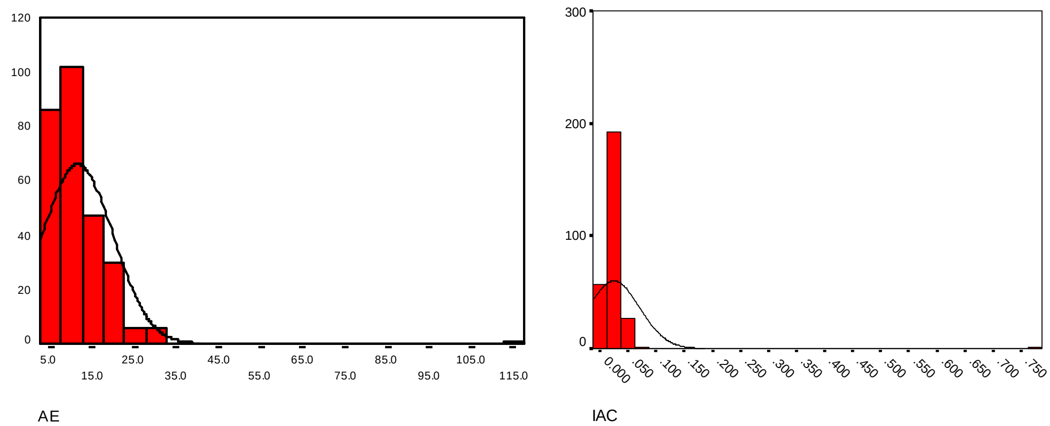


Figure 4.5: Histogram of EMP at the ED level, with normal curve fitted.

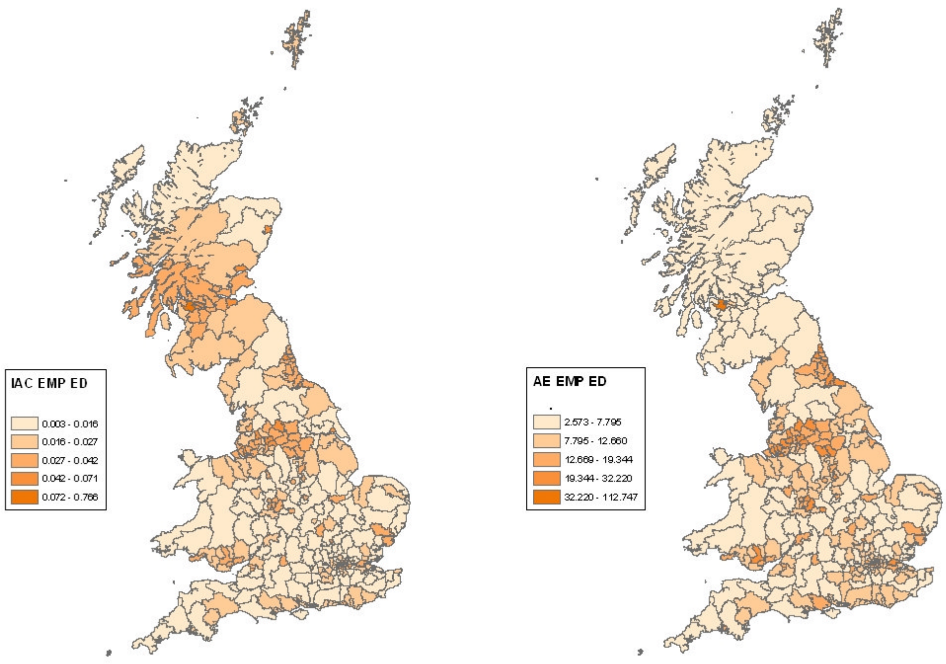


Figure 4.6: AEs and IACs for EMP over the UK aggregating between Individual and ED level.

Figure 4.6 depicts the spatial distribution of the measures for the first of the two employment variables, EMP, at the ED level. Although there are clear differences between the two distributions of the two measures, there are distinct common patterns. There are major differences in the relative magnitude of the two measures in Scotland, with the AEs portraying the Scottish data as relatively stable and scale free whilst the IACs suggest that there is a relatively high level of within-area homogeneity and therefore a likely higher magnitude of the scale effect in the Districts in Scotland. The Districts exhibiting the highest magnitudes of the IACs in Scotland are those in more urban areas, such as Glasgow, Edinburgh and the Central Belt, as well as Dundee and Aberdeen. As rurality increases in the more Northern Districts the level of within-area homogeneity shown by the IAC falls. The urban areas of England and Wales clearly show higher levels of homogeneity and greater incidence of the scale effect, for both the IAC and AEs. For both measures, the major cities such as London, Newcastle, Manchester, and Birmingham exhibit high magnitudes of scale effect. However, higher levels of IACs and AEs can also be observed in many of the Districts in which the smaller urban areas are located, such as Swansea and Cardiff in Wales, Cambridge and Southampton. Therefore, the EMP variable can be considered to be relatively homogeneous in the Districts that represent urban areas. The converse is true for the rural areas, where the levels of within-area homogeneity, as measured by both the AE and IAC, are lower. This is observable in the Northern Districts in Scotland, the majority of Wales, especially on the Western side, and the more rural Districts in the Lake District. Again, there is a pattern of difference developing between the urban and rural areas.

4.3.1.4. UNEMP

The second employment variable is UNEMP, the proportion of the population who are unemployed. The scale effect is much lower for this variable, as described by the low mean, and maximum values for both the AE and IAC observed in table 4.4. With the exception of the NONW variable, the minimum value of the AE and the IAC is the lowest, thus suggesting low scale effect. The Coefficients of Variation are not excessively high for this distribution, relative to the distributions for the other variables, and therefore the UNEMP measures are not as variable in magnitude as those for the NONW variable. This again can be observed in the maximum values.

The histograms in figure 4.7 describe the distribution similarly. The AE and IAC both exhibit distributions that are positively skewed, and neither of them reflects normality, as tested by the Kolmogorov-Smirnov test. However, although the overall distributions of the AE and IACs for the UNEMP variable are less dispersed than for the variables discussed above, the histograms depict a less concentrated distribution for the magnitudes observed, thus suggesting relatively more spread than has previously been observed. There are four outliers identifiable on the AE histogram. These Districts are Preston (Lancashire), Knowsley (Merseyside), Middlesbrough, and Kingston-upon-Hull. All these Districts have highly concentrated proportions of UNEMP demonstrating the expected link between high incidence of the scale effect and high levels of homogeneity. For the population adjusted IAC the outliers are Dundee and Renfrew.

Measure	AE	IAC
Mean	5.5830	0.0105
Coefficient of Variation	0.5042	0.6717
Minimum	1.3540	0.0006
Maximum	16.9778	0.0677

Table 4.4: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on UNEMP at the ED level.

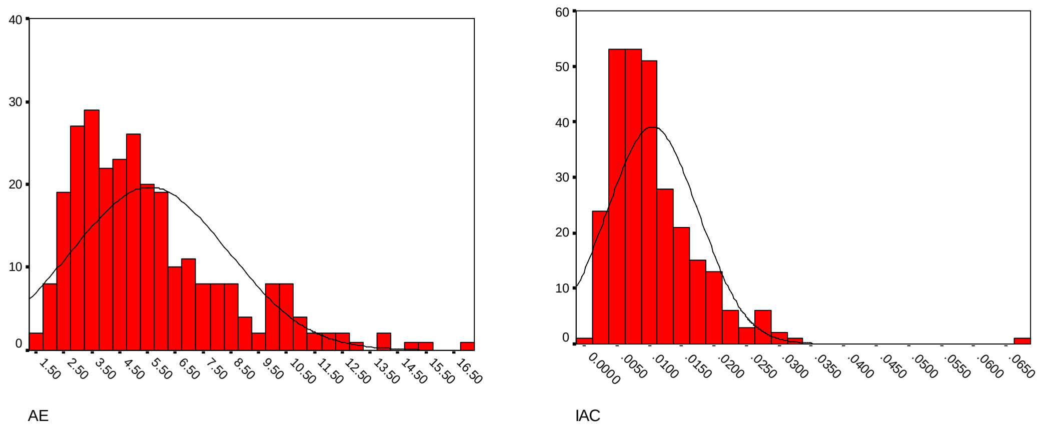


Figure 4.7: Histogram of UNEMP at the ED level, with normal curve fitted.

The spatial distribution for UNEMP is presented in figure 4.8. Both the AE and IAC maximum values are much lower in comparison to those observed for the EMP variable. The urban areas of London, Newcastle, Manchester and Birmingham demonstrate higher levels of AEs and IACs as with the other variables discussed, suggesting that the scale effect is greater in those urban areas than in some of the more rural districts, and that there is higher within-area homogeneity in those areas, than is present in many rural Districts in the South of England such as South Norfolk, North Suffolk, Braintree and Uttlesford, and Dorset. The urban belt across the North of England including Manchester eastwards to Leeds and York also demonstrate higher AEs and IACs. The urban areas of Wales also demonstrate relatively high incidence of the scale effect, as does the West coast of Wales, which is more rural. This is a result that has not been observed in the other variables discussed above.

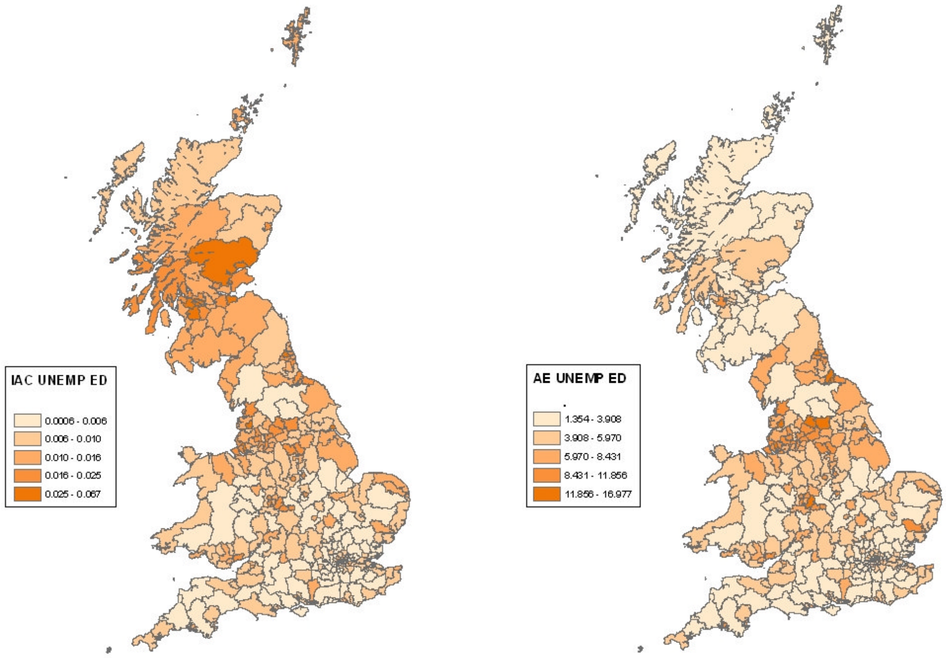


Figure 4.8: AEs and IACs for UNEMP over all UK aggregating between Individual and ED level.

As with the other variables above, there is a marked distinction between the two measures for the Scottish data. With the IACs the incidence of the within-area homogeneity and the scale effect appear relatively large compared to England and Wales, suggesting that there is a relatively high level of homogeneity in the levels of unemployment. As with the examples discussed above, the highest values in Scotland are observed for the urban Districts, such as Glasgow, Edinburgh, Dundee and Aberdeen. The more rural Districts in northern and lowland Scotland exhibit lower levels of the scale effect. The AE demonstrates that Scotland has less severe scale effect, as the northern and lowland areas have values contained in the lowest categories. The more urban Districts again exhibit higher levels of AE, suggesting higher incidence of the scale effect, although it is not as high in comparison with the AE magnitudes for the Districts in the UK. Therefore, although the overall pattern described by the two measures is similar, the relative magnitudes to the rest of the dataset are largely different. Although the incidence of higher magnitudes is not linked to the proportion of a given variable, in that high levels of homogeneity can theoretically be observed with both high proportions and low proportions of a given variable, in the cases where the magnitude of a variable is clustered tightly, it appears to be the case that the incidence of the measures of the scale effect for the UNEMP variable does resemble the likely distribution of unemployment. For instance, the older mining areas, which have declined, and now exhibit higher levels of unemployment in Wales and the North of England are represented with high levels of AE and IACs. With these areas this is not surprising as old mining areas will be communities where employment options were limited. A similar conclusion can be drawn from the old industrial areas in the North West, here there is also a higher level of homogeneity. The south of England in general, an area which has lower levels of unemployment, and markedly lower levels of community wide unemployment as would be observed in an old mining area, exhibits lower levels of within-area homogeneity.

4.3.1.5. LLTI

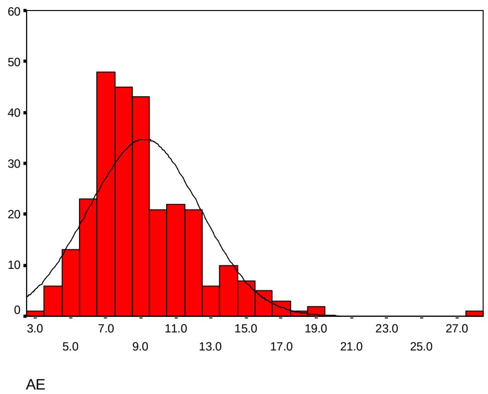
At the ED level the IAC for LLTI is relatively low in comparison with many of the other variables, in all areas (the highest value being 0.18 in Renfrew SAR District, Scotland) as demonstrated in Table 4.5. Indeed, it is lower than has been observed for the UNEMP variable. Other SAR districts exhibiting high IACs for LLTI include Aberdeen, and Dundee in Scotland. Therefore, it is possible to generalise that Scotland has higher within-area homogeneity for LLTI than either England or Wales, at the ED level, in other words there may be a clustering of the population in Scotland whose health outcomes are very similar with respect to the LLTI variable. The overall Coefficient of Variation for the LLTI variable is relatively high, (only the NONW and EMP variables exhibit higher values). Therefore, the variability of the IACs for the LLTI variable is relatively high in comparison to the variability of the other variables investigated here. This suggests that the LLTI variable exists in pockets, or small areas, rather than in large portions of the populations in Districts. Thus, the incidence of LLTI tends to be concentrated, with the majority of the homogeneity reflecting an absence of the variable. For the AE, the Coefficient of Variation is similar or slightly lower than those observed for many of the other variables. Figure 4.9 depicts a distribution for the AE measure that demonstrates a dispersed distribution of values, although it is still positively skewed and does not match a normal distribution.

Similarly, the IAC is positively skewed and non-normal. For the AE the outliers are Durham, Ipswich, Kingston-upon-Hull and Renfrew. For the IAC measure, Dundee remains as an outlier in the distribution. The District of Renfrew, Scotland, is also an IAC outlier.

The distribution of LLTI for the UK is presented in figure 4.10. It can be observed that the magnitudes of the scale effect measures are relatively low for LLTI in comparison to the measures observed for the other variables such as A60P and NONW. It is worth noting, however, that the incidence of LLTI is not a high incidence variable, such as those relating to tenure, relatively low, and therefore high within-area homogeneity at the ED level is likely to be observed in areas where there is a homogeneously low incidence population, with a few clusters of homogeneous high incidences of LLTI, such as in old mining towns in Wales or the North of England, as seen in the outlier areas discussed below.

Measure	AE	IAC
Mean	9.1994	0.0193
Coefficient of Variation	0.3464	0.6769
Minimum	2.8017	0.0066
Maximum	27.8903	0.1844

Table 4.5: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on LLTI at the ED level.



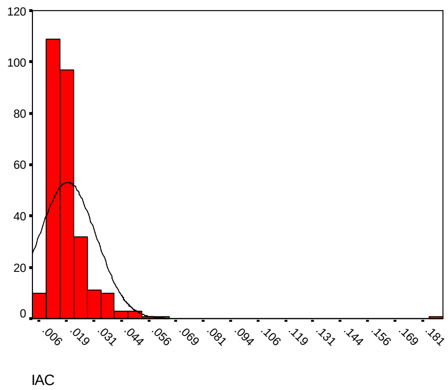


Figure 4.9: Histogram of LLTI at the ED level, with normal curve fitted.

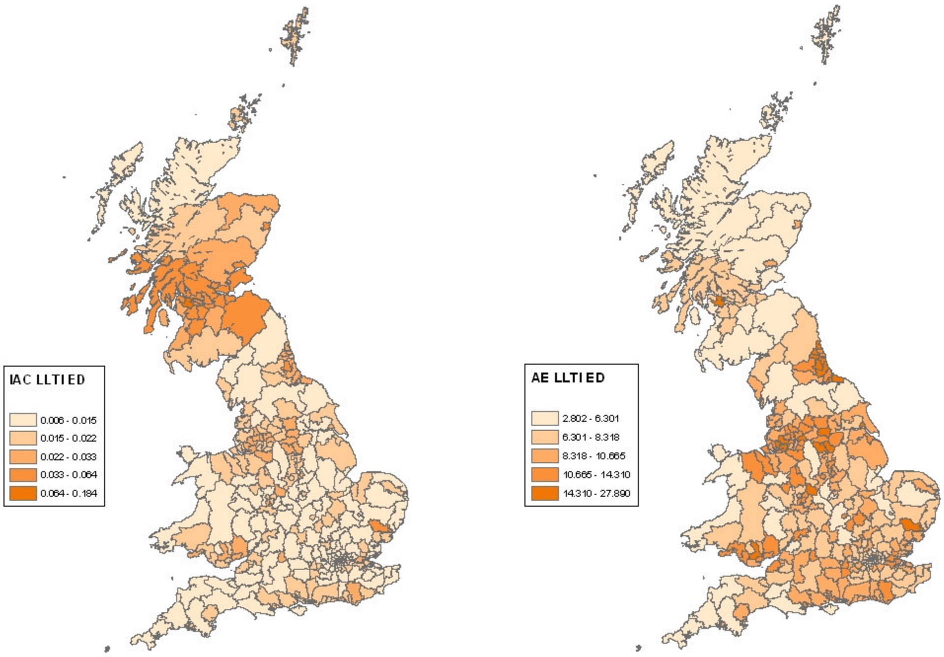


Figure 4.10: AEs and IACs for LLTI over all UK aggregating between Individual and ED level.

For England and Wales, using the AE measure, there are a large number of relatively high values, indicating a number of Districts likely to suffer from the scale effect in analysis. As before, the majority of them occur in the more urban Districts, although East Anglia, excluding South Norfolk, a rural area also exhibits relatively high incidence. This is also the case for the District of Berwick on Tweed and surrounding area, which is rural and exhibits a relatively high AE. Similarly, the Districts in Powys and Clwyd in Wales, both relatively rural, exhibit relatively higher AEs than has previously been observed. Scotland, which for many of the other variables presented has relatively low magnitudes for the scale effect using the AE measure, has a number of relatively high Districts for the LLTI variable. These include not only the urban areas of Glasgow, Edinburgh, Aberdeen and Dundee, but also the more rural District of Argyll and Bute.

Using the IAC measure it is possible to demonstrate that there is more within-area homogeneity in the LLTI variable in the Scottish Districts than was highlighted by the AE measure. With the exception of the Highlands and Islands Districts, the Scottish IACs are all relatively high. This suggests that, not only is the scale effect relatively high for the Scottish LLTI data, but also there is a greater degree of within-area homogeneity in the Scottish districts than is observable in the Districts in much of England and Wales. Although the major urban centres of Manchester, Birmingham and Newcastle are still clearly identifiable as areas of relatively high IACs, there is a less apparent urban to rural split as there are rural areas as discussed above, which also exhibit high AEs and IACs. Therefore, it is not possible to generalise to the extent where it would be possible to identify that rural areas have different IACs or AEs than urban areas.

4.3.1.6. CAR0

In comparison to the other variables presented above, the CAR0 variable has relatively high incidence of the scale effect, as highlighted by the measures of AE and IAC. The ranges of the variable are relatively large, especially in comparison to variables such as UNEMP or LLTI. Moreover, the means, although closer to the minimum than the maximum, are greater in magnitude than has been observed previously (see table 4.6). However, the Coefficients of Variation are not high, in

Measure	AE	IAC
Mean	52.2707	0.1166
Coefficient of Variation	0.44272	0.5415
Minimum	17.0553	0.0486
Maximum	168.9989	0.7989

Table 4.6: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on CAR0 at the ED level.

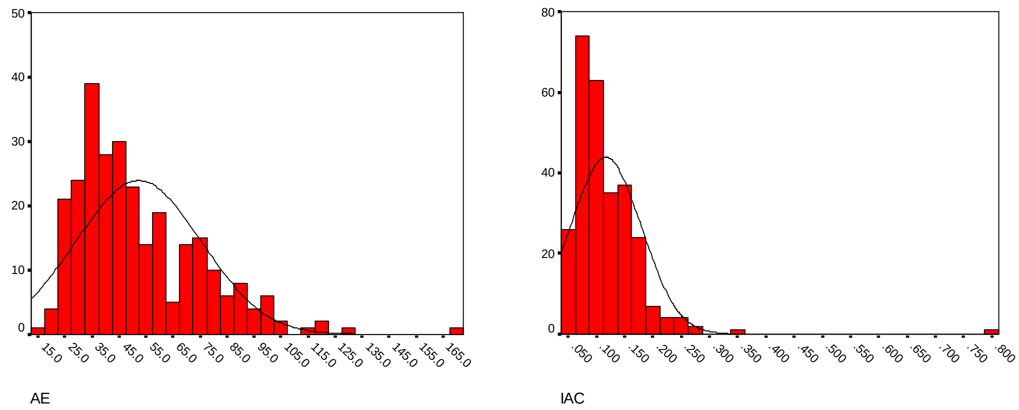


Figure 4.11: Histogram of CAR0 at the ED level, with normal curve fitted.

comparison to other variables, such as EMP, demonstrating that the means are greater than the standard deviations, and therefore that the data distribution is relatively clustered about the mean. The maximum values for the measures are greater than has been observed so far for other variables in this analysis, thus describing the fact that the CAR0 variable is more susceptible to the scale effect than other variables. However, reference to the histograms described in figure 4.11 demonstrates that the high values of the measures for the CAR0 variable are outliers in the distributions as the positively skewed histograms for both the AE and IAC have large tails. The majority of the magnitudes of the scale effect are observed within the first half of the histogram distribution, especially for the IAC, a fact which is supported by the relatively low mean values, and this outlier nature of the measure is confirmed by the lower Coefficients of Variation. Therefore, there are a small number of areas that exhibit high homogeneity within the CAR0 variable. The outlier Districts for the AE distribution are Middlesborough and Kingston-Upon-Hull. Kingston-Upon-Hull is also an outlier in the IAC distribution, as is Dundee.

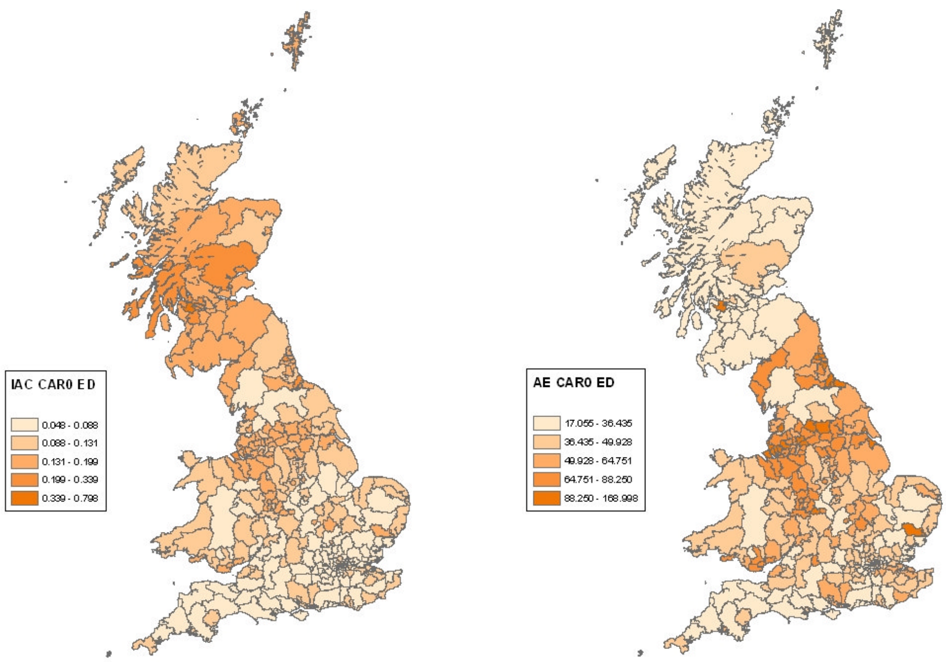


Figure 4.12: AEs and IACs for CAR0 over all UK aggregating between Individual and ED level.

The IACs and AEs calculated for the CAR0 variable are mapped in figure 4.12. It is notable that as with the majority of the other variables discussed, the greatest difference between the AE and IAC measures is the relative magnitudes of the measures in Scotland. Although there are a number of relatively high AEs present in Scotland (Angus and Perth and Kinross, along with Glasgow), the majority of the Districts are relatively low. This is not the case in Wales, where there is a greater indication of the scale effect in the Districts on the Western coast. It is possible to observe in the major urban areas identified previously relatively high level of scale effect using the AE, although they are less clearly defined than the more rural Districts surrounding them.

The lowest incidences of the scale effect, observed from the AE measures are present in the South East of England, through a belt in the south of England, and also South Lakeland, and Richmondshire in the north. The AE associated with these Districts suggest that there would be a relatively low scale effect. As with many of the other variables, the IACs provide a different interpretation of the potential scale effect, and also provide information relating to the within-area homogeneity of the Districts. As was noted above, the greatest difference is apparent in the Scottish Districts, where the IACs suggest relatively high within-area homogeneity, and therefore relatively severe incidences of the scale effect. In contrast, the areas highlighted in the South of England, demonstrate relatively low scale effects through low IACs. The belt of low scale effect running through the South of England becomes more apparent using the IAC. There is a more visible pattern across the Midlands to North of England from Birmingham to the North suggesting that there is greater within-area homogeneity in the CAR0 variable in these regions and Districts than in the South of England.

4.3.1.7. OO

In comparison with the other variables considered above, the tenure variables of the percentage of owner occupiers (OO) and the percentage of local authority renters (RLA, presented below) are considered to have the most severe incidence of the scale effect. Housing type tends to be one of the more clustered variables under consideration, and housing estates of various sizes are useful areas with which basic spatial units can be constructed. Thus, it is likely that within the housing variables there will be a greater degree of homogeneity than has previously been observed, and this will be observable in the higher values of the AEs and IACs. The summary statistics for the AEs and IACs of the OO variable are presented in table 4.7. The mean values are much greater in magnitude than has been observed previously, indicating a greater degree of scale effect in the variable. In comparison with the other variables the coefficients of variation are relatively low, suggesting a distribution for OO as a smaller relative range of values than has been observed in the previous variables, as the standard deviation is low in comparison to the magnitude of the mean. Nevertheless, the incidence of the scale effect overall, is greater in the OO variable. With the exception of NONW and the other tenure variable RLA, the maximum values observed for the OO variable demonstrate the most severe incidences of the scale effect present in the UK census data, from the sample of variables described here.

Measure		
Mean	112.9902	0.2487
Coefficient of Variation	0.3822	0.3398
Minimum	13.6054	0.0301
Maximum	224.4525	0.5240

Table 4.7: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on OO at the ED level.

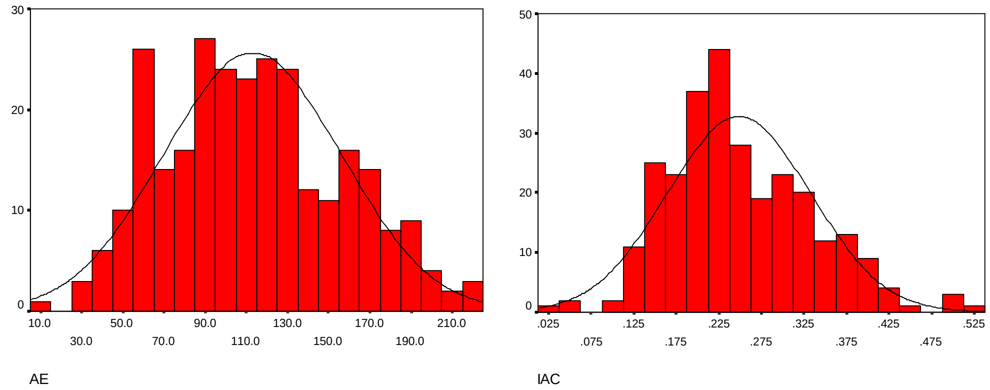


Figure 4.13: Histogram of OO at the ED level, with normal curve fitted.

Figure 4.13 confirms the observations from the table (4.7). The distribution is closer to a normal distribution, although it does not reflect normality using the Kolmogorov-Smirnov test, and is positively skewed. However, the mean and peaks of the distribution are more centrally located within the histogram. This is as described with the tabular data. Moreover, unlike the heavily skewed distributions described previously, there are no clearly identifiable outliers in the AE distribution. However, within the IAC distribution there are some outliers. These are Bearsden and Milngavie (Strathclyde) and Kilmarnock. It is notable that both of these are in Scotland, demonstrating a higher degree of homogeneity in housing stock in Scotland than in both England and Wales. It is possible that this is due to the differences in the right to buy legislation of the 1980s, where a high proportion of council owned houses were sold in England and Wales.

Figure 4.14 presents the OO IAC and AE measures mapped for all of the UK. There is a clear distinction between the Scottish AEs and the Scottish IACs for the OO variable. The relative magnitudes of the AEs suggest that statistical analysis in Scotland will be relatively stable between different scales. The IACs demonstrated that there is relatively severe scale effect in the Scottish OO data. Moreover, the IACs in Scotland demonstrate that in terms of owner occupancy, there is a relatively high degree of within-area homogeneity in the EDs for each of the Districts. However, although there are marked differences between the AEs and IACs for Scotland and those in England and Wales, the patterns observed in England and Wales are largely similar. In both cases, the majority of the Welsh Districts have relatively low IACs, with the exception of those on the border with England, where the IACs are greater.

As with the other variables discussed above, the South Eastern edge of England is relatively scale free, using the IAC and AE measures, suggesting that there is low within-area homogeneity in those Districts. The majority of central and Northern England exhibits relatively medium to high IACs and AEs. The urban areas are again visible as Districts with higher scale effects, and this is especially the case in the areas surrounding London and the South East, along with Manchester. Although there are differences between the two measures, the OO tenure variable describes similar patterns within the data, with the exception of Scotland. For many of the Districts in England and Wales, those in the highest AE categories are also in the highest IAC category. Similarly, those in the lowest AE category are also in the lowest IAC categories. This suggests that although the IACs are adjusted for populations, thus explaining the differences observed between the AEs and IACs in the Scottish data, those areas where the population is relatively similar such as England and Wales have patterns of scale effect, which are consistent between the different measures. It is notable that the patterns of the scale effect within Scotland remain comparable between the two measures.

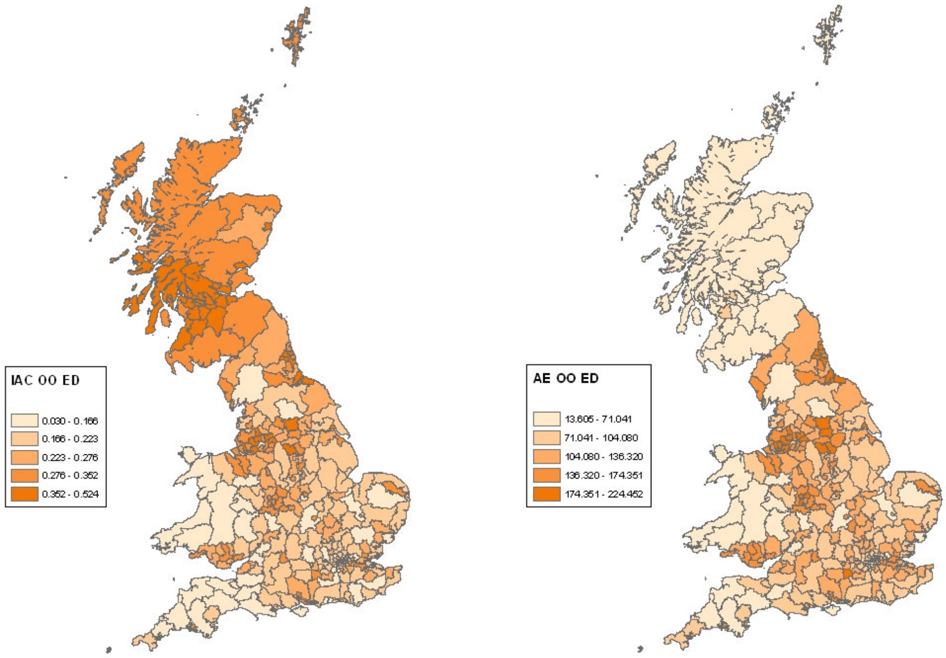


Figure 4.14: AEs and IACs for OO over all UK. Aggregating between Individual and ED level.

4.3.1.8. RLA

The last of the eight variables considered is the percentage of local authority renters (RLA) and is the second of the two tenure variables. As with OO, the relative incidence of the scale effect and the levels of within-area homogeneity are expected to be relatively high. This is demonstrated to be the case and is described in table 4.8.

Measure	AE	IAC
Mean	144.0186	0.3178
Coefficient of Variation	0.3410	0.2894
Minimum	39.9205	0.0816
Maximum	277.8767	0.5900

Table 4.8: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on RLA at the ED level.

It is notable, that although the magnitudes of the scale effect measures are relatively high, the coefficients of variation are again relatively low, thus describing a distribution that is close to the normal curve, and does not have large outliers. Although neither the minimum nor the maximum are greater than those observed for the NONW variable, they are nevertheless greater than has been observed for many of the other variables discussed here. The mean values of the distributions are much closer to the midpoints of the distribution. In the case of the IAC measure, the mean is lower than the mid-point. This suggests that the distribution will not be positively skewed, and is similar to a normal distribution. The normality of the measure is confirmed by the Kolmogorov-Smirnov test, which demonstrates that both the AE and IAC distributions are significantly normal. This is apparent from the histograms depicted in figure 4.15. As with the OO variable, the distributions in the histograms do not demonstrate significant tails and there are no statistical outliers. This reflects the lower coefficients of variation than have been observed in the table. However, there is still a District in the IAC histogram that appears to stretch the distribution. This District is Dundee City, Scotland. This was also the highest value found for the OO variable, which demonstrates that there is high within-area homogeneity in both the tenure variables for this District. The two highest AE Districts however, Kingston-upon-Hull and Wigan, are in England, and demonstrate the difference in the measures achieved by the population adjustment that the IAC introduces.

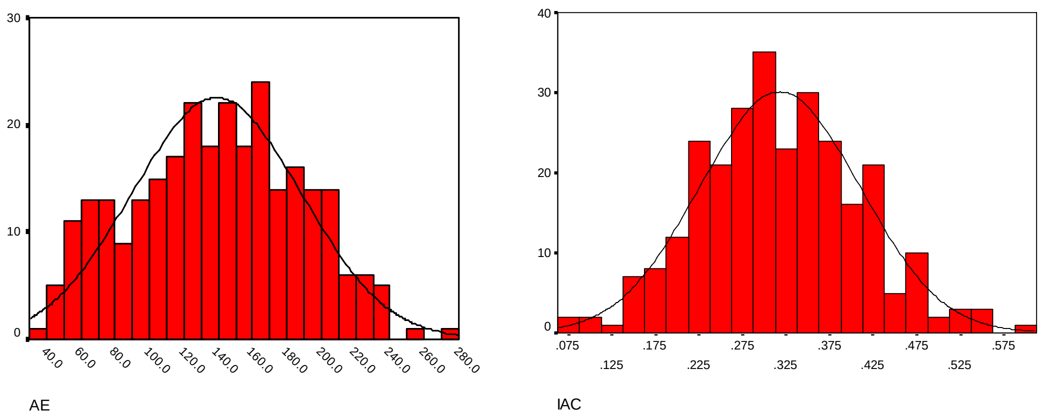


Figure 4.15: Histogram of RLA at the ED level, with normal curve fitted.

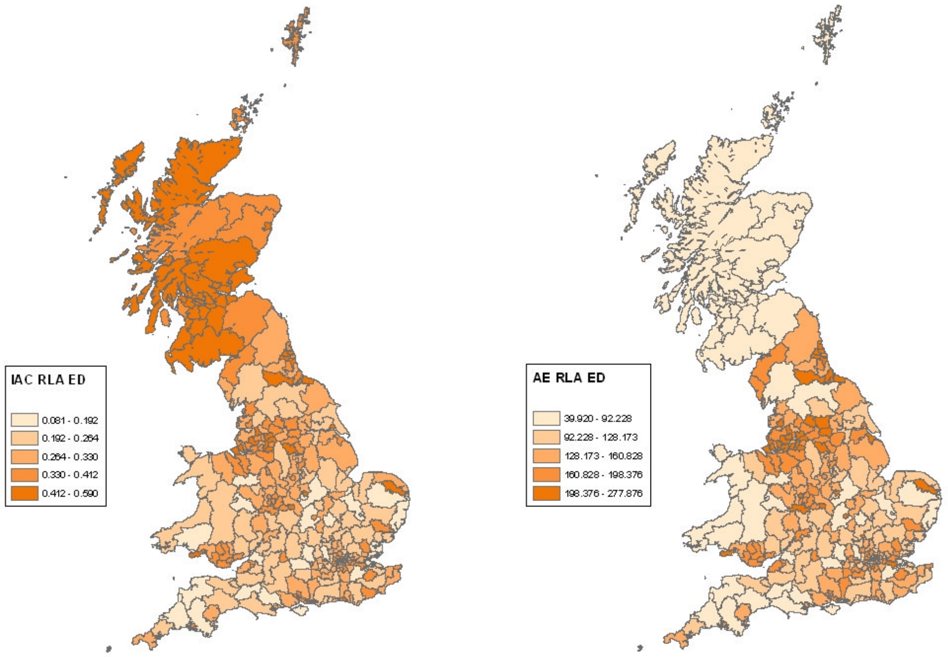


Figure 4.16: AEs and IACs for RLA over all UK aggregating between Individual and ED level.

These measures for RLA are mapped in figure 4.16. The distribution of the AEs is considerably more marked than that of the other tenure variable, OO. The RLA variable relates to the proportion of housing rented from local authorities, or new towns in England and Wales, whilst the Scottish data refers solely to local authority renters. There is a marked difference in levels of homogeneity between the urban and rural areas, as has been identified with many of the previous variables. However, it is visually greatest for the RLA AEs and IACs. Those Districts with low IACs and AEs, such as South Norfolk, the South East of England, Rutland and Corby, along with those in the Lake District are all in relatively rural Districts, or Districts that have large rural areas within them. As with all the other variables discussed, the higher incidences of the AEs and IACs occur within the more urban Districts around Manchester, Newcastle and Birmingham. The Scottish AE again relates differently to the English and Welsh AEs due to the population size differences, resulting in the scale effect in the Scottish data appearing lower. However, in terms of the IACs, the within-area homogeneity is relatively high in Scotland against that of much of England and Wales as the differences in populations has been accounted for, and the values are directly comparable. Furthermore, according to the IACs, the scale effect in

Scotland will be relatively severe. Within England, as with the OO data, those Districts that exhibit relatively high or low AEs also exhibit relatively high or low IACs respectively. Again this suggests comparability between the AE and IAC measures.

4.3.2. AEs and IACs at the Ward Level

As with the ED level AEs and IACs presented above, the Ward level data for the eight variables presents a story of the scale effect in the UK Census data. As has been noted above, the population sizes of the Ward level data in England and Wales and Scotland are of similar magnitudes, and therefore, it is expected that there will be fewer observable differences between the Scottish and the English and Welsh data. It is expected that, in general, the overall pattern will be that the AEs are larger than have previously been observed, as the scale effect between the individual level and the Ward level is greater as the change in scale of analysis is greater. However, as the extent of the Wards is greater, then it is also expected that the IACs observed for the Ward level will be lower than observed above, as the levels of within-area homogeneity should be lower. This is the case in almost all cases, with a number of exceptions. These occur in the NONW, and employment variables, as well as with LLTI and CAR0 for the English Districts of Districts of Bath, Wokingham, North Devon, North and East Dorset and Ogwr, Wales.

4.3.2.1. A60P

Overall, the Ward level AEs measured for the A60P variable would be expected to be greater than observed for the A60P variable at the ED level. Table 4.9 demonstrates that this is the case, as the mean of the AE is greater. The IACs also are as expected and are lower than observed at the ED level, demonstrating that the Wards in Districts have lower within-area homogeneity than observed in the ED data. This is expected, as Wards are larger spatial entities, comprising a number of EDs, and thus it is likely that there will be some examples that exhibit lower homogeneity. Similarly, the overall AE is greater for the Wards, denoted by the higher AE maximum, whilst the maximum IAC is lower than observed in the ED data. For both measures, the Coefficient of Variation is greater. This demonstrates that the overall distribution for the A60P variable at the ward level has more variation within the range of observed values.

Measure	AE	IAC
Mean	77.5836	0.0162
Coefficient of Variation	0.7107	1.0948
Minimum	10.1695	0.0012
Maximum	514.9961	0.1789

Table 4.9: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on A60P at the Ward level.

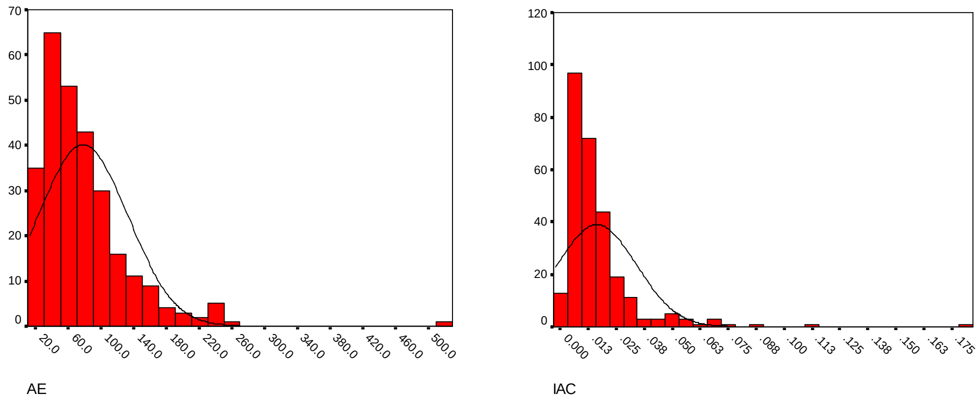


Figure 4.17: Histogram of A60P at the Ward level, with normal curve fitted.

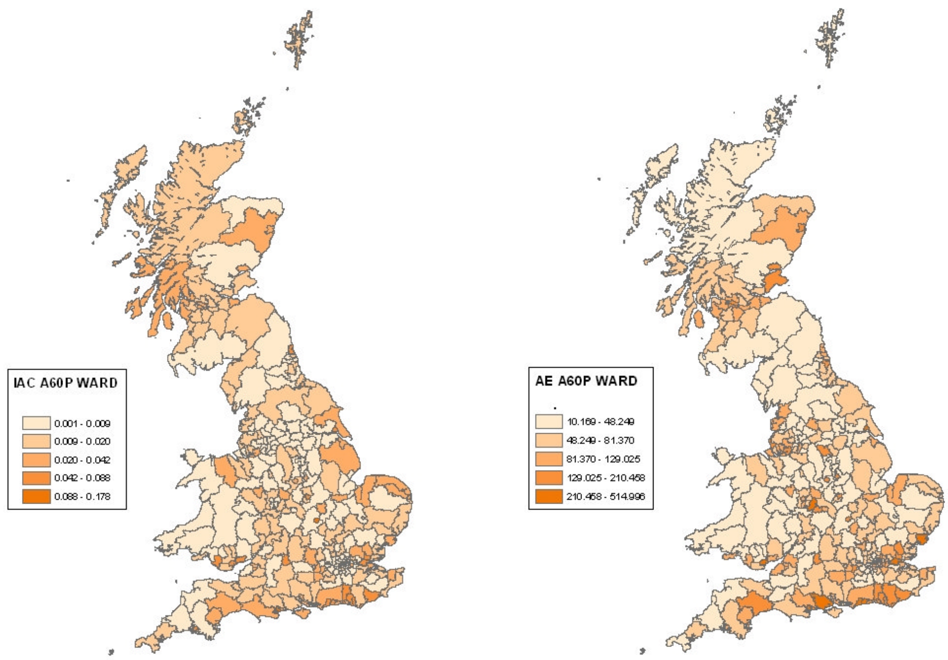


Figure 4.18: AEs and IACs for A60P over all UK aggregating between ED and Ward level.

As with the ED level data, the histograms in figure 4.17 demonstrate a positively skewed distribution, with large tails suggesting a large number of outliers. In both the AE and IAC distributions, there are two outliers, both of which make the distribution appear significantly more skewed than would be the case if they were omitted. For the AE the outliers are Birmingham, Kingston-Upon-Hull, Poole and Renfrew. The highest observation for the IAC measure is also the Poole District and Birmingham, Kingston-Upon-Hull, New Forest and Thurrock are also outliers.

Figure 4.18 presents the distribution of the measures for the A60P variable at the Ward level plotted upon a District map of the UK. An initial comparison of the two measures, the AE and the IAC demonstrate that there is much less difference between the patterns described by the two measures at this level. This is as expected. The urban to rural differences observed at with the ED level measures remain, with the major urban centres of London, Birmingham, Manchester and Newcastle in England, along with Cardiff and Swansea in Wales and Glasgow in Scotland, clearly visible as Districts with relatively high homogeneity in the A60P variable. There is also what can be termed a coastal effect, with areas of high homogeneity in many coastal Districts, especially on the South coast of England. These are all places with large proportion of over 60s in the population and can be characterised as retirement areas. However, there are some differences between the two measures. For instance, the North West has higher IACs than AEs, suggesting that there is relatively high within-area homogeneity in the Districts of the Lake District, in the A60P variable. The other noticeable trend from the IACs is that many of the smaller Districts have the highest IACs for the A60P variable. Many of these will be in the urban areas. This pattern is especially true in the South of England.

4.3.2.2. NONW

At the ED level, the NONW variable had the most severe scale effects. This is again the case at the Ward level. There the mean AE and IAC are greater than are observed for any other Districts, whilst the maximum IAC value observed is greater than has been observed for any other variable at the Ward level. However, this maximum, of 0.48 observed in the SAR District of Braintree and Uttlesford, Essex, is lower than the maximum observed at the ED level. The proportion of the NONW variable in

Braintree and Uttlesford is 1.31% demonstrating a low proportion, which although low is not the lowest proportion in the UK (Kincardine and Deeside with 0.9%). However, the NONW population is highly concentrated in a few Wards within the District, confirming its presence as an outlier with a high IAC. Again this confirms that the maximum level of within-area homogeneity at the Ward level is lower than at the ED level, which given the size of the population in the zones is as would be expected. There is a wide variation in values, denoted by the high coefficients of variation. These have the greatest magnitude observed for all variables, at all levels of analysis, and as they are greater than 1 demonstrate that the standard deviation is greater than the mean denoting high variability.

Measure	AE	IAC
Mean	358.8392	0.0388
Coefficient of Variation	2.2483	1.6603
Minimum	1.6413	0.0001
Maximum	7623.096	0.4814

Table 4.10: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on NONW at the Ward level.

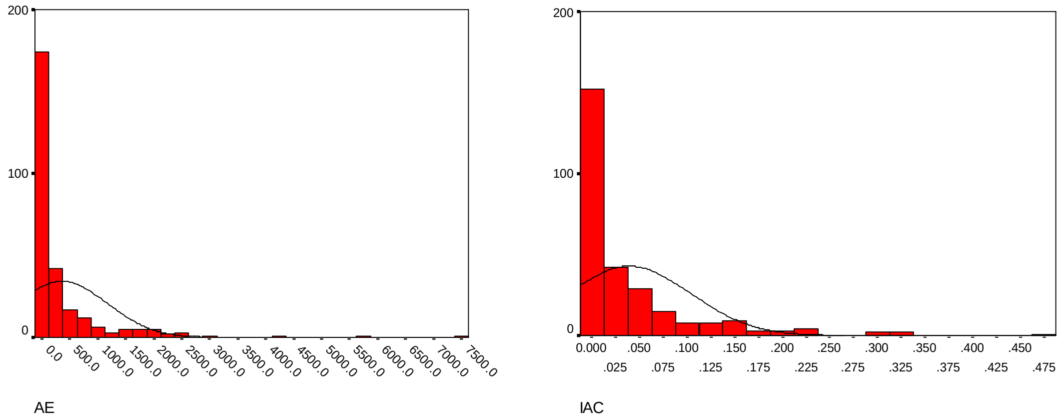


Figure 4.19: Histogram of NONW at the Ward level, with normal curve fitted.

Figure 4.19 confirms the analysis of the distribution above. The histograms of both AE and IAC demonstrate distributions that are positively skewed and non-normal. There are a number of obvious outliers for both the AE and IAC, although the population adjusted IACs have a larger spread of values along the tail, denoting a less clustered distribution. The outliers for the AE are the Districts of Birmingham, Basingstoke and Dean (Hampshire), Bradford (West Yorkshire), and Leicester, all places where the common perception is a high proportion of non-whites in the population, and where the non-white population there is likely to be highly clustered.

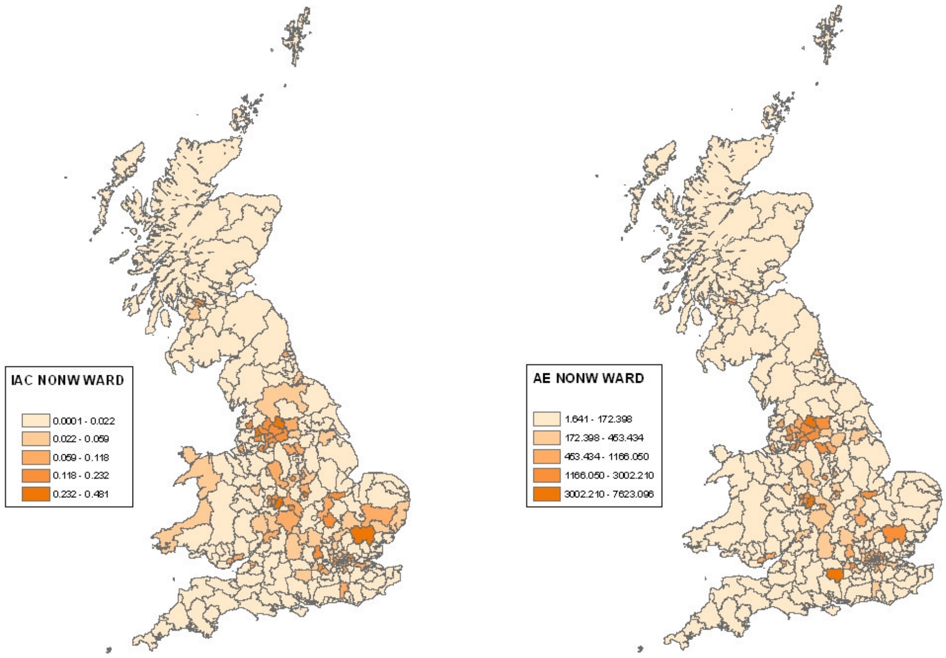


Figure 4.20: AEs and IACs for NONW over all UK aggregating between ED and Ward level.

For the IACs, the outliers are the Braintree District (Essex), Leicester, Birmingham, Blackburn (Lancashire) and Sheffield. There are two notable facts concerning the two measures. Firstly, the Bradford District which exhibits a high value for the AE does not have such a severe value for the IAC, and whilst most of the AE and IAC outliers are areas with high proportions of non-whites (Leicester has the 9th highest proportion, Birmingham the 17th highest, Bradford 29th highest, and Blackburn the 33rd highest), the IAC outlier of Braintree (174th out of the 278 Districts), does not have a high proportion.

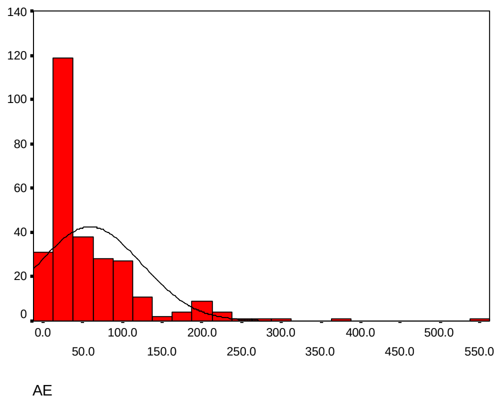
The spatial distributions of the AEs and IACs are presented in figure 4.20. The pattern depicted by both measures is similar to that observed in the measures for the ED level data. Although this is an expected result, it does not necessarily follow that Districts with relatively high or low measures at one spatial scale should have similar magnitudes of measures at a different scale. It is notable in both the AE and IACs that there are few Districts with relatively high levels of homogeneity and incidence of the scale effect. However, there are some large changes in the magnitude of the scale effect for some of the Districts. For example, the District of Trafford, Manchester, has a high, outlier AE for NONW between the Individual and ED level, (119.41) whilst the AE between the ED and Ward level is 1891.19 which is in the centre of the distribution, and does not represent an outlier position. For NONW, much of the UK is dominated by the lower levels of homogeneity. However, there are clusters of higher level of within-area homogeneity (measured by the IACs), which are observed in Districts in more urban areas. For instance, the only District in Scotland with an IAC greater than the lowest group (0.0001 to 0.022) is the District of Glasgow. Therefore, at the Ward level, the NONW variable, which represents the proportion of the population who belong to ethnic groups other than white does not form a homogeneous group. This could, as with the results at the ED level, be a consequence of a low proportion. The West coast of Wales does not fit with the urban trend, as it is a fairly rural area, yet the IACs are as high as those observed in the more urbanised Districts surrounding Cardiff and Swansea. The West coast of Wales is not highlighted as an area with higher scale effects using the AE measure. The IACs and AEs provide similar information for both the Districts with relatively low or relatively high incidences of the scale effect. However, those Districts with scale effect measures in the mid-point of the distribution, such as the Welsh West coast, or the Southern section of East Anglia with higher IACs do not appear in the distribution of the AEs. This suggests that for the NONW variable, the AEs are sufficiently able to identify the extreme low or high cases of the scale effect, whereas the IAC is able to identify not only these extreme cases, but also those areas that fit within a general range of scale effect magnitudes.

4.3.2.3. EMP

The EMP variable at the ED level had relatively low AE and IAC values. This is the case at the Ward level also. The levels of the AEs and IACs are much lower than was observed in the NONW variable, and therefore it is possible to conclude that the relative magnitude of the scale effect will be lower. However, the mean (seen in table 4.11) for both the distributions is clearly skewed positively as the mean magnitudes for both measures is closer to the minimum observed AE and IAC than to the mid-point for either distribution. The coefficients of variation for AE and IAC, although lower than observed for the NONW variable, are still greater than 1. Again, this describes a distribution that has a high degree of variability. The range of values confirm this to be true. The minima for the EMP variable are low for both measures. This suggests that there are some Districts that will exhibit little scale effect, and are highly heterogeneous at the local level. The two lowest Districts for both measures are North Devon with Torridge (in Devon) and South Northamptonshire. However, reference to the histograms in figure 4.21 demonstrates that these Districts are not outliers. Both the AE and IAC measures are skewed positively and non-normal, with outliers skewing the distribution at the higher magnitudes. In the AE measure there are three outliers. These Birmingham, Bradford and Oldham. The highest IAC value occurs in the Middlesbrough District, with Newport (Gwent, Wales), Kingston-upon-Hull, Leicester, Derby, Plymouth and Luton completing the outlier set.

Measure	AE	IAC
Mean	58.9613	0.0099
Coefficient of Variation	1.1057	1.0538
Minimum	2.4481	0.0004
Maximum	542.9118	0.0779

Table 4.11: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on EMP at the Ward level.



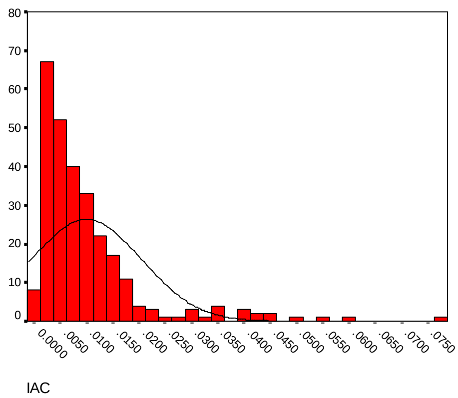


Figure 4.21: Histogram of EMP at the Ward level, with normal curve fitted.

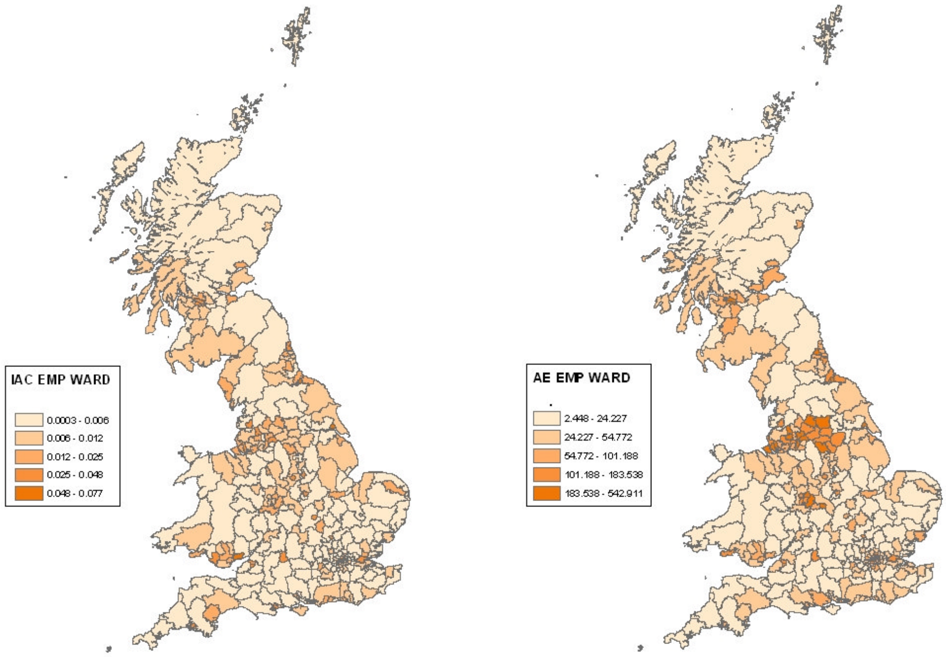


Figure 4.22: AEs and IACs for EMP over all UK aggregating between ED and Ward level.

Figure 4.22 presents the Ward level IACs and AEs for the EMP variable. As with the ED level measures, the AEs and IACs for the EMP variable exhibit far greater spatial dispersion than the concentration observed in the measures for the NONW variable discussed above. As with the measures for the previous variables there is an urban to rural divide within the values obtained. However, it is not as clear as with some other variables, such as those representing tenure. Whilst the highest values of both the IACs and AEs are observable in urban Districts, there are also relatively high IACs observable in more rural areas. For instance, both Dumfries and Galloway in the Scottish borders and the District of Allerdale and Carlisle in Cumbria can be considered as rural, despite the fact that they have reasonable urban centres within them. However, they exhibit relatively high AEs and IACs.

In Scotland, the West coast, with the exception of the Highlands and Islands has relatively high AEs and IACs for the employment variable, suggesting that there is relatively high within-ward homogeneity in the distributions of the level of employment within the Districts in this area of Scotland. The only other Districts in Scotland with relatively high observed IACs and AEs are those of the urban centres, including Edinburgh, Aberdeen and Dundee. There is a similar pattern in the magnitudes of the IACs and AEs in England and Wales. There is a high degree of similarity between the distributions of the two measures, with values that are high for the IAC measure also appearing to be high for the AE measure. This is true for the Districts surrounding Manchester, and the North East around Newcastle. In the Midlands the majority of the Districts also remain similar between the two measures, although the Districts contain Stafford and Congleton show a fall in the magnitude of the measure from the AE to the IAC. This is also the case on the South coast of England, where the Districts of Christchurch along and the New Forest demonstrate a fall in the magnitude of the scale effect, indicated by the AE and IAC measures. There are numerous other examples of this process between the two measures. However, in all examples, the changes appear to only affect those Districts that have mid-point values in the range associated with each measure. The relative extremes of the two measures remain constant with those Districts with relatively high magnitudes of the AE also exhibiting relatively high magnitudes for the IACs, and vice versa.

4.3.2.4. UNEMP

The second employment variable is UNEMP, the proportion of people who are unemployed. Table 4.12 presents the key statistical summary of the distribution at the ward level. It is clear from the table that the magnitude of the scale effect will be lower in comparison to the magnitude of the scale effect in the EMP variable presented above, as the mean and maximum values are lower. The minimum observed value of the AE is also lower than was observed for the EMP variable. However, the minimum observed value for the IAC is not lower. The lowest value for the AE occurs in the Tower Hamlets District, London. The lowest IAC value occurs in the South Ham, West Devon District. The Tower Hamlets District has the second lowest value for the IAC, whilst the South Ham, West Devon District has the third lowest AE value. The coefficients of variation are again relatively high, especially in comparison to the coefficients observed at the ED level for the UNEMP variable. For both the AE and the IAC they are of similar magnitude, and greater than one. This implies that the standard deviation is greater than the mean, indicating that there is a high degree of variability in the scale effect measures for the UNEMP variable. Reference to the histograms in figure 4.23 demonstrates that the distribution is highly positively skewed, supporting the evidence in the Coefficient of Variation. As before there are a large number of Districts with both high AEs and IACs that appear as outliers. These values will have a large effect on measures such as the Coefficient of Variation making the distribution appear more skewed than it is for the majority of the Districts. The outliers in the AE measure are Birmingham, Bradford and Sheffield. The biggest outlier for the IAC measure is Plymouth. The Districts of Derby, Kingston-Upon-Hull, Leicester, Plymouth, Preston and Newport also have values that could be considered outliers.

Measure	AE	IAC
Mean	37.8977	0.0065
Coefficient of Variation	1.0776	1.0513
Minimum	3.6388	0.0003
Maximum	305.6109	0.0526

Table 4.12: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on UNEMP at the Ward level.

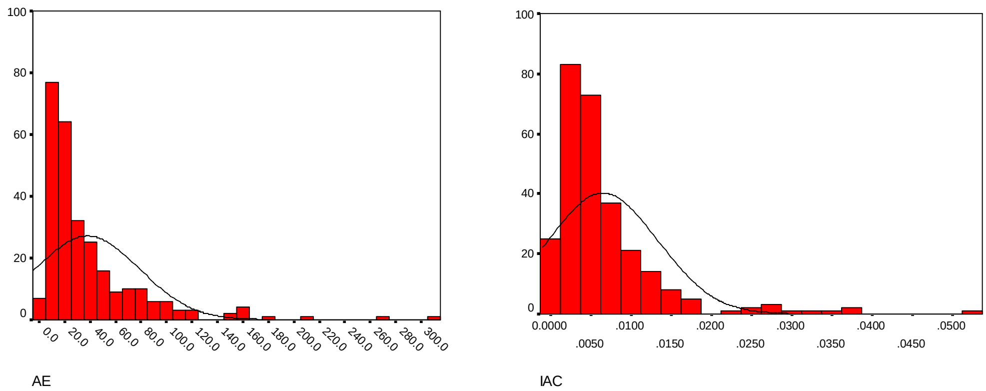


Figure 4.23: Histogram of UNEMP at the Ward level, with normal curve fitted.

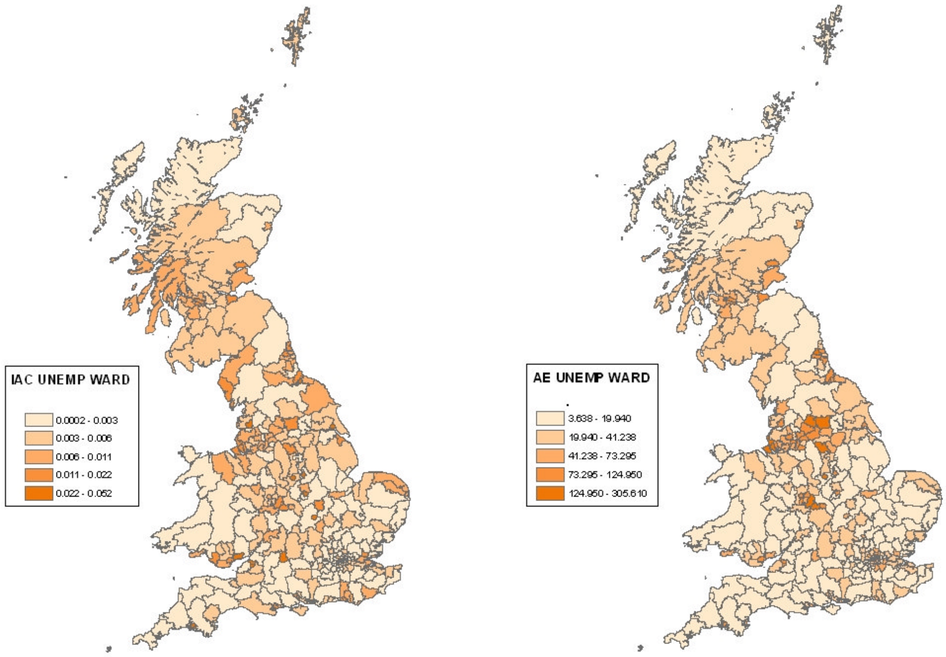


Figure 4.24: AEs and IACs for UNEMP over all UK aggregating between ED and Ward level.

The spatial distribution for the UNEMP variable is presented in figure 4.24. Again the overall pattern of the both the AE and IAC measure is of a dispersed distribution. There are clustered areas of high and low magnitudes of the scale effect, and as with the other variables at both scales there is a visible difference between those Districts that could be considered as urban, and those that could be considered as rural. This distinction is more pronounced with the AE measure than with the IAC measure, where there are more relatively high values of IAC in the more rural Districts, Unlike the previous discussions where there has been a high degree of similarity between the IAC and AE magnitudes for each variable, there are marked differences in England and Scotland, although the Districts in Wales appear relatively stable. The majority of the change appears in the Midlands of England, with only two Districts changing relative magnitude in Scotland. Districts such as the Broadland (Norfolk) and Great Yarmouth (Norfolk), Lincoln and surrounds, along with Walsall and other West Midlands Districts all demonstrate an observable increase in the magnitude of the scale effect between the AE and IAC measures. Other Districts, such as Sedgefield in the North East, and Colchester and Southend-on-Sea demonstrate a fall in the magnitude of the predicted scale effect between the AE and the IAC measures.

Therefore, it is not possible to determine that there is a definitive expected change between the two measures, and whereas before the Districts with value at the extreme tails of the range, the lowest and highest magnitudes, have remained in the same groupings between the variables, this is not the case for the UNEMP variable. In the case of UNEMP only those Districts with relatively high values have remained unchanged between the two measures.

4.3.2.5. LLTI

At the Ward level, the IACs for LLTI are much lower than they were at the ED level. This is as expected as the Ward areal units are much larger and more likely in general to include different sorts of areas. The LLTI variable has the lowest incidence of the scale effect with the lowest observed means and maximum values, of all the variables (see table 4.13). The minimum is not the lowest of the variables. The small range of the distribution is reflected in the relative values observed for the Coefficient of Variation for both the AE and IAC measure. In both cases it is lower than one, indicating relative stability in the distribution in comparison with the other distributions discussed above.

Measure	AE	IAC
Mean	34.2128	0.0064
Coefficient of Variation	0.6688	0.8941
Minimum	5.2980	0.0007
Maximum	147.9873	0.0420

Table 4.13: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on LLTI at the Ward level.

The SAR Districts with relatively high IACs at the ED level tend to exhibit relatively high IACs at the Ward level as well. However, there are some notable differences. Firstly, in Scotland Renfrew tends to have scale effects, which are amongst the highest in the country, as is the case for Glasgow. However, areas such as Perth and Kinross and the Highlands show less within-area homogeneity. This would suggest that the processes that contribute to the scale effect do not occur with the same strength at the Ward level as they do at the ED level. This could be a reflection that the boundary definition is such that it does not reflect the processes, as with potential rural to urban influences. In Wales, where the IACs were not as high, there are now a number of SAR Districts that exhibit high IACs, with a similar magnitude to the highest areas in Scotland and England, although this is still lower than the IAC value in the highest category for the ED level analysis. This suggests that for these areas in Wales, there is high within-area homogeneity at the Ward Level. The Coefficient of Variation for the LLTI variable at the Ward level is greater than that observed at the ED level. In other words, the Ward level IACs for LLTI have a greater degree of variability from the mean IAC value for LLTI. However, the Ward level LLTI IAC Coefficient of Variation is lower than all the other coefficients of variation present in the analysis, showing that the amount of variation in the IACs for LLTI is relatively low.

The histograms in figure 4.25 demonstrate that, as with the other histograms discussed the distributions of the AE and IAC measures are positively skewed, and do not have a normal distribution. The distribution is positively skewed for both variables by the influence of a number of outliers with high values. These outliers are in Sheffield, Liverpool Leeds and Wakefield, in the North of England along with Renfrew and Dunfermline in Scotland. There are a greater number of outliers in the IAC distribution. These are Middlesbrough, Newport, Northampton, Preston, Oldham, Ogwr, Mid Glamorgan, Blyth Valley, and Plymouth (Devon).

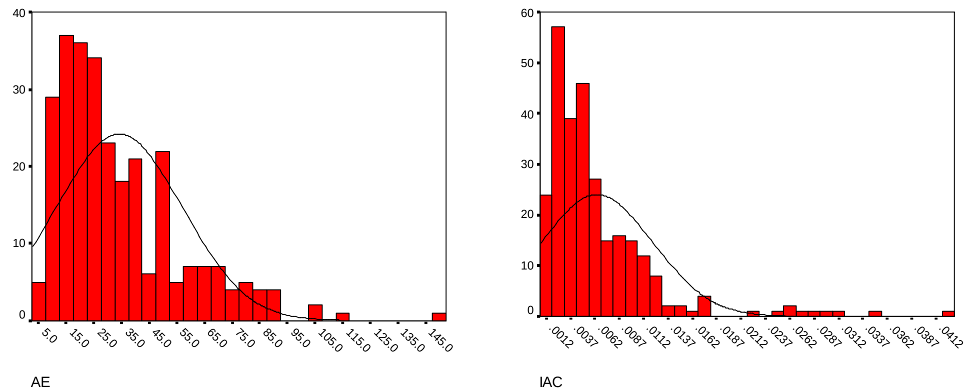


Figure 4.25: Histogram of LLTI at the Ward level, with normal curve fitted.

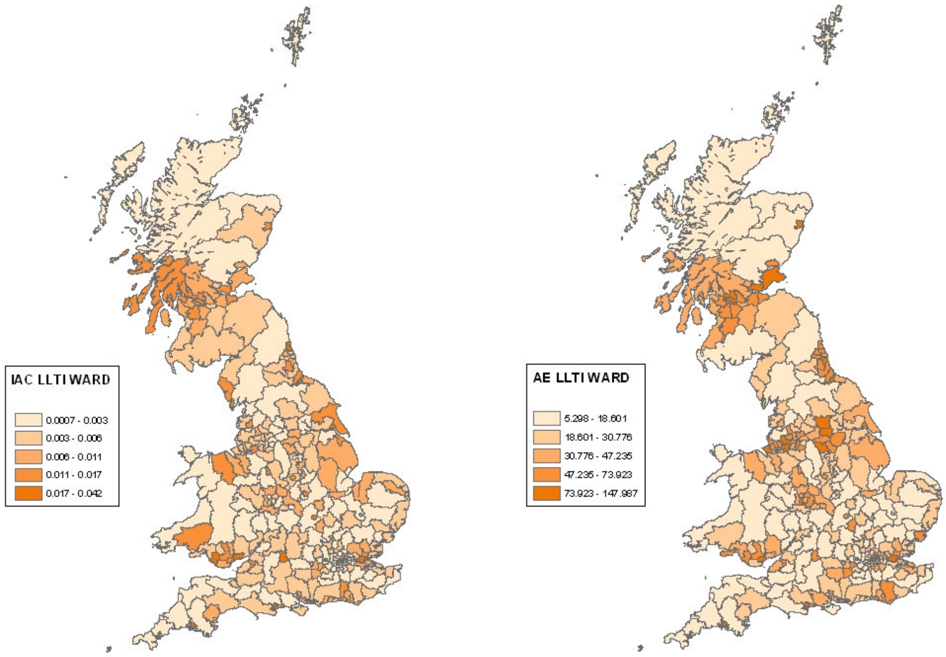


Figure 4.26: AEs and IACs for LLTI over all UK aggregating between ED and Ward level.

The LLTI variable, in figure 4.26, reinforces the patterns described above. In England and Wales, the clear urban to rural split is evident. The Scottish data do not conform to this pattern, with many of the Southern Districts in Scotland exhibiting relatively high values for both the measures. Therefore, it is possible to conclude for Scotland that with the exception of the Highlands and Islands areas (two Districts), Banff, and Perth and Kinross, there is relatively high within-area homogeneity (from the IAC measure). However, this is relative within the LLTI variable. In comparison with the other variables discussed in the Chapter, the IACs and AEs and not high, and therefore the overall assessment of the scale effect for the LLTI variable is that it will not be severe, as there is little homogeneity to be observed.

England and Wales demonstrates the urban to rural split. The urban Districts in Wales, such as those around Cardiff and Swansea, exhibit high levels in both the IAC and AE measure, whilst central Wales, which is much more rural, exhibits lower values for the two measures. This is also true in England, with the IACs and AEs for the urban areas, such as Manchester, Birmingham, and Newcastle being relatively high. The Southern coast Districts such as Poole, Bournemouth, and Southampton and those Districts in the built up areas of the South West of England also have relatively high IACs and AEs for the LLTI variable. The more rural areas in England, such as South Lakeland, North Yorkshire, South Norfolk and North Suffolk, and the Districts in Hereford and Worcester all exhibit relatively low AEs and IACs. Some of the other Districts in the rural areas demonstrate a change in the magnitude in the scale effect measures. For instance, the Districts in Oxfordshire all show an increase in the relative rank position of the scale effect prediction between the AE and the IAC. Therefore, the measures in England and Wales for the LLTI variable demonstrate less stability, through the presence of greater IACs than has been observed for some of the other variables such as A60P or the employment variables. However, it is still possible to identify Districts that will be relatively susceptible to the scale effect (using the AE) and that have relatively high within-area homogeneity (using the IAC).

4.3.2.6. CAR0

The percentage of the population without access to a car was highlighted above as a variable that had a relatively high incidence of the scale effect, and that had relatively high levels of within-area homogeneity at the ED level of aggregation. This is also the case with the CAR0 data when aggregated to the Ward level. The AE measure exhibits greater incidence of the scale effect as both the mean and maximum observed values for the CAR0 distribution are greater than has been observed in the previous variables (see table 4.14).

Measure	AE	IAC
Mean	372.4324	0.0677
Coefficient of Variation	0.9050	0.9063
Minimum	57.6865	0.0063
Maximum	2313.962	0.4631

Table 4.14: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on CAR0 at the Ward level.

The IAC, which is adjusted for areal unit population size demonstrates that there are lower levels of within-area homogeneity than, were observed at the ED level. This indicates by the overall lower values observed in the mean and overall maximum. The same pattern is observed with the minimum values, whereby the minimum observed for the AE is greater than that observed for the ED level AE, whilst the IAC is lower than that observed for the ED IAC. This demonstrates the difference in information conveyed by the two measures, and the effects of the population adjustment. The AE provides a rough indication of the scale effect and its likely relative magnitude, whilst the IAC provides an indication of the level of within-area homogeneity. The Coefficient of Variation is relatively large for both distributions, and is greater than observed at the ED level. The fact that it is close to 1 indicates that the mean and standard deviation are similar suggesting a highly variable distribution.

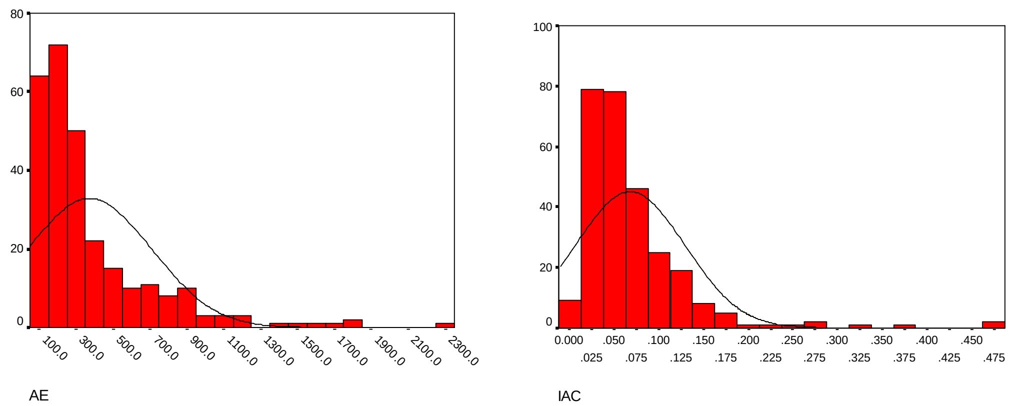


Figure 4.27: Histogram of CAR0 at the Ward level, with normal curve fitted.

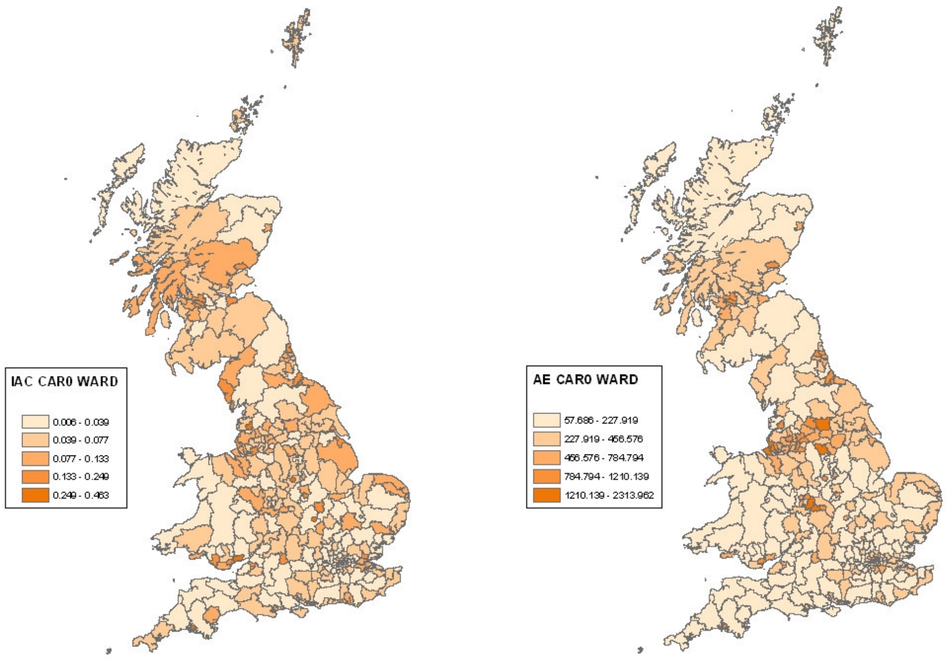


Figure 4.28: AEs and IACs for CAR0 over all UK aggregating between ED and Ward level.

The histograms in figure 4.27 demonstrate that the distribution is positively skewed and non-normally distributed. Therefore, the high coefficients of variation observed could be explained by the presence of a number of outlier values, which result in a long tail for the distribution. The biggest outlier value for the AE distribution is the Sheffield District, South Yorkshire. Derby, Sefton and the Wirral are the other AE outliers. The outliers in the IAC distribution occur in Derby, Newport, Preston, Middlesbrough, Plymouth, and Northampton. It is notable that all these districts have been identified as outliers in previous variable analyses.

The CAR0 variable exhibits a highly dispersed pattern using the two measures, and the urban to rural split previously observed in other variables and at other scales is not obviously visible in the maps shown in figure 4.28. In comparison with the other variables discussed above, CAR0 exhibits one of the largest ranges of IAC and AE values. Therefore, there is a greater range of potential magnitudes of the scale effect within the CAR0 data. There are also greater pockets of high within-ward homogeneity. The adjustment of the data through the IACs in comparison to the AEs is clearly visible, some Districts that have relatively low AEs appear to have relatively high IACs after adjustment. This is the case for the District of Corby and Kettering, which has an AE of 311.2, which falls in the second group for the AE. However, the IAC for the District is 0.136, which lies within the top grouping for the IAC measure.

4.3.2.7. OO

The last two variables presented report tenure information for the Districts. The first of the tenure variables is the percentage of the population living in owner occupied housing. As with the ED level analysis, the Ward level tenure variables exhibit high values for both the AE and the IAC measures. The AE measure is consistently greater than was observed at the ED level, with the minimum, maximum and mean values all showing an increase in magnitude. However, this does not imply that Districts where the highest AEs were observed at the ED level will also have the highest AEs at the Ward level. For instance, the greatest ED AE was observed in Wigan. At the Ward level, the Wigan District has the 49th highest AE. Conversely, the highest AE at the Ward level is observed in the Leeds District, whilst at the ED level the Leeds District were 15th in the distribution. The coefficients of variation are relatively high for this

Measure	AE	IAC
Mean	622.1152	0.1136
Coefficient of Variation	0.8506	0.9125
Minimum	25.3171	0.0020
Maximum	3094.7810	0.7230

Table 4.15: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on OO at the Ward level.

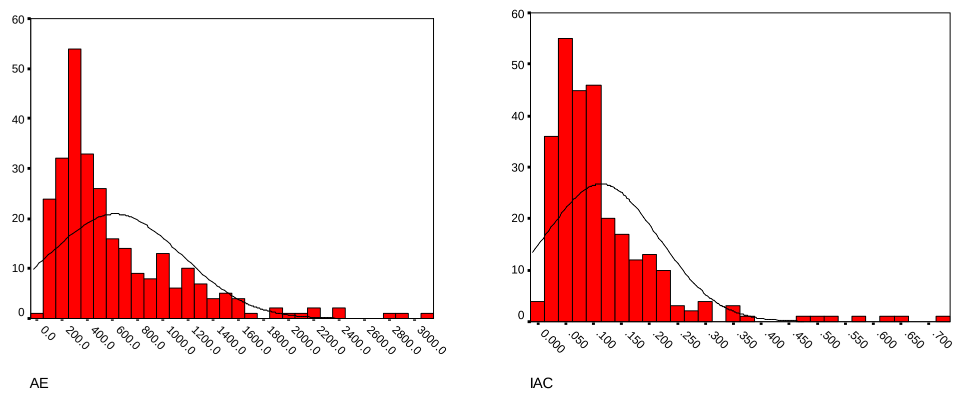


Figure 4.29: Histogram of OO at the Ward level, with normal curve fitted.

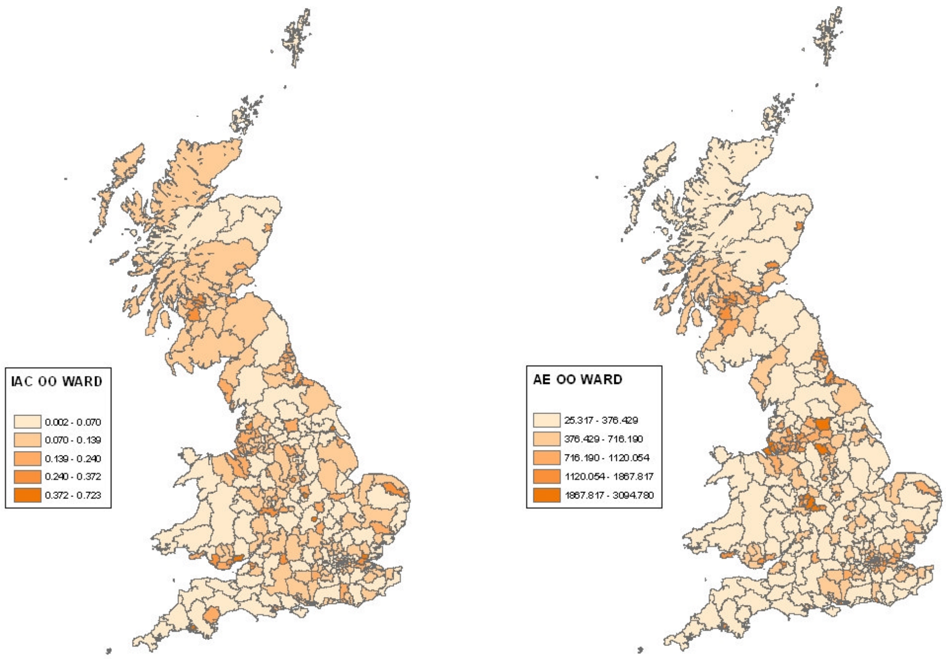


Figure 4.30: AEs and IACs for OO over all UK aggregating between ED and Ward level.

variable, as with the CAR0 Ward level variable. They are close to 1 demonstrating that the standard deviation and the mean are similar in magnitude. This suggests that the distribution is likely to be skewed. Reference to the histograms in figure 4.29 demonstrates that this is the case, and both the AE and IAC are positively skewed, and do not follow the normal distribution, unlike the OO (and RLA) variable at the ED level. This demonstrates that there are more outliers in the OO data at the Ward level and as a result there are some areas of very high homogeneity. This may reflect the fact that, at the Ward level the processes operating in the tenure data are matched by the boundaries of the Wards (this issue is discussed further in Chapter 7). It is possible to identify a group of outliers for both distributions that contribute to the high values of the coefficients of variation and the skewed nature of the histograms. As was noted above, the highest AE is observed in the Leeds District. The other outliers for the AE measure are Leeds, Sheffield, Portsmouth, Kingston-upon-Hull, Liverpool and the Wirral. The IAC distribution also exhibits outliers. These are the Districts of Basildon, Leicester, Newport, Plymouth, Kingston-upon-Hull, Middlesbrough and Northampton, all within England. For the IAC, the first Scottish District is Bearsden and Milngavie in East Dunbartonshire.

Figure 4.30 depicts the maps for the two measures. In comparison with the magnitude of the measures observed at the ED level, both the Ward level AEs and the IACs are greater, although the position of the Districts in the distribution has changed. For instance, many of the Scottish Districts appeared to have the most severe scale effect for the UK in this variable at the ED level in both measures. This pattern is not replicated with the Ward level data, and the Scottish data does not have high scale effect using the AE measure, in comparison with some of the higher magnitude areas in England and Wales. The urban to rural split in the data is less pronounced in the OO Ward level measures, although it is still possible to highlight a number of Districts that contain the largest urban centres, such as Manchester, Birmingham and Newcastle. The major difference between the AEs and IACs can be observed in the changes between values in what can be defined as the semi-rural Districts in England. For instance, the District containing Great Yarmouth and the surrounding rural areas of Norfolk, along with many of the other rural Districts exhibit lower AEs. This suggests that these Districts would not be highly susceptible to the scale effect. However, this is not the case when the IAC variable is mapped. Using this measure for the OO variable it can be suggested that the scale effect is more severe in England. However, the values are still relatively low in comparison to the IACs observed in other less rural Districts in the UK.

4.3.2.8. RLA

The second of the two tenure variables is the RLA variable. The measures are presented in table 4.16.

Measure	AE	IAC
Mean	780.9960	0.1455
Coefficient of Variation	0.8107	0.9293
Minimum	87.3355	0.0093
Maximum	4252.2530	0.9583

Table 4.16: Mean, Coefficient of Variation, Minima and Maxima for the scale effect measures, on RLA at the Ward level.

Again, the incidence of the scale effect, for both the AE and the IAC, is relatively high. The AEs are much larger than those observed at the ED level for the RLA variable, and those observed in the other variables at the Ward level, with the exception of the NONW variable. The mean for the AE is closer to the minimum than the mid-point of the distribution, suggesting that the distribution will be skewed. The maximum observed IAC value is the highest for all the variables discussed, and at 0.95 is very close to complete homogeneity. This occurs in the Plymouth District. The RLA variable is also the only one considered here where the Ward level IACs are greater than those observed at the ED level. For both measures, the Coefficient of Variation is relatively high, describing a distribution that is likely to have a high degree of variability, or long tails with outliers. Reference to the histograms in figure 4.31 demonstrates that this is the case. Unlike the ED level data, neither the AE distribution, nor the IAC distribution reflects the normal distribution, as both are positively skewed. This concurs with the low means, and confirms that both distributions have long tail with outliers. Both distributions have a number of clearly identifiable outliers. For the AE measure, the two greatest outlier districts are the Districts of Portsmouth and the District of Sheffield. The other outliers with high AEs include Kingston-upon-Hull, Solihull, The Wirral, Leeds, Liverpool, Birmingham and

Manchester. The identifiable outliers within the IAC distribution are the Districts of Plymouth as noted above, Middlesbrough, Newport, Thamesdown, Kingston-upon-Hull, Northampton and Leicester.

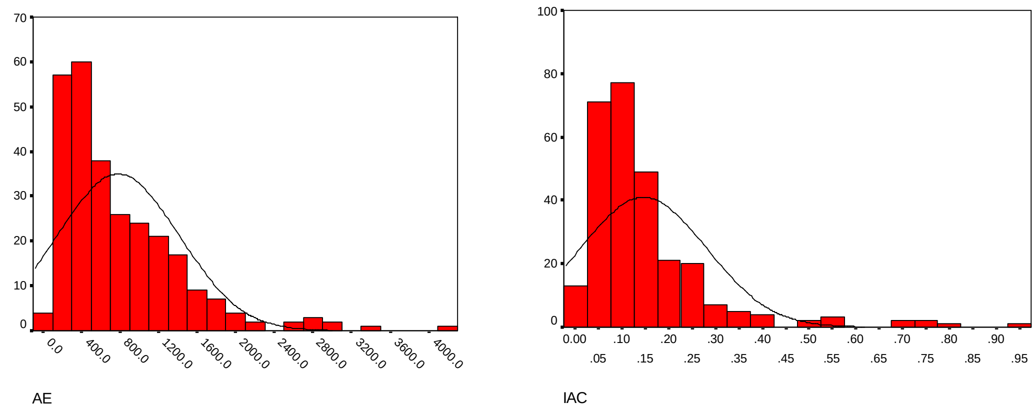


Figure 4.31: Histogram of RLA at the Ward level, with normal curve fitted.

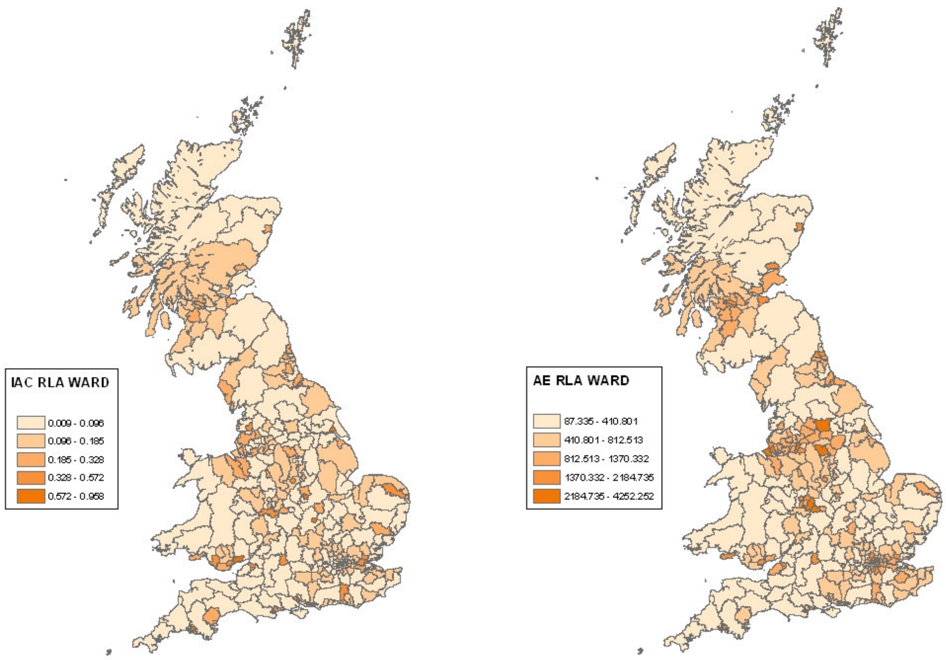


Figure 4.32: AEs and IACs for RLA over all UK aggregating between ED and Ward level.

Figure 4.32 displays the AEs and IACs for the UK at the Ward level. As with the other tenure variable (see figure 4.30), the overall pattern described by figure 4.32 demonstrates a more dispersed distribution of measures in comparison to the ED level RLA measures, and also the OO ED level variables. Within the AE measure, it is possible to identify the urban to rural split that has been discussed previously.

However, it is not as clearly marked with the RLA variable measures. Whilst the highest values of the AE appear in the urban areas, such as central London, Birmingham, Manchester, and Newcastle the semi-rural and more rural Districts that surround these areas also exhibit relatively high values for the AE measure. The highly rural Districts, such as those in Devon and Cornwall, the Western coast of Wales, and the North of England, along with those on the English and Scottish boarders all exhibit relatively low levels of AEs. This pattern remains constant when the AEs are compared to the IACs. However, there are a number of Districts (such as Macclesfield, Congleton, or Workington) that demonstrate a change in the relative magnitude of the incidence of the scale effect when the IAC measure is used. For instance, the Districts around Manchester have relatively high AEs, including the Districts between Manchester and Birmingham. Using the IAC measures these Districts do not have such relatively high incidence of the scale effect, and demonstrate lower than expected levels of within-area homogeneity. The overall lower incidence of the scale effect and lower levels of within-area homogeneity are to be expected, as the histograms (figure 4.31) demonstrate that there are high concentrations of AEs and IACs with lower values of AE and IAC. The high incidence values discussed only occur in a few Districts. Therefore, although there are high incidences of the scale effect and Districts with high within-area homogeneity, they are relatively uncommon for the RLA variable, the overall distribution of the RLA variable demonstrating relatively low incidences of the scale effect and low within-area homogeneity.

4.3.3. The scale effect between EDs and Wards

The sections above have compared the scale effect between individual level data (represented through the SAR) and aggregate level data (represented through either EDs or Wards). However, the scale effect also occurs when the level of analysis changes between two aggregate levels. It is not possible to present the IAC measure for the assessment of changes between aggregate levels, as the definition of the IAC requires individual level data. However, this is not the case with the AE. Therefore, the section below discusses the scale effect for the eight variables between the ED and Ward level using the AE measure.

4.3.3.1. A60P

Of the AEs presented so far, those providing an indication of the magnitude of the scale effect between the ED and Ward would be expected to be the lowest. This is due to the fact that the change in scale between the ED and Ward is less than the change in scale between the individual and ED, or the individual and Ward. This is demonstrated to be the case with the A60P variable. Table 4.17 demonstrates the key statistical measures for the A60P variable. In comparison to the measures for A60P presented above, the mean is relatively low, suggesting that there is relatively little incidence of the scale effect when aggregation changes between the ED and Ward levels. The minimum value of 0.8 (observed in the Clackmannan and Stirling District in Scotland) is much lower than has been observed in the other A60P measures, and indicates relative stability. The maximum of 16.1 (observed in the Kirkcaldy and North Fife District, in Scotland) is also relatively low. However, the Coefficient of Variation is greater than has been observed for the A60P variable at the other scales. This suggests that although the overall levels of the AE are lower for aggregation between the ED and Ward, there is a greater degree of variability in the distribution. This is demonstrated by the histogram (figure 4.33). As with all previous distributions, the histogram is positively skewed and does not reflect a normal distribution. The skewedness, and the high Coefficient of Variation, is demonstrated by the presence of a number of outliers, with relatively high AEs. The outliers are Kirkcaldy (Scotland) as already described, along with Birmingham, Poole, Glasgow City and Cunninghame (Strathclyde). It is notable that the Districts within Scotland demonstrate higher AEs at this scale than has previously been the case. For both the previous scales of measurement, the Scottish AEs have been relatively low. This suggests that the ED to Ward aggregation process produces a greater magnitude of scale effect than is present in the English and Welsh data. Considering the average unit sizes for the two regions, this is not a surprising result, as the Scottish EDs are substantially smaller than those in England and Wales, whilst the Ward units for both areas are of a relatively similar size.

Measure	AE
Mean	3.6708
Coefficient of Variation	0.5494
Minimum	0.8000
Maximum	16.140

Table 4.17: Mean, Coefficient of Variation, Minima and Maxima for the AE on the A60P variable.

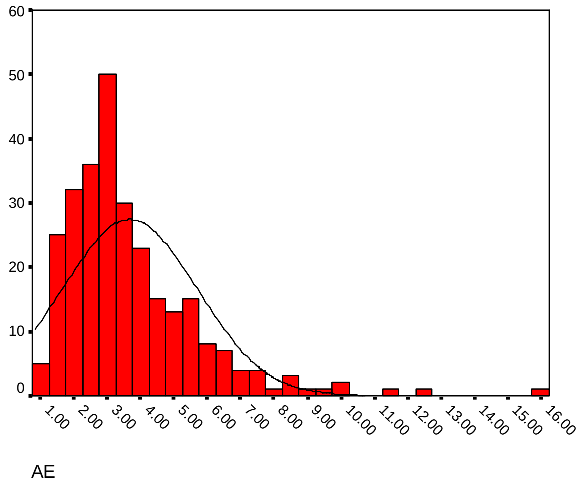


Figure 4.33: Histogram of the AE between ED and Ward for A60P.

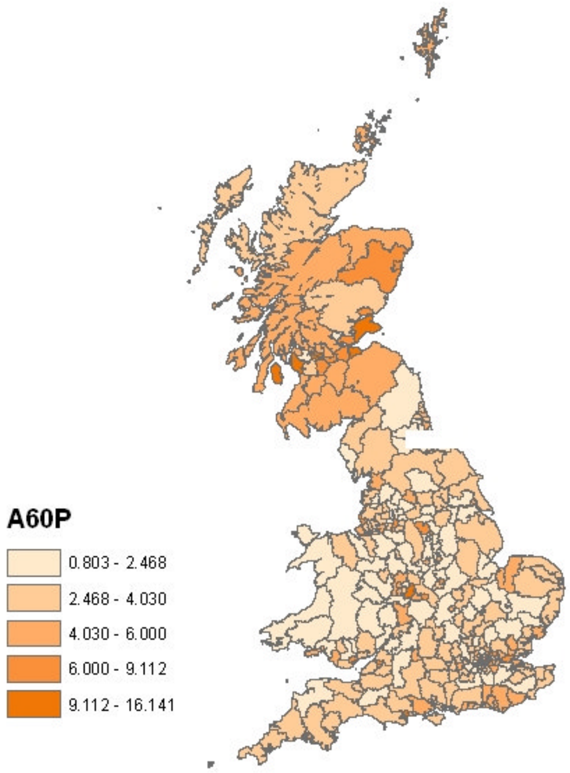


Figure 4.34: AEs for A60P for the UK between the ED and Ward levels.

Figure 4.34 maps the AE measure for the A60P variable. It is possible to identify that many of the higher AE values occur in the Districts in Scotland. The urban to rural split, identified in the previous discussions is less clearly visible for this AE. However, it remains the case that some of the highest values of the AE are to be observed in London, Birmingham, the Manchester area, and Newcastle. However, some rural Districts, such as North Norfolk, Cornwall, Devon as well as North Wales also demonstrate some relatively high AE values. The lowest AE values are observed in the Districts of the counties of Powys (Wales), Buckinghamshire, Leicestershire and Northumberland (all in England). There are relatively high magnitudes of the AE in the South coast areas of England also. It is interesting to note that the areas identified as outliers in the previous discussions for the A60P variable, as well as the general pattern is not reflected in the magnitudes of the scale effect measures here. Therefore, the processes and influences that cause high scale effects between the individual level data and an aggregate level are not the same as those between two aggregate levels, in the case of the A60P variable.

4.3.3.2. NONW

In the previous discussions, the NONW variable has had the lowest and greatest magnitudes of for all the variables. The minimum is not the lowest observed in this section. The maximum is far greater than is observed for any of the other variables discussed. Therefore, the NONW variable is the variable most severely influenced by the scale effect in the analysis. The mean of 9.82 and the maximum of 562.6 suggest that it the distribution of the AE is skewed positively. This is demonstrated to be the case in the histogram (figure 4.35).

Measure	AE
Mean	9.8244
Coefficient of Variation	4.1918
Minimum	0.8800
Maximum	562.64

Table 4.18: Mean, Coefficient of Variation, Minima and Maxima for the AE on the NONW variable.

This is the case, as almost the whole distribution is accounted for in the first two bars of the histogram. Considering the actual data, the skewedness of the distribution, and the excessively high Coefficient of Variation can be explained. Of the 278 District, 276 have values under for the AE measure under 40. The remaining two Districts, Basingstoke and Dean (Hampshire) and Braintree (Essex) have AEs of 562 and 402 respectively. This clearly makes them outliers on the distribution. It is worth noting that these Districts were also highlighted as outliers in the NONW AE analysis at the Ward level.

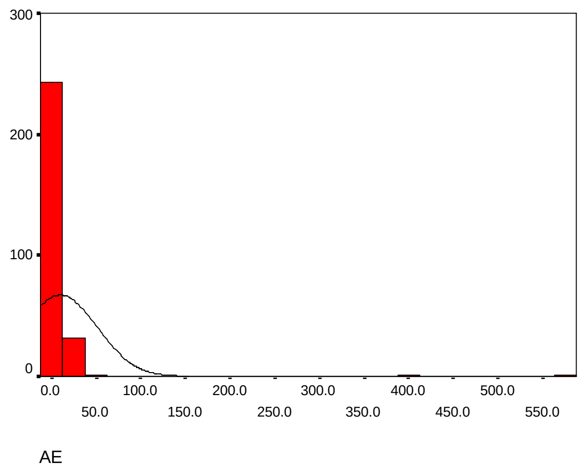


Figure 4.35: Histogram of the AE between ED and Ward for NONW.

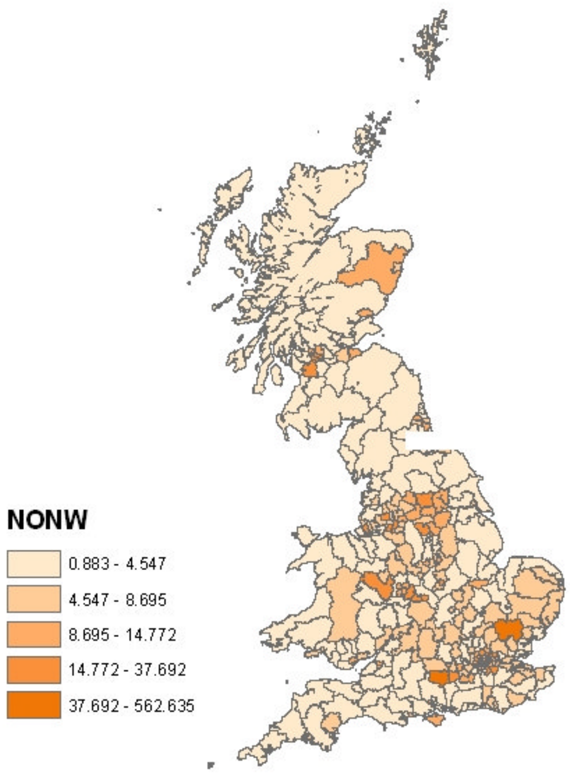


Figure 4.36: AEs for NONW for the UK between the ED and Ward levels.

Figure 4.36 demonstrates the spatial distribution of the AEs across the UK. Unlike the previous figures, it is not possible to provide wide generalisations regarding the distribution of the magnitudes of the AE. Indeed, England appears like a chessboard, suggesting that the distributions have a highly dispersed spatial nature. It is possible to identify the major urban areas, as before, with higher AEs. The more rural Districts, such as those in Devon and Cornwall, and the North of England along with the Scottish Boards all have lower AEs, as would be expected. The central area of England has higher levels of AE, suggesting that central England would exhibit a relatively high degree of scale effect in analysis of the NONW variable. The high levels of scale effect appear to be associated with Districts that would be expected to have very high or very low proportions of non-white residents. This again supports the suggestion that the scale effect is linked to the level of homogeneity in an area.

4.3.3.3. EMP

The EMP variable has shown relatively low incidences of the scale effect. The AE values in table 4.19 demonstrate this to be the case for this change in aggregation. The distribution measures, the mean, minimum and maximum suggest a distribution that has relatively low scale effect, although there are a number of Districts that can be considered as outliers as the mean is substantially below the maximum. All of the values are below those observed for the aggregation between the individual and the ED and the individual and the Ward. This is as expected.

Measure	AE
Mean	4.6052
Coefficient of Variation	0.6794
Minimum	0.6300
Maximum	23.980

Table 4.19: Mean, Coefficient of Variation, Minima and Maxima for the AE on the EMP variable.

The histogram (figure 4.37) demonstrates that the distribution is positively skewed, and although it does not reflect the normal distribution there is a spread of values throughout the distribution. This is confirmed by a Coefficient of Variation of 0.6, which indicates that the standard deviation is less than the mean, indicating a relatively low range. However, there are a number of outliers in the distribution, where there are districts with high AEs. These Districts are Birmingham and Glasgow City. It is notable that neither of these Districts were identified by the previous analysis with the EMP variable.

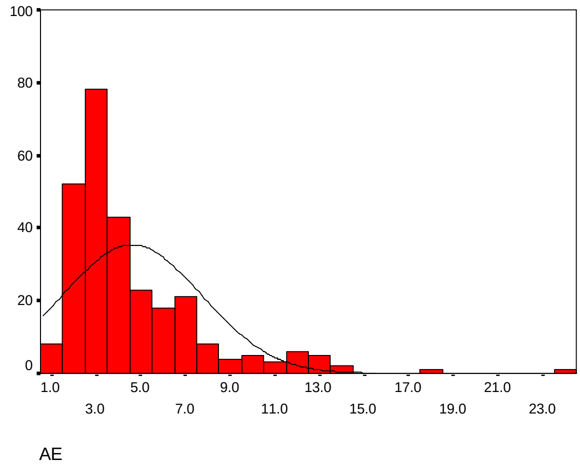


Figure 4.37: Histogram of the AE between ED and Ward for EMP.

Figure 4.38 maps the AEs for the UK Districts. There is a clear urban to rural divide again with the AEs. However, this is not the case for all of the Districts. For instance,

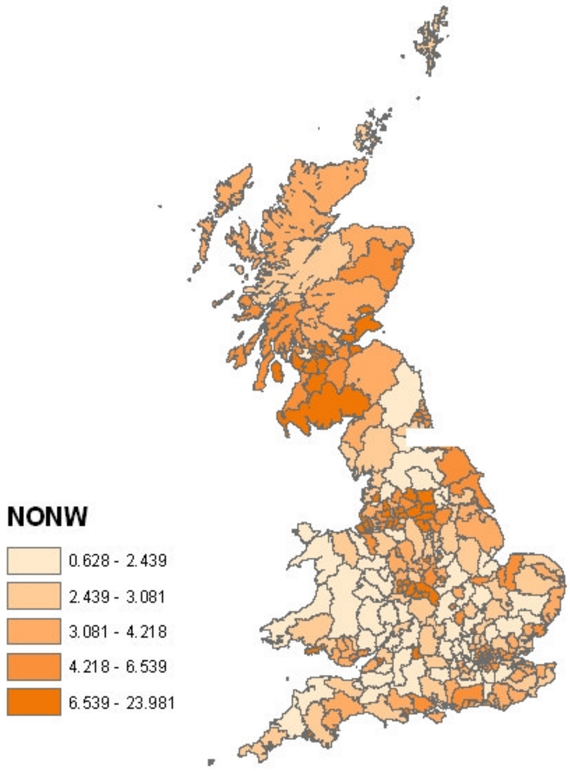


Figure 4.38: AEs for EMP for the UK between the ED and Ward levels.

the Districts in Norfolk have higher AEs than would be expected given that they are relatively rural in their composition. This can be contrasted with the Districts in Suffolk, a very similar county that has much lower AEs except in the coastal Districts. These can be considered as having a different composition however, as the rural coast of Suffolk, and Norfolk, have a strong tourism base, which may influence the employment structures of the areas. In Wales, the AEs are low, with the exception of those observed in the urban Districts such as Swansea and Cardiff. As would be expected, the AEs for these Districts are larger in magnitude. As before, the Scottish data has some of the highest AE in the UK. With the exception of Falkirk and the Shetlands and Orkney Islands, all of the Districts in Scotland have AEs that fall within the top three Quintiles. This suggests, as would be expected, that the scale effect between the EDs and Wards in Scotland is relatively severe. This contrasts with the relatively low magnitude of the scale effect observed for Scotland when individual level data are compared to ED level data.

4.3.3.4. UNEMP

The second unemployment variable, UNEMP, also has relatively low scale effects. The mean of the distribution is 5.9, which is higher than was observed between the individual and ED level ($\overline{AE}$ = 5.5), but is lower than was observed between the individual and Ward levels ($\overline{AE}$ = 37.8). The minimum is greater than has been observed for the other variables above. Therefore, the distribution is relatively tight, although there are clearly outliers as the Coefficient of Variation is still relatively high at 0.6. The mean is again substantially lower than the maximum observed value for the AE, and this suggests that the distribution will be positively skewed.

Measure	AE
Mean	5.9348
Coefficient of Variation	0.6393
Minimum	1.1100
Maximum	24.130

Table 4.20: Mean, Coefficient of Variation, Minima and Maxima for the AE on the UNEMP variable.

Reference to the histogram (Figure 4.39) demonstrates this to be case. The histogram demonstrates that there are a number of outliers for the UNEMP variable that are influencing the distribution. The outliers are the Districts of Birmingham, Dundee City (Tayside, Scotland) and Leeds (West Yorkshire) along with The Wirral, Edinburgh, Kirkcaldy and Sheffield. All three of these Districts can be considered to be urban. Moreover, all three have areas of relatively high unemployment, which may contribute to the high magnitude of the scale effect. This would be the case if they were spatially clustered.

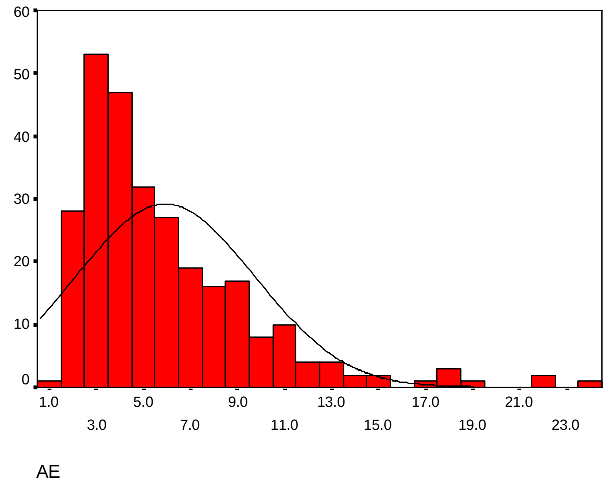


Figure 4.39: Histogram of the AE between ED and Ward for UNEMP.

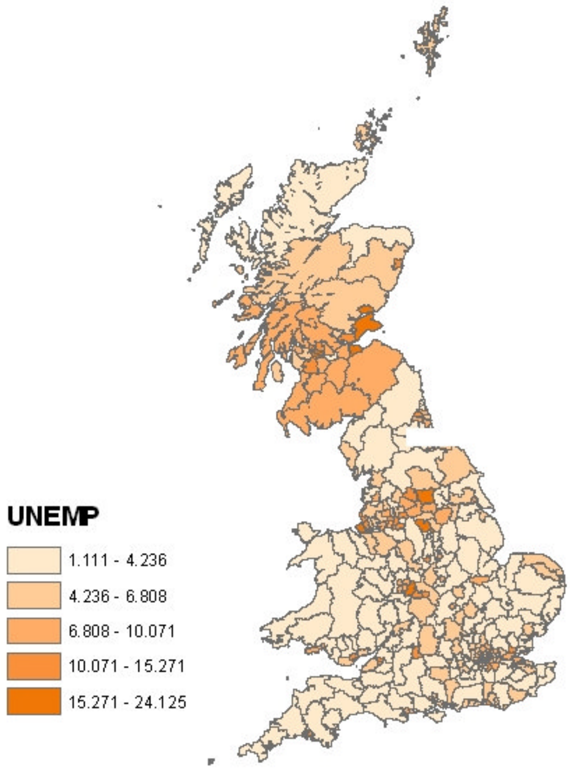


Figure 4.40: AEs for UNEMP for the UK between the ED and Ward levels.

The AEs for the UK spatially present a similar pattern to the previous descriptions. A large proportion of the country has low AEs for the UNEMP variable. Those areas that exhibit high AEs tend to be the urban areas, such as London, Manchester, Birmingham, as well as some of the more urban areas of Scotland such as Edinburgh and Glasgow. Higher AEs are also observed for the urban areas of Wales, such as Cardiff and Swansea. The North of England, with the exception of the urban areas, the rest of Wales, Eastern England and the South West of England all exhibit low AEs, suggesting that the magnitude of the scale effect will not be very high in these areas. Overall Scotland has a higher incidence of the scale effect, as indicated by the AE than England or Wales, and this is as expected, given the change in scale.

4.3.3.5. LLTI

In the previous analysis, the LLTI variable has demonstrated relatively low incidences of the scale effect. When the scale effect is measured between the ED and Ward level aggregations, the scale effect is still low, although in comparison to the other variables discussed at this level of aggregation, it is not substantially lower. In fact, the UNEMP variable above actually displays less scale effect (See table 4.21). The minimum is the highest observed for this section, demonstrating that there are no pockets with the LLTI variable that are relatively unsusceptible to the scale effect. With the exception of the NONW variable, which has been demonstrated to be highly susceptible to the scale effect, the mean AE for LLTI is the highest observed in this section, as is the case for the maximum. Therefore, the LLTI variable, the variable with the least scale effect in the other analyses has the second highest incidence of the scale effect when considering aggregation between the ED and Ward levels.

Measure	AE
Mean	6.7621
Coefficient of Variation	0.6497
Minimum	2.1600
Maximum	27.690

Table 4.21: Mean, Coefficient of Variation, Minima and Maxima for the AE on the LLTI variable

There are a number of outliers identifiable from the histogram (figure 4.41). These are Dundee City (Tayside, Scotland) and Glasgow City (Scotland), Edinburgh, Aberdeen and Eastbourne. It is notable again that, unlike the previous discussions, the outliers for the AEs are in Scotland. Those Districts in England and Wales that frequently appear as outliers in at other spatial scales do not appear as outliers for this distribution. For instance the common outliers of 6th out of the 278 Districts, whilst Leeds, also a common outlier, occurs 7th.

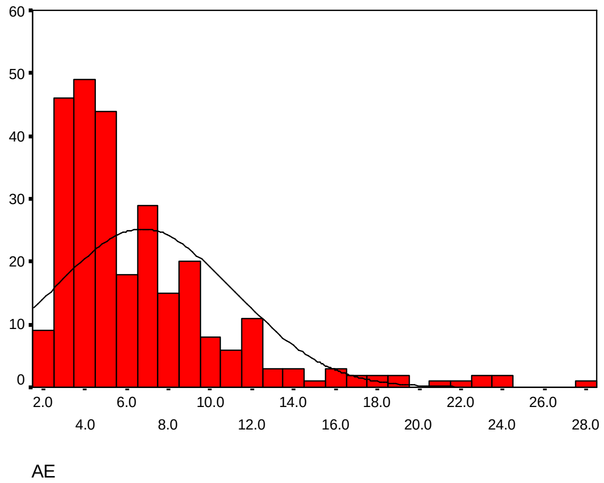


Figure 4.41: Histogram of the AE between ED and Ward for LLTI.

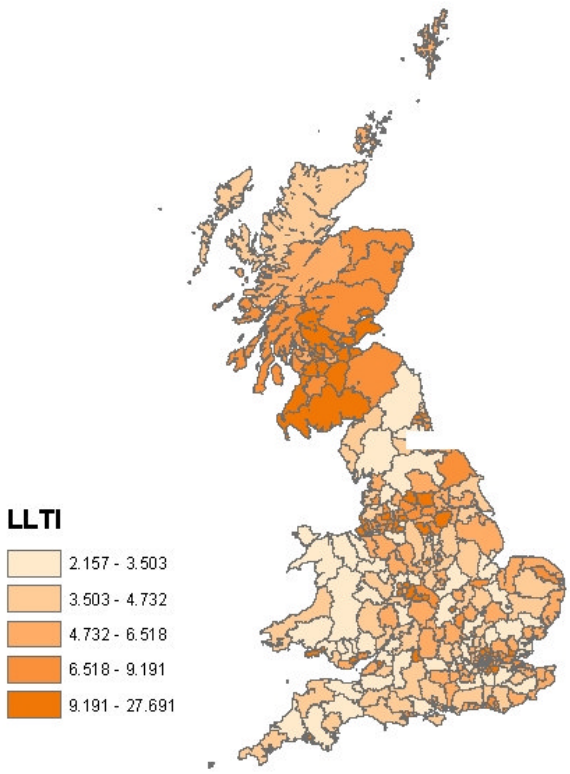


Figure 4.42: AEs for LLTI for the UK between the ED and Ward levels.

Figure 4.42 maps the spatial distribution of the AEs for the LLTI variable. Scotland clearly has a high incidence of the scale effect as none of the Districts has an AE in the lowest quintile. The urban areas, as with the other variables, have relatively high AE. This is the case in the North West around the Manchester District, and also the midlands around Birmingham. The Districts of London do not reflect this pattern, with a number of them, such as Barnet, and Enfield in the north and Bromley and Croydon in the South having AE values in the lowest quintile. Other London Districts, such as Havering or Bexley in the East and Hillingdon in the West demonstrate much higher AE values, and indicate relatively high incidence of the scale effect. The rural areas in the North of England such as Cumbria (excluding the District with Carlisle), rural and central Wales as well as the rural Districts of Devon and Cornwall demonstrate low incidence of the scale effect as well. It is notable that the rural Districts of Norfolk and Suffolk have relatively high incidence of the scale effect, especially those Districts that contain coastal areas.

4.3.3.6. CAR0

The CAR0 variable has low incidence of the scale effect between the ED and Ward level of aggregation (see table 4.22). The mean is not as low as has been observed

Measure	AE
Mean	1.7206
Coefficient of Variation	0.6909
Minimum	0.2900
Maximum	12.12

Table 4.22: Mean, Coefficient of Variation, Minima and Maxima for the AE on the CAR0 variable.

previously (in the EMP or A60P variables for instance). The minimum AE value is the lowest observed for this change in aggregation, as is the maximum. This suggests that the aggregation between the ED and the Ward levels of analysis is relatively free from the scale effect. This is not the same as stating that the aggregation is free from the scale effect. As there are still Aggregation Effects present the scale effect still occurs. This does however serve to highlight the fact the magnitude of the scale effect is highly dependent on the variable that is under analysis. The Coefficient of Variation is again below 1, but greater than 0.5 which suggests a distribution that is relatively stable but that has a number of Districts that are outliers.

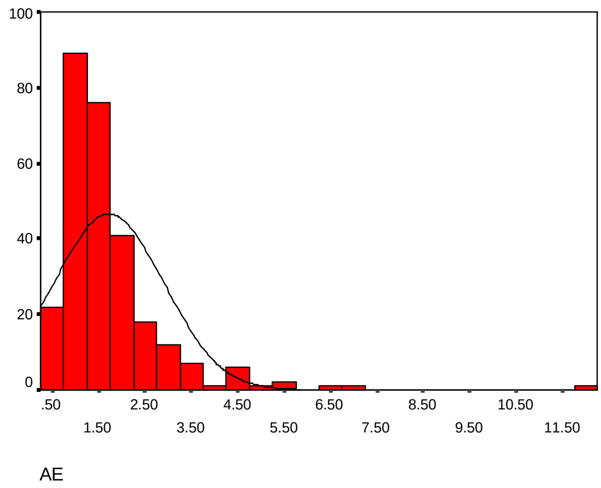


Figure 4.43: Histogram of the AE between ED and Ward for CAR0.

Reference to the histogram (figure 4.43) enables the identification of an outlier Districts at the extreme of the distribution. This District is Bearsden, (Strathclyde, Scotland). The other outliers are Aberdeen, Leeds, Sheffield, Edinburgh, Glasgow, and Dundee City. It is notable again that the highest AEs observed in aggregation between the ED and Ward levels are observed in the Scottish data. The highest value in the English and Welsh data is for the Brighton District and lies 6th out of 278 Districts. The value of the AE is less than half that observed in Aberdeen City.

The high values observed in Scotland can clearly been seen in figure 4.44. With the exception of the Highlands and Islands Districts, the Scottish Districts all have AEs greater than the base quintile, suggesting relatively high scale effect. However, the scale effect in these Districts is still low as the overall distribution of AEs for the CAR0 variable is low. As has already been discussed above, there is the urban to rural split in the AEs, with the urban areas generally exhibiting higher AEs than the rural areas. London has a range of values, with the Districts in the North, North East and South West exhibiting higher AEs than those in the North West and South East of London.

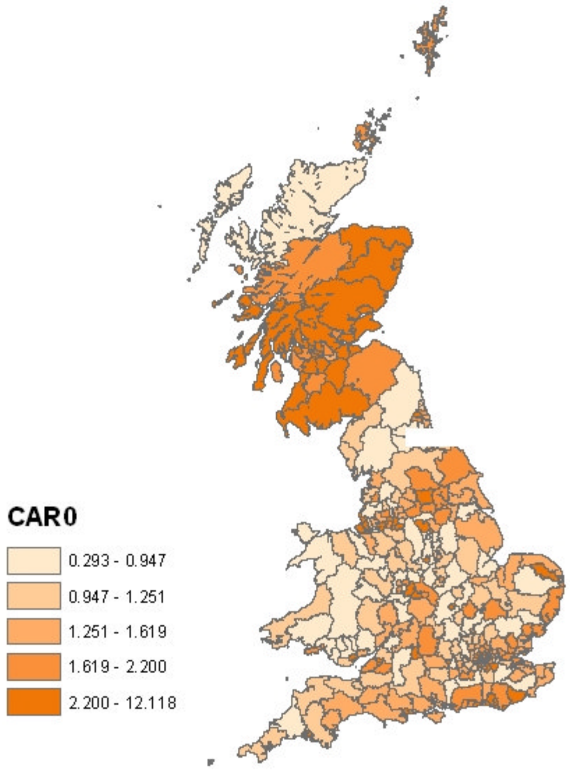


Figure 4.44: AEs for CAR0 for the UK between the ED and Ward levels.

4.3.3.7. OO

After the NONW variable the tenure variables of OO and RLA have demonstrated the highest incidence of the scale effect within the AE measure. This continues to be the case, although for the aggregation between the ED and Ward the CAR0 variable is also greater than those reporting tenure. The mean of 5.3 is the third greatest at this level, whilst the minimum and the maximum are also the third highest. For this aggregation change, therefore the OO has relatively severe scale effect. However, in

Measure	AE
Mean	5.3758
Coefficient of Variation	0.7492
Minimum	1.28
Maximum	25.35

Table 4.23: Mean, Coefficient of Variation, Minima and Maxima for the AE on the OO variable.

comparison to the changes in aggregation observed above, the AE has relatively low incidence of the scale effect, in line with the other variables considered here.

Moreover, although the range of values is relatively high, the distribution is positively skewed, as the Coefficient of Variation (the second highest at this scale) and the histogram (figure 4.45) demonstrate. As before, it is possible to identify a number of Districts that are outliers in the distribution. The outliers are: Aberdeen, Dundee City, Glasgow City, Edinburgh City, Plymouth, Eastwood, and Bearsden. Again, half of the outliers are in Scotland, which in comparison with the other AE measures (individual to ED and individual to Ward) is unusual.

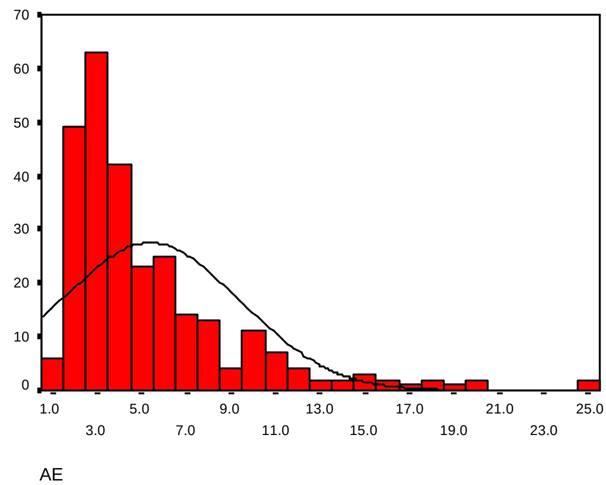


Figure 4.45: Histogram of the AE between ED and Ward for OO.

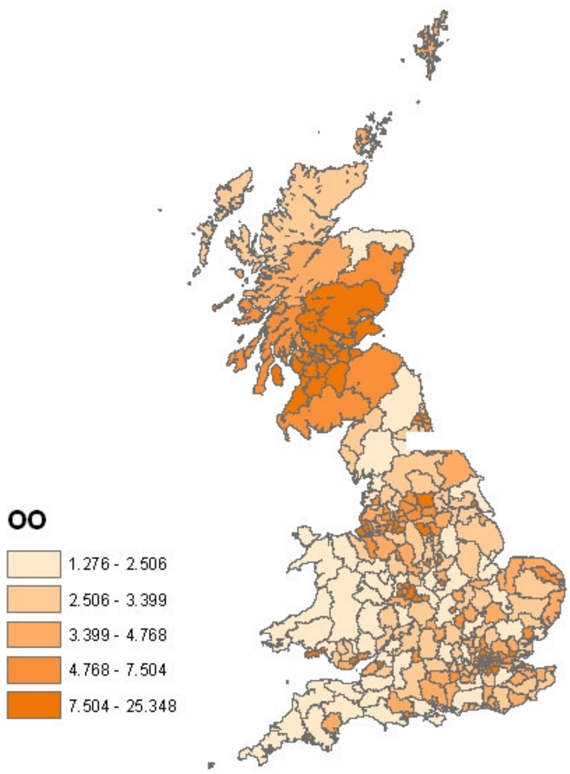


Figure 4.46: AEs for OO for the UK between the ED and Ward levels.

The concentration of higher AEs in Scotland can be observed in figure 4.46. With the exception of Banff District, the Scottish Districts all exhibit AEs that occur in the higher quintiles of the AE distributions. Wales is relatively scale effect free, with only the urban centres of Swansea and Cardiff exhibiting AEs above the base quintile. This is also the case for all of Devon and Cornwall, with the exceptions of the Districts of Plymouth and Exeter, both more urbanised. The other urban Districts, such as Manchester, Birmingham and Newcastle all exhibit relatively high AEs. For the OO variable, the AEs in London are also high, without the North to South or East to West divide that has been observed in the LLTI or CAR0 variable.

4.3.3.8. RLA

The second tenure variable, RLA also exhibits relatively high scale effect, and the AEs are of a similar magnitude to those observed with the OO variable. The mean, minimum and maximum are all of a similar size, as is the Coefficient of Variation. Therefore, the two tenure variables have a distribution for the scale effect that is very consistent. This can be observed in the histogram (figure 4.47), where as before the distribution is positively skewed. There are a number of identifiable Districts which appear as outliers in the distributions. These Districts are Dundee City, Glasgow City, Edinburgh City and Aberdeen City. With the exception of Aberdeen City, these are the same Districts that were outliers with the OO variable.

Measure	**AE**
Mean	5.2885
Coefficient of Variation	0.7410
Minimum	1.22
Maximum	25.43

Table 4.24: Mean, Coefficient of Variation, Minima and Maxima for the AE on the RLA variable.

Figure 4.48 presents the AEs mapped by SAR District. Comparison with figure 4.46, for the OO variable demonstrates that, although the distributions are statistically very similar there are some spatial differences once the data are mapped using quintiles to split the distributions. The London Districts are largely the same, as is the case in

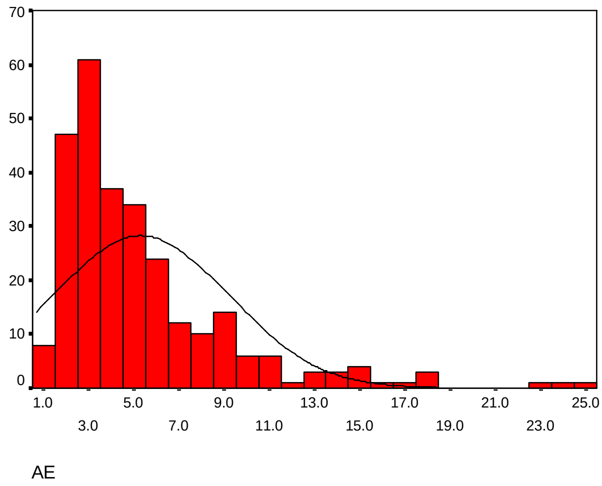


Figure 4.47: Histogram of the AE between ED and Ward for RLA.

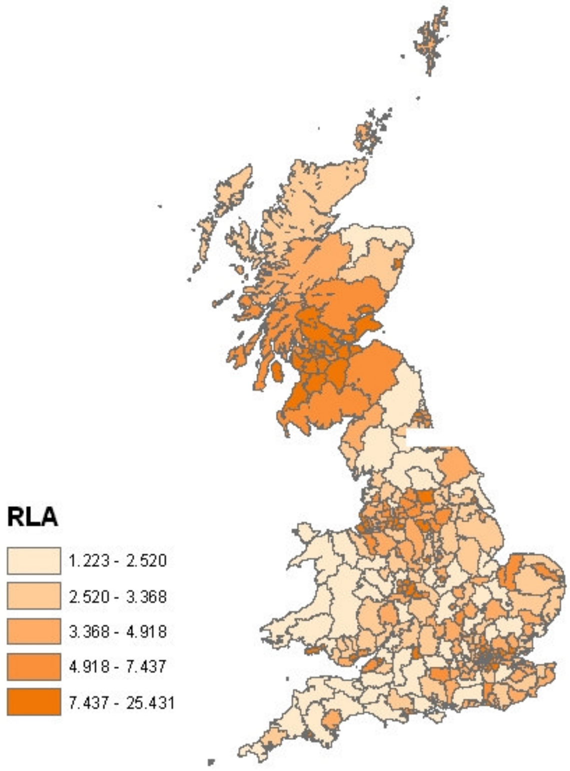


Figure 4.48: AEs for RLA for the UK between the ED and Ward levels.

Devon and Cornwall, although the District of Carrick increases AE with an observation in a higher quintile. The greatest differences between the two distributions can be observed in central England. Although the urban Districts of Manchester and Birmingham maintain relatively high AEs in the top quintile, the Districts surrounding them change AE magnitude. For instance, Staffordshire has an increase in AE, as the recorded quintile changes from the second to the third. Similar, Kesteven (Lincolnshire) increases the magnitude of the scale effect. However, other Districts on the Western side of England, such as such as the Derbyshire Dales or Richmondshire (North Yorkshire) demonstrate a fall in the magnitude of AE and therefore the scale effect. The urban Districts in Wales maintain a high magnitude of AE. However, the more rural Districts of Monmouth increase the incidence of the scale effect in the RLA variable. Therefore a statistically similar distribution such as has been observed for the OO and RLA variable can have a spatially difference distribution, highlighting different trends, and potentially processes. The outliers for the RLA variable are Dunfermline, Plymouth, Aberdeen, Glasgow, Edinburgh and Dundee City.

In all the variables discussed above with AEs between the ED and Ward levels of aggregation, a large number of Scottish Districts have been identified. This is in contrast with the AEs at the other levels. The AEs between the individual and ED levels of aggregation are unlikely to have Scottish outliers as the magnitude of the aggregation between these levels is relatively small in comparison with the magnitude of the aggregation in England and Wales. Likewise, the level of magnitude between the individual and Ward levels is similar for both the Scottish data and the English and Welsh data, therefore meaning that the Scottish data are unlikely to stand out. However, the magnitude of the aggregation between the ED and Ward level is far greater for the Scottish data due to the greater increase in size. The consequences of this are the greater AEs, and the increased incidence of the scale effect. This, therefore, supports the argument that the scale effect is a consequence, not solely of the absolute level of aggregation, be it ED or Ward, but it is also a function of the *change* in magnitude.

4.4. Discussions

Presented above is an overview of the patterns and processes that are identifiable within the scale effect measures of AE and IAC. It is necessarily an overview, and attempts only to identify the key trends within the data as a prior analysis before attempts are made to understand the nature of the scale effect in more depth. Importantly the brief summary presented above shows that there is clearly evidence of the scale effect in UK Census data. For research based on Census data this is an important finding. Hence, we see that use of the IAC enables direct comparisons of the causes of the MAUP across scales. Within the same scale it enables comparison across variables to identify districts with potentially high or low levels of homogeneity. However, it does not provide insight into what factors may influence the incidence of the scale effect and the relative levels of within-area homogeneity, either in terms of the factors that may influence the relative magnitude of the measure, such as the proportion of a given variable, or the population density. Secondly, although it is possible to obtain a value for the within-area correlation, this value describes the District as a whole. Given that there are 278 covering the whole of the UK, the spatial extent of the District is relatively large containing at least 120,000 people (Marsh, 1993, p.305), and therefore, an AE or an IAC will provide a useful, but heavily generalised measure of the scale effect.

The descriptive analysis of the AEs and IACs at the ED level for the UK has demonstrated that there is a great deal of information to be obtained from the two measures. The importance of realising the impacts of differences in the size of populations under analysis is clearly important with the difference between the Scottish and English and Welsh data. Whilst it may not be crucial to ensure that the populations are exactly comparable for a rough analysis where the AEs may suffice, when population sizes within districts are vastly different, as is the case between the Scottish data and the data for the rest of the UK, the IACs are clearly the correct measure to use. The analysis also demonstrates that, although the scale effect within the MAUP is largely unpredictable, it is not the case that there are no trends within the data. Excluding the Scottish case, where many variables are different from England and Wales as the Census units are constructed using different processes at the ED level, the highest magnitudes of both the AEs and the IACs were identified in the Districts relating to the urban areas. Conversely, the lowest magnitudes of the AEs and IACs were frequently observed in those Districts that had a largely rural construction. This suggests that there are important differences in the within-area homogeneity of Districts in the ED constructions in England and Wales, and that these differences in structure have impacts upon the incidence of the scale effect.

Table 4.25 presents a review of all the Districts identified as outliers using the AE measure. It is useful to present all the outliers together in a table, as it identifies a number of Districts that are both frequently outliers within a given measure, and also

	Aggregation Effect 2								Aggregation Effect 3							
	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Basingstoke and Dean																
Blackburn																
Birmingham																
Bradford																
Calderdale																
Dunfermline																
Durham																
Ipswich																
Kingston-upon-Hull																
Kirklees																
Knowsley																
Leeds																
Leicester																
Liverpool																
Middlesbrough																
New Forest																
Oldham																
Preston																
Poole																
Portsmouth																
Renfrew																
Rochdale																
Sefton																
Sheffield																
Solihull																
Thurrock																
Wakefield																
Wirral																

Table 4.25: Positive outlier Districts for the AEs for the aggregation between the individual and ED and the individual and Ward level.

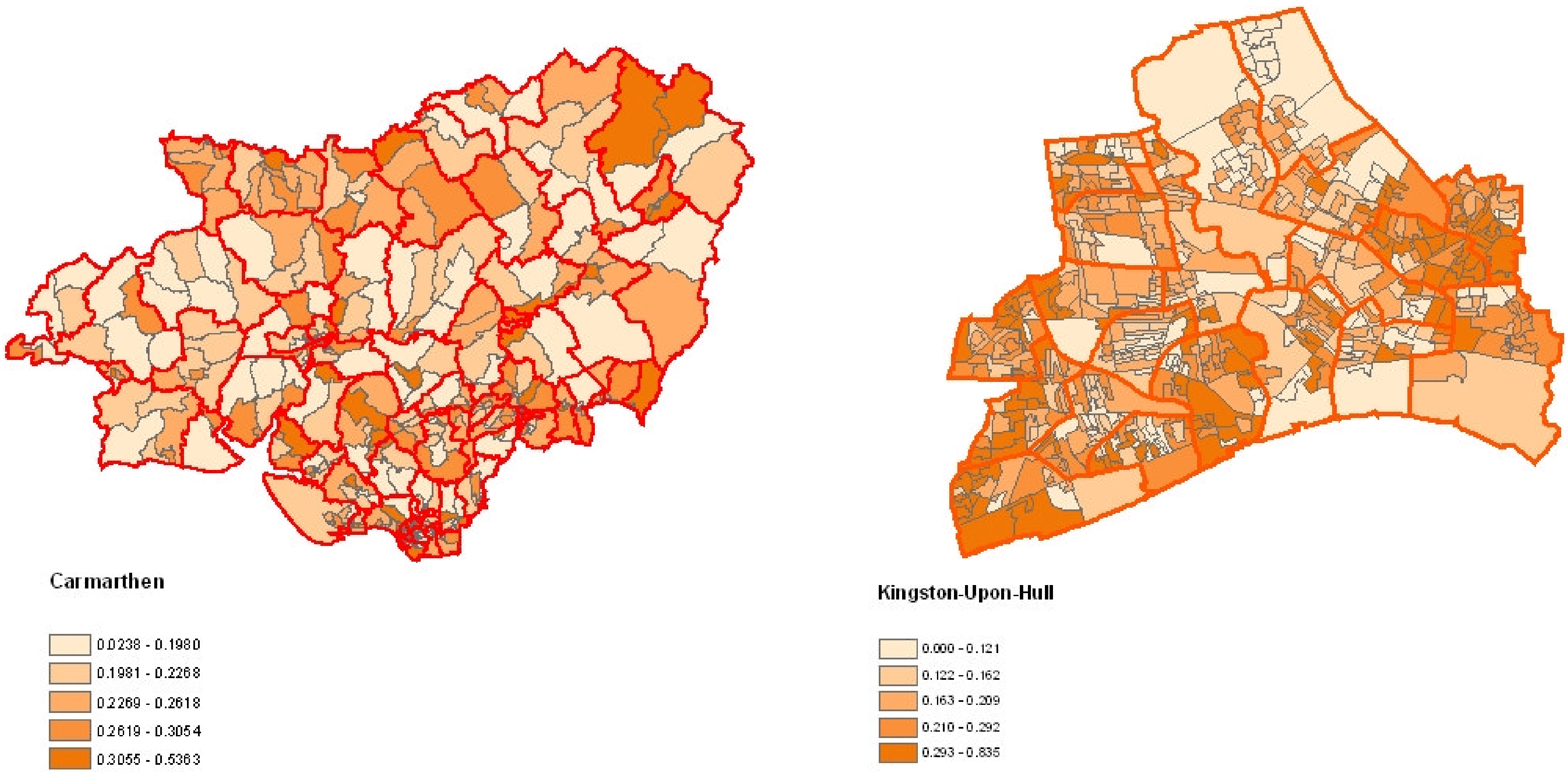


Figure 4.49: Comparison using the percentage of A60P with the lowest AE District and the highest AE District.

a number of outliers that occur for both measures in a given variable. Kingston-upon-Hull District, Sheffield and Birmingham are most frequently identified as outliers for the AEs at both the ED and Ward levels. However, none of these districts have the highest proportions for any of the variables. Ranking the variables in terms of their proportions demonstrates that Kingston-upon-Hull is has a relatively high proportion for the OO variable (25^{th} out of 278) and a relatively low proportion for RLA (262^{nd}).

Therefore, the proportions for either variable are not the highest for either variable, highlighting that the distribution rather than magnitude of the proportion of a variable is more important in the determination of the scale effect. Figure 4.48 demonstrates a comparison between the District with the least scale effect in the A60P variable, which is Carmarthen, and the District of Kingston-Upon-Hull. It is clear from the figure that there is a greater degree of clustering in the Kingston District, suggesting that the clustering is an important factor in the production of higher incidences of the scale effect.

A major pattern identifiable from table 4.25 is that the majority of the outliers are in or above the Midlands of the England, with only Basingstoke and Dean, Ipswich, the New Forest, Poole, Portsmouth and Thurrock out of the 28 in the South. All the outliers occur in relatively urban areas, near large cities and towns and none of the outliers can be considered as representing a rural area, with the possible exception of the New Forests. At the ED level, the NONW variable has the most outliers (eight). With the exception of Birmingham and Leicester, all the outlier Districts are in the North of England. At the Ward level, the NONW variable only has four outliers, three of which (Leicester, Birmingham and Bradford) are also identified at the ED level. The fourth outlier, Basingstoke and Dean is the only Southern District (Hampshire), and is also the only NONW outlier that has a low proportion of NONW residents opposing the higher proportions observed in the other Districts described above. For instance, the outlier districts of Bradford, Oldham and Blackburn are 29th, 49th and 33rd out of 278 in terms of the highest proportions of NONW. This again does not support the notion that there is a link between the scale effect and the proportion of a variable is not demonstrated. The outliers for the LLTI variable also appear to form a consistent group. The outliers at the ED level are Durham, Kingston-upon-Hull and Ipswich. All these places are relatively small cities (Durham and Kingston) or large towns (Ipswich). Unlike the NONW variable, the outliers for LLTI at the Ward level are different, with no commonality. The Ward outliers are Dunfermline, Leeds, Liverpool, Renfrew, Sheffield and Wakefield. Two of these are in Scotland (Dunfermline and Renfrew) whilst the other Districts are all in the North of England.

It is noticeable that the OO and RLA tenure variables have no statistical outliers at the ED level, whilst at the Ward level of aggregation seven and eight outliers respectively, which is more than any of the other variables at this level. Moreover, those Districts that are outliers for the OO variable are, with the exception of the additional RLA outliers, also outliers for RLA. This is not surprising as OO and RLA form the most common types of housing in the UK, and therefore, if homogeneity is particular high in one of the two variables, the distribution of the second variable is also likely to be highly homogeneous.

Table 4.26 presents the outliers for all variables in the IACs at both the ED and Ward level. There are a number of similarities and differences between the IACs and AEs, which are apparent from the two tables. Firstly, the ED level IAC outliers are less dispersed across the country than they were for the AEs, where the outliers were spread over a greater number of districts (13 districts verses 16). The two districts with the most outliers at the ED level are Dundee and Renfrew, both in Scotland. Dundee did not appear as an AE outlier, whilst the district of Renfrew was and outlier only at the ED level for the AE distribution. It is also noticeable, that many of the outlier Districts for the ED level IACs are outliers for only one variable, with are fewer variables being outliers for a number of different variables, as was the case with the ED level AE outliers. This is less the case for the Ward level IACs, where there are more common outliers. For instance, Middlesbrough, Newport and Plymouth are outliers for all variables except the A60P and NONW variable at the Ward level. This implies that there is a high degree of homogeneity in these Districts at the Ward level. At the ED level neither of these Districts are identified as outliers, for EMP, UNEMP, LLTI, CAR0, OO or RLA. Whilst, OO has two ED IAC outliers (Bearsden and Milngavie and Kilmarnock, both in Scotland) RLA does not. Indeed, at the ED level, the Districts have the 14th (Middlesbrough) and 70th (Newport) highest IAC values. Moreover, unlike the AEs where outliers at the ED level were also outliers at the Ward level, the Ward level IAC outlier Districts are not common with the outliers at

	IAC ED								IAC Ward							
	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Basildon																
Bearsden & Milngavie																
Birmingham																
Blackburn																
Blyth Valley																
Bradford																
Braintree																
Calderdale																
Derby																
Dundee																
Kilmarnock																
Kingston-upon-Hull																
Kirklees																
Leicester																
Luton																
Middlesbrough																
Newport																
Northampton																
Ogwr																
Oldham																
Plymouth																
Poole																
Preston																
Renfrew																
Rochdale																
Sheffield																
Thamesdown																
Thurrock																
Wakefield																

Table 4.26: Positive outlier Districts for the IACs for the aggregation between the individual and ED and the individual and Ward level.

the ED level. Indeed, there are only 4 districts that are outliers at both level of aggregation, compared with 6 for the AE distribution.

The NONW variable again has the greatest number of outliers, eight, at the ED level. These Districts identified as NONW outliers are the same as those at the AE ED level. This similarity is not reflected at the Ward level, as neither Braintree nor Sheffield are identified as NONW outliers in the AE distribution. The similarity between the Districts identified as outliers, despite the differences between the two measures, implies that the outliers for the NONW variable can be considered areas that will demonstrate significant incidence of the scale effect, and have highly homogeneous structures that are reflected within the boundary definitions used in the aggregations.

Using the IAC measure, a smaller proportion of the outlier Districts are located in the South of England. As with the AE measure, the majority of the Districts can be considered as Urban, with only Bearsden & Milngavie in Scotland representing a more rural area. Those Districts in the South are Basildon, Northampton, Poole, Plymouth and Thamesdown (Wiltshire). Welsh District of Newport is present in both the AE and IAC and with the IAC outliers Wales is also represented by the District of Ogwr (Mid Glamorgan). This represents seven Districts not in the North of the UK out of the total 29 IAC outlier Districts.

The descriptive analysis of the Ward level measures also revealed a number of useful details about the incidence of the scale effect in UK Census data. Firstly, the magnitude of the AE rose in all cases between the ED and Ward levels. This is as expected. The change in scale from individual level analysis to Ward level analysis is greater than observed between the individual and ED levels of analysis. Conversely, the magnitude of the IACs fell for most variables. The exception to this was observed with the OO variable, where the IACs actually increased. This is potentially possible because the Ward boundaries of a given District, or set of District reflects the definition of the OO variable well. Therefore, the Ward boundaries in the Bearsden and Milngavie District, the OO IAC outlier, may also coincide with the boundaries of housing estates. Figure 4.49 demonstrates that this is the case. The more urbanised Wards, demonstrate a concentration of low proportions of the OO variable, whilst the more rural Wards, in the North of the District demonstrate high proportions of the OO

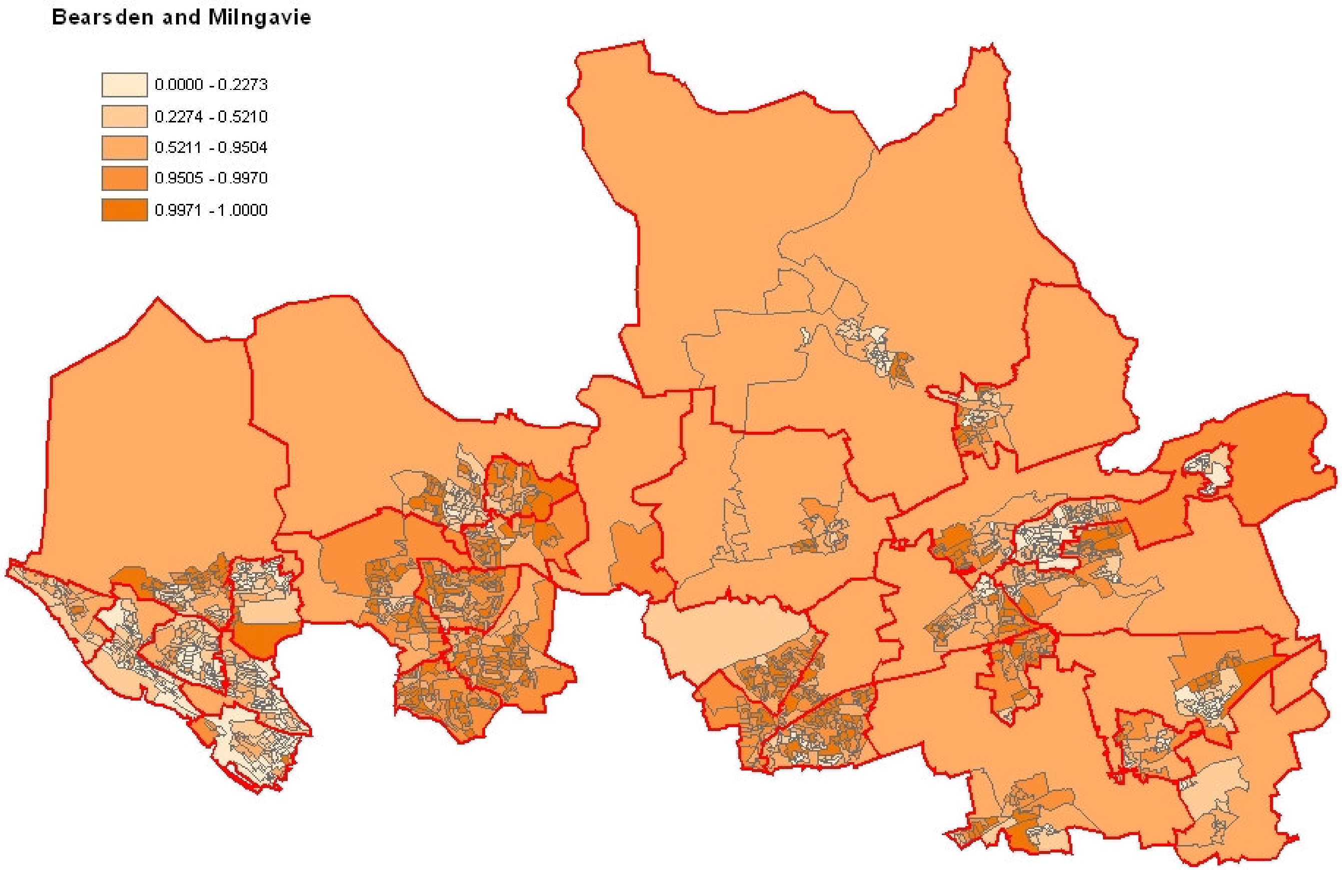


Figure 4.50: Proportion of the OO variable by PPS demonstrating the high within-area homogeneity of the Bearsden and Milngavie District, Strathclyde, Scotland. Data ordered by quintiles.

variable. The population of the Bearsden and Milngavie District clearly has high within-ward homogeneity in the OO variable.

The last section of descriptive analysis considered the AEs for the aggregation between the ED and Ward level units. These results were expected to demonstrate that the level of AE was less than had been observed between the individual and Ward aggregation, but was likely to be similar in magnitude to that between the individual and ED. The results demonstrated that the individual to Ward aggregation was more severely affected by the scale effect than the ED to Ward aggregation. However, it was also the case that the individual to ED aggregation was a greater magnitude than the ED to Ward. This suggests that individual to aggregate changes are affected by the scale effect more than the changes between two aggregate levels. The trends in terms of the aggregation sizes were not as expected. It was expected that the trends would be similar to those observed in the other analyses. Thus, the NONW variable would exhibit the most scale effect, with the tenure variables, OO and RLA, exhibiting similar magnitudes. Although the NONW was the most severe affected in terms of the indicated scale effect, it was not the case that the tenure variables were similarly affected. The LLTI variable had the second greatest scale effect between the ED and Ward levels, despite previously being the most stable variable according to the AE indicators. The last trend for this data that was investigated was the difference between the English and Welsh data and the Scottish data. The change between the ED and Ward level in Scotland is greater than it is for the English and Welsh data. Therefore, it would be expected that the AEs would be greater for the Scottish data, than for the English and Welsh data. This is the case, as for most variables the outliers are Scottish. Moreover, the Scottish Districts always appear in the top half of the distribution.

Overall, therefore, there are a number of points, which can be made regarding the incidence of the scale effect in the 1991 UK Census. These are:

- There was a distinct difference observable between the Districts that could be characterised as urban (frequently city based) and rural, where the urban Districts tended to have greater AEs and IACs.

- The impact of the scale effect appears to be very much dependent on the variable, even when those variables are related, as those depicting tenure (with the RLA and OO linked) or employment (with EMP and UNEMP) are the scale effects will not necessarily reflect their pair variable.
- NONW, CAR0, OO and RLA are the variables most effected by the scale effect, out of those considered here
- Ward level AEs are greater than ED level AEs, indicating greater scale effect as the magnitude of the aggregation increases
- Ward level IACs are smaller than ED level IACs indicating a fall in the levels of within-area homogeneity as the magnitude of aggregation rises, excepting for the OO variable.
- In general, the values for the IACs and AEs are concentrated around a small range. However, for each variable there are a number of Districts that exhibit outlier values that appear far greater than the majority of the scale effect magnitudes identified. Thus, for each variable, with the exception of the OO and RLA at the ED level have a few variables with very high scale effects
- The scale effect is pervasive in the UK Census and requires further investigation.

Chapter 5

Assessing Measures of the Scale Effect

5.1. Introduction

It has been shown that the scale effect exists in UK Census data (see Chapter 4). In this section it is proposed that incidence of the scale effect will be observed, through the use of change correlation coefficients for differing scales of areal units. Using the methodology proposed by Tranmer and Steel (2001) it has been demonstrated that there is the potential to quantify these scale effect in terms of the Aggregation Effect (AE) and Intra-Area Correlation (IAC) measures (see Chapters 3 and 4 for more details). However, these measures have not been tested to determine whether or not the incidences of the scale effect that they suggest actually occur in statistical analysis of areal data. This analysis follows the process outlined in section 3.4 of the methodology.

Two alternative Ward geographies have been constructed in to assess the impact of homogeneity on the scale effect. Two ED level SAR Districts are used here as test areas where the EDs are reaggregated a number of times into unique higher level areal unit solutions. The scale effect measures are calculated and correlation analysis has been used to determine the ability of the measures to predict incidence and magnitude of the scale effect. Reigate was chosen partly for consistency as it was the original SAR District with which Tranmer and Steel (2001) published their results, and partly as it has been identified as an area with relatively low scale effect through the AEs and IACs. Therefore it would be a useful area to assess, regarding whether or not it is possible to produce large scale effects, and if so, whether or not they can be measured. The second District of Bradford was chosen to provide a contrast to Reigate as it has higher magnitudes of the scale effect. This investigation will enable the assessment of the measures as indicators of the scale effect. Moreover, it will also enable further investigation into the causes of the MAUP, and specifically the scale effect, to determine the influence of partially known data structures on subsequent aggregations. Finally, the analysis presented here will demonstrate the statistical significance of the scale effect, in the magnitude of the changed correlation coefficients. The following sections outline the aggregation process, provide theory regarding the likely relationships between the measures and the analysis, review the measures for both the publication geographies and the pseudo geographies, and finally consider the relationships between the measures and the statistical analysis.

5.2. Theory

A major element of the MAUP is the arbitrary nature of the areal units used for the data. Therefore, a legitimate investigation explores different realisations of areal units for a given dataset. This exploration investigates homogeneity for a variable, and the subsequent Aggregation Effects and IACs, and the impact this has for the Aggregation Effects and IACs of the other variables in the analysis. However, before presenting the results of the study, it is useful to consider the influence that aggregation is likely to have on the scale effect measures, the AE and IAC, of the variables for a given District.

The Aggregation Effects are likely to vary in a similar manner to those of the publication data. Although the aggregation process focuses on a single variable, attempting to maximise the within area homogeneity it is unlikely that the AEs, which provide a rough indication of the internal homogeneity, will be greater than those obtained from the publication geography for that variable. This is especially true of the LLTI variable used in the Reigate SAR, as LLTI has a low incidence in this SAR District, as with the majority of the rest of the Country. Clearly, high level of homogeneity will be difficult to achieve in a low incidence variable. However, it is useful to use a low incidence variable, as if a high magnitude of the scale effect can be introduced then it would suggest that there are more influences that contribute to the scale effect than simply the degree of homogeneity observed for a variable in a given area. However, the absolute level of homogeneity may not be the key issue in the determination of the magnitude of the scale effect. As data are aggregated into higher level coverages, so the level of homogeneity will fall as it is more unlikely that large groups of people will achieve the same magnitude of similarity (homogeneity) that can observed in smaller groups, such as EDs. The change in the degree of homogeneity is one of the determinants behind the incidence and magnitude of the scale effect. The greater the change in the levels of homogeneity, the greater the change in the processes contained within the areal units, and therefore the structure of the data, and so the greater the magnitude of the scale effect. This is because the

Aggregation Effect is constructed using the weighted variance. As homogeneity falls, so the weighted variance will increase. As the higher level of aggregation provides the numerator in the Aggregation Effect equation, so an increase in numerator relative to the denominator will produce a larger Aggregation Effect. Thus, if homogeneity is maximised in a given variable as the aggregation process increases, moving between EDs and Wards for instance, then the drop in homogeneity will be less. Therefore, the scale effect between these two datasets will also be less. In this case a lower aggregation effect would be observed, as the aggregation effect is not a measure of absolute scale effect within the data. Rather, it is a measure of scale effect between two levels of data.

After the analysis in Chapter 4, it is expected that the Aggregation Effects for the tenure variables (OO and RLA) will be the greatest. The CAR0 variable also tended to exhibit relatively high levels of the Aggregation Effects, and therefore high scale effect. The remaining variables of A60P, NONW, EMP, UNEMP and LLTI are expected to demonstrate relatively low levels of AE and also IAC, therefore demonstrating low levels of scale effect and homogeneity. For this analysis there are three potential incidences of the scale effect that can be measured. The first considers the AE between the Individual and Ward level data. The second considers the AE between the ED level and Ward level data. The third measure considers the IAC between the Individual level and the Ward level. It is expected that in all cases the Individual to Ward level measures will be the greatest, as this is the greatest change in aggregation. The EDs to Wards are likely to be much lower. It is also possible to observe an Individual to ED effect, and this will be referenced throughout the study, although it is not directly influenced by the aggregation process undertaken. In general terms it is assumed that the greater the aggregation effect, the greater the incidence of the scale effect, as observed in the change of the correlation coefficients. The IAC gives an indication of the magnitude of the scale effect for an area, (for more details see Chapter 3).

These propositions are tested below, using multiple realisations of a zonal system, calculating the IACs for the homogeneity variable, and then analysing using some basic statistic tests to identify if the results are stable under this aggregation. IACs and scale analysis are also calculated for the other variables suggested by Tranmer and Steel (2001)

5.3. The Zone Construction

It was necessary to construct alternative realisations of the publication level geography. As individual level data are not available, the basic building blocks of the new coverages would be the ED level areal units. To enable comparability, the new coverages were constructed to be consistent with the Census publication Wards, and are therefore known herein as Pseudo Wards.

The two regions chosen were selected for a number of reasons. The first discussed is that of Reigate. This choice reflects the District selected by Tranmer and Steel (2001) for the introduction of the AE and IAC measures. Thus, the continued use of this District enables reference back to the original work. Moreover, the Reigate District also has range of urban and rural areas within its bounds, and therefore has areas of contrast. When attempting to produce different zonal coverages such areas of contrast are advantageous as they provide distinct natural groupings that can be split or combined for analysis. The second SAR District selected was Bradford. Initial analysis showed that Bradford has a high concentration of people recorded by the 1991 Census as Non-White (over 50% in some areas). There was also high concentration observed in the CAR0 variable. Therefore, higher levels of homogeneity were thought to be obtainable as there would be distinct concentrations that could be exploited in the aggregation process.

5.4. Reigate

The LLTI variable was used for the aggregation of the Reigate SAR (see figure 5.1 for the ED distribution). The zone construction process was run until ten alternative realisations of the Ward level Census coverage for the Reigate SAR District and then the Bradford SAR District had been created. The Reigate SAR has 39 Wards, and this number of zones was maintained for all the realisations to enable comparability. The average population of 4841 people was maintained as a target average for the zonal systems. After experimentation with different parameters, a lower limit of 3700 people per zone was chosen, as these parameters consistently gave realisations with 39 zones. It is standard that population characteristics are given a weighting of 1.

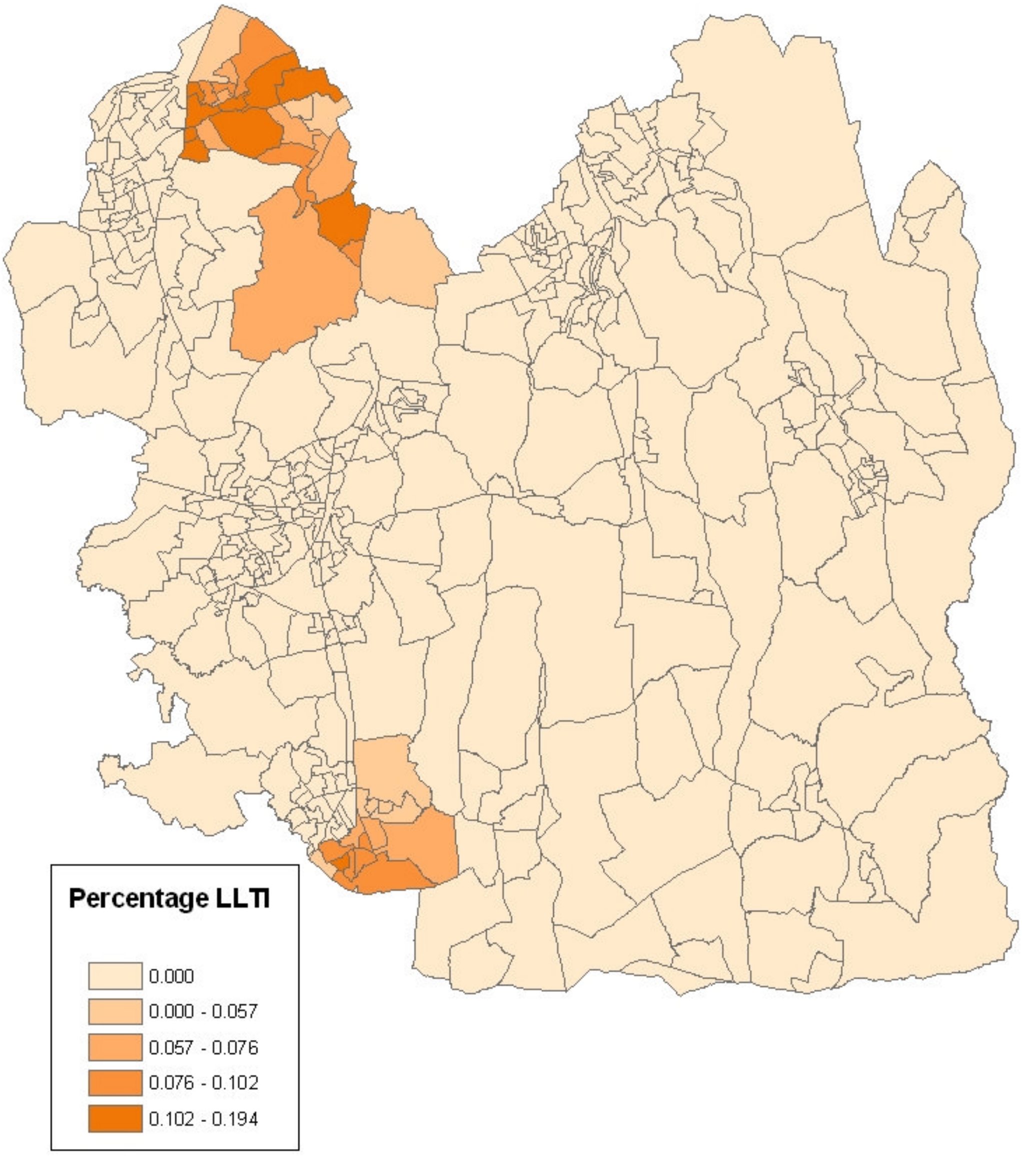


Figure 5.1: Percentage of LLTI at the ED level in the Reigate SAR District, using quintiles.

Shape was identified as an important criterion for the aggregation, and in order that it was maintained in the aggregation process it was given a weighting of two. This meant it was twice as important to achieve good compactness of shape than to achieve the correct population levels. This resulted in reasonably realistic zone shapes that were not excessively long or thin. The most important criterion for the study was homogeneity. Thus, homogeneity was given a weighting of three. In practice, even with a high weighting for the homogeneity it was difficult to achieve consistently high levels of homogeneity, measured using the IAC. Thus, the assessment below will consider the impact of differing levels of homogeneity on the scale effect and how well the IAC measures describe the impact of the homogeneity and therefore scale effect on correlation analysis of the eight variables.

5.4.1. Results for Reigate

Below the weighted variances, AEs and IACs are presented for the Pseudo Wards in the Reigate District. They are presented with the publication results, to provide comparison.

5.4.1.1 Weighted Variance Results

Weighted variance values were calculated for all eight variables in each of the realisations (see table 5.1), and can be compared to the publication geography weighted variances (see the upper part of table 5.1). The construction of a zonal system using the homogeneity of the LLTI variable clearly has implications for all the variables considered, even if there is little change in the magnitude of the three measures reported. For instance, the tenure variables of OO and RLA have weighted variances below that found in the publication geography. Therefore, there is less between zone homogeneity in the Pseudo coverages for the tenure variables than there is in the publication coverages at the Ward level. In turn, this would be likely to lead to a reduction in the scale effect observed in statistical analysis in the RLA variable. The other tenure variable, OO displays weighted variance that is greater than that observed in the publication geography. With the exception of Pseudo Ward 3, the weighted variance is almost double that observed in the publication geography. Unlike the RLA variable, this implies that there is a greater level of between zone variation in this data variable, in turn suggesting that the level of scale effect would be greater. Thus, aggregating using the LLTI variable to determine levels of homogeneity has the effect, in this dataset of increasing the weighted variance for these variables. However, this is not the case for all the variables. For instance, the CAR0 variable the third highest in this set, the Pseudo Ward results are consistently lower than those observed for the publication Wards.

For all the other 5 variables considered in this analysis, A60P, NONW, EMP, UNEMP and LLTI the weighted variance is similar to the level observed in the publication ward level data. For instance, the publication Ward geography for LLTI has a weighted variance of 1.24. This was the variable used as the homogeneity variable in the AZM aggregation process. Here the range of weighted variances is from 0.97 to 1.22. None of these are higher than that of the weighted variance observations in the publication geography, thus demonstrating that the publication geography has greater within area variation and lower between-area variation for the data when grouped at the Ward and Pseudo Ward levels of aggregation. From this, the AEs for the Pseudo Geographies would be expected to be lower than in the Publication Geographies and the IAC values, describing the within-area homogeneity, would also be expected to be lower. However, the range of values will enable an insight to be gained into the interaction between the weighted variance, measures of scale effect such as the IACs and the practical existence of scale effect in statistical analysis such as correlation coefficients.

SAR	0.158	0.028	0.250	0.032	0.078	0.102	0.158	0.095
ED	2.872	0.179	1.581	0.062	0.575	3.160	14.546	14.218
Ward	5.069	0.609	3.673	0.182	1.243	10.955	45.904	47.763
	A60P	**NONW**	**EMP**	**UNEMP**	**LLTI**	**CAR0**	**OO**	**RLA**
Pward 1	5.9552	0.6421	3.7806	0.0942	1.1008	8.1349	33.9982	33.9633
Pward 2	6.1720	0.6397	3.6016	0.1324	1.1118	9.3848	30.6985	32.4434
Pward 3	5.6199	0.7011	3.2728	0.0995	0.9665	7.6353	25.1166	26.2342
Pward 4	5.9425	0.6073	3.2843	0.1133	1.0429	7.9368	30.5979	31.7418
Pward 5	5.8121	0.8147	3.5727	0.1082	1.0366	8.2800	34.4408	36.6391
Pward 6	5.7454	0.6317	3.0416	0.1069	1.1443	9.9301	34.1294	37.4477
Pward 7	5.2304	0.6844	3.0643	0.1187	1.0570	7.8858	29.7254	32.9340
Pward 8	6.1446	0.7450	3.7279	0.1134	1.0335	9.3003	34.2131	35.6677
Pward 9	5.8853	0.7223	3.2837	0.1169	1.2424	7.9447	34.0451	36.5177
Pward 10	5.8526	0.7247	3.8137	0.1111	1.2253	7.8446	30.5078	36.7752

Table 5.1: Weighted Variances for the publication geography and the 10 Pseudo Ward Zone Systems.

Table 5.2 compares the weighted variances of the Pseudo geography to the range and mean weighted variances of the variables for the whole of the UK. It is clear for the Reigate SAR data, even when aggregated using one of the analysis variables as the homogeneity measure in the aggregation process, that the level of weighted variance between the areal units with the zonal system is never extreme. In all cases the weighted variance observed in all the Pseudo geographies is closest to the minimum values than to the maximum values. This is consistent to the weighted variances observed in the publication data for Reigate and is, therefore, expected.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Minimum	1.444	0.009	0.612	0.083	0.539	1.179	13.352	3.354
Maximum	90.325	1271.79	129.798	18.711	19.455	101.99	692.932	700.929
Mean	12.775	35.284	14.409	1.831	3.777	16.597	129.156	125.121
Median	10.321	1.136	8.239	0.935	2.956	10.994	82.930	81.865

Table 5.2: Maximum, minimum and mean weighted variances for the whole UK SAR Districts.

5.4.1.2. Aggregation Effects

The aggregation effect provides a value for a quantitative indication of the level and magnitude of the scale effect. These are not adjusted by the population or number of zones, and so it is not practical to use as a measure for comparing across highly variable zonal systems. However, it is relevant to this study for comparison as the population in each of the Pseudo Ward systems is identical in terms of average population size and the number of units. The following discussion is divided into two sections. Firstly the Aggregation Effects between the Individual and Pseudo Ward level are considered, while the second section deals with the Enumeration District to Pseudo Ward Aggregation Effects.

5.4.1.2.1 Individual to Ward

The upper section of table 5.3 presents the AEs for the publication geographies, both at the Enumeration District and Ward level. They can be contrasted with the lower section of table 5.3, which gives the Aggregation Effects for the 8 variables within the 10 Pseudo Ward geographies. As would be expected the overall pattern is largely similar to that of the weighted variances, which as the Aggregation Effects are a function of the weighted variance is not surprising. The first 6 variables, A60P, NONW, EMP, UNEMP, LLTI and CAR0 all have Aggregation Effects very similar to those in the publication ward geography. The Aggregation Effects for A60P and NONW variables are slightly higher in the pseudo geography. This would suggest that the aggregation effect is more severe in this variable. However, the EMP UNEMP, LLTI and CAR0 all exhibit Aggregation Effects lower than in the publication geography, suggesting that the scale effect will be less severe in the statistical analysis of these variables in comparison to the scale effect observed between the different levels of aggregation using the publication geography. Assessing the stability of correlation analysis, and the statistical significance of the coefficient changes, is examined in section seven.

In comparison, the tenure variables of OO and RLA exhibit lower Aggregation Effects than observed in the publication geography. However, the Aggregation Effects are still greater than those observed for all other variables, suggesting that the scale effect is still the most severe for these variables. These results suggest that statistical analysis will be more stable in the Pseudo Wards for these variables as the scale effect is theoretically reduced. One hypothesis to explain this could be that there is a greater degree of homogeneity in these variables. This will be explored in the following section through the use of the IAC measures. Finally, any reduction of homogeneity is likely to reflect a fall in the potential aggregation effect. Both of these hypotheses will be explored in section 5.3.

ED	18.137	6.41	6.332	1.945	7.422	30.946	91.850	149.325
Ward	32.009	23.68	14.708	5.704	16.040	107.270	289.858	501.641
	A60P	**NONW**	**EMP**	**UNEMP**	**LLTI**	**CAR0**	**OO**	**RLA**
Pward 1	37.603	23.029	15.138	2.953	14.201	79.6584	214.678	356.709
Pward 2	38.972	22.941	14.421	4.151	14.344	91.8977	193.842	340.746
Pward 3	35.486	25.145	13.104	3.118	12.468	74.7664	158.596	275.532
Pward 4	37.523	21.781	13.150	3.551	13.455	77.7183	193.207	333.378
Pward 5	36.700	29.217	14.305	3.393	13.373	81.0792	217.473	384.813
Pward 6	36.278	22.653	12.179	3.351	14.763	97.2371	215.506	393.305
Pward 7	33.026	24.545	12.269	3.721	13.637	77.2192	187.697	345.899
Pward 8	38.799	26.718	14.927	3.554	13.333	91.0705	216.034	374.610
Pward 9	37.161	25.903	13.148	3.666	16.028	77.7959	214.974	383.538
Pward 10	36.955	25.991	15.271	3.482	15.807	76.8162	192.638	386.243

Table 5.3: Aggregation Effects (Individual to Pseudo Ward) for the publication geography and the 10 Pseudo Ward Zone Systems.

It is useful to compare the results of the Pseudo Ward geography with the Aggregation Effects observed in different SAR Districts within the UK. This analysis should be recognised as tentative as the Aggregation Effects are not comparable measures for the reasons outlined above. This will however give an indication of the Aggregation Effects for the variables over the whole country. Table 5.4 presents the highest, lowest and average Aggregation Effects for each of the variables.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Minimum	10.169	1.6413	2.4481	3.6388	5.2980	57.686	25.317	87.335
Maximum	514.99	7623.1	542.91	305.61	147.98	2313.9	3094.7	4252.25
Mean	77.583	358.83	58.961	37.897	34.212	372.43	622.11	780.96
Median	66.125	48.276	33.186	23.689	27.388	68.023	445.48	587.09

Table 5.4: Maximum, minimum and mean Aggregation Effects at the Ward level for all UK SAR Districts using publication geography.

The first five variables identified above as having values similar to those observed in the publication geography have Aggregation Effects closer to the minimum Aggregation Effects for the whole of the UK. They are also below the mean aggregation effect values for the variables. This suggests that the Aggregation Effects, and therefore the scale effects in these variables are relatively low in comparison to other SAR Districts. The exception to this pattern in this group of variables is UNEMP. In this case two of the created geographies exhibit Aggregation Effects above the minimum from the publication geography (Pseudo Ward 2 and 9). In the other 8 Pseudo Ward geographies the aggregation effect is below the observed minimum. This suggests that there is lower scale effect in this data as aggregation occurs between the individual level and the Ward areal level. The last 3 variables identified as having Aggregation Effects below that observed in the Reigate publication geography show Aggregation Effects closer to the minimum aggregation effect and are consistently below the mean observed aggregation effect for the whole country. Therefore, the scale effect is demonstrated to be relatively low for these data in these zonal systems. However, it must again be noted that these values do not reflect comparability in relation to the different populations of the areas, which when comparing data from zones of different sizes.

5.4.1.2.2 ED to Ward

Table 5.5 presents the Aggregation Effects quantifying the scale effect between the ED and Pseudo Ward level zonal systems for the pseudo wards (lower section) and publication geography (upper section). The major trend in these Aggregation Effects is that they are consistently all lower than the Aggregation Effects in the previous section. This is as expected, as the level of aggregation between ED and Ward level

Ward	1.764	3.694	2.322	2.932	1.121	3.466	3.283	3.359
	A60P	**NONW**	**EMP**	**UNEMP**	**LLTI**	**CAR0**	**OO**	**RLA**
Pward 1	2.073	3.085	2.390	1.518	1.913	2.5741	2.337	2.388
Pward 2	2.148	3.037	2.277	2.134	1.932	2.9696	2.110	2.281
Pward 3	1.956	3.369	2.069	1.603	1.679	2.4160	1.726	1.845
Pward 4	2.068	2.983	2.076	1.826	1.812	2.5114	2.103	2.232
Pward 5	2.023	3.914	2.259	1.744	1.801	2.6200	2.367	2.577
Pward 6	2.000	3.035	1.923	1.723	1.989	3.1421	2.346	2.633
Pward 7	1.820	3.288	1.937	1.913	1.837	2.4953	2.043	2.316
Pward 8	2.139	3.579	2.357	1.827	1.796	2.9428	2.352	2.508
Pward 9	2.048	3.470	2.076	1.884	2.159	2.5139	2.340	2.568
Pward 10	2.037	3.482	2.411	1.791	2.129	2.4822	2.097	2.586

Table 5.5: Aggregation Effects (Enumeration District to Ward/Pseudo Ward) for the Ward and 10 Pseudo Ward Zone Systems.

(aggregating from around 500 people in an areal unit to 4-5000) is less than between the individual level and Ward level (an aggregation from the individual person, 1, to a Ward areal unit of 4-5000 people). The results for the ED to Pseudo Ward Aggregation Effects do not follow the same trend as the data presented in the previous section. In the Individual to Pseudo Ward level aggregation effect the first five variables within the analysis had Aggregation Effects similar to those observed in the publication geography. However, the Aggregation Effects for the ED to Pseudo Ward level analysis show that the magnitude of the scale effect is significantly different. The A60P variable has Aggregation Effects higher than observed in the publication geography, as do the NONW and EMP variables, while the other 4 variables (UNEMP, LLTI, CAR0 and RLA) all have Aggregation Effects that are much lower than in the publication geography. The last variable for tenure, OO, has an aggregation effect that is similar to that observed in the publication geography, and the scale effect between these levels would be expected to be similar to that observed using the publication data structure. Therefore, for these variables, the scale effect between the ED and Pseudo Ward level should be reduced in comparison to the scale effect observed in the publication geography data.

LLTI was the variable used for homogeneity in the construction of the Pseudo Wards. However, as can be observed in the AE results, this was not achieved, as the AEs are lower for the Pseudo Geographies than for the Publication Geographies. Therefore, lower scale effects would be expected. As would be expected, the unemployment (UNEMP), car ownership (CAR0) and number of local authority renters (RLA) are linked to the LLTI variable, as the ability of a person to work and therefore purchase a car and their requirement for local authority provided housing can be inhibited by poor health.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Minimum	0.8037	0.8832	0.6280	1.1111	0.735	2.1573	1.2767	1.2237
Maximum	16.141	562.63	23.981	24.125	15.190	27.690	25.348	25.431
Mean	3.6331	7.9186	4.5472	5.8826	3.5983	6.7019	5.3187	5.2301
Median	3.1703	4.8782	3.5375	4.7432	3.0559	1.427	3.8823	3.9464

Table 5.6: Maximum, minimum and mean Aggregation Effects between Enumeration Districts and Wards for all UK SAR Districts using publication geography.

Table 5.6 presents the maximum, minimum and mean Aggregation Effects observed between the ED and Ward level for the whole of the UK SAR Districts. They demonstrate that the Aggregation Effects observed in the Pseudo Ward coverage are relatively low in comparison with the Aggregation Effects observed for the 278 SAR Districts in the United Kingdom. It is noteworthy that in no cases are the Aggregation Effects observed in the created geography higher than those in the publication geography. This does not demonstrate that the maximum level of homogeneity was achieved by the LLTI variable in the publication geography. Rather it demonstrates the difficulty of achieving high levels of homogeneity in a low incidence variable.

5.4.1.3. Intra Area Correlations

The second measure of the scale effect and the homogeneity within the SAR District between the areal units that the zonal system is comprised of is the Intra-Area Correlation (IAC). These have been calculated for each of the Pseudo Ward systems and for each of the 8 variables. This enables a comparison of the different system with respect to their impact on the scale effect. This is done in the second part of this section.

Ward	0.0064	0.0047	0.0028	0.00097	0.0031	0.0219	0.0596	0.1034
	A60P	**NONW**	**EMP**	**UNEMP**	**LLTI**	**CAR0**	**OO**	**RLA**
Pward 1	0.0076	0.0046	0.0029	0.0004	0.0027	0.0162	0.0442	0.0735
Pward 2	0.0078	0.0045	0.0028	0.0007	0.0028	0.0188	0.0399	0.0702
Pward 3	0.0071	0.0050	0.0025	0.0004	0.0024	0.0152	0.0326	0.0567
Pward 4	0.0075	0.0043	0.0025	0.0005	0.0026	0.0158	0.0397	0.0687
Pward 5	0.0074	0.0058	0.0027	0.0005	0.0026	0.0165	0.0447	0.0793
Pward 6	0.0073	0.0045	0.0023	0.0005	0.0028	0.0199	0.0443	0.0811
Pward 7	0.0066	0.0049	0.0023	0.0006	0.0026	0.0157	0.0386	0.0713
Pward 8	0.0078	0.0053	0.0029	0.0005	0.0025	0.0186	0.0444	0.0772
Pward 9	0.0075	0.0052	0.0025	0.0006	0.0031	0.0159	0.0442	0.0791
Pward 10	0.0074	0.0052	0.0029	0.0005	0.0031	0.0157	0.0396	0.0796

Table 5.7: Intra-Area Correlations for the publication and Pseudo Ward geography.

The top section of table 5.7 presents the IACs from the publication geography for comparison. The bottom section of table 5.7 presents the IACs for the Pseudo geography. The IACs are necessarily lower than the Aggregation Effects as they are adjusted by the size of the population. The OO variable, along with UNEMP and A60P exhibit lower levels of homogeneity in the IACs, than observed in the publication geography. With respect to the scale effect it is likely that this will result in a greater stability in the statistical analysis, which will be confirmed in the following section through reference to correlation coefficients. The LLTI variable should exhibit a higher level of IAC than in the publication geography as the homogeneity has been maximised in the zone structure. This does not imply that an absolute high IAC should be observed. Rather it should be a value greater than that in the publication geography. The values observed in the Pseudo geography range from 0.0024 to 0.0031. While this may not appear to be excessively large, the LLTI variable has previously been identified as one where there is limited scale effect (see above and Chapter 4), and because of the low proportion of the population with LLTI conditions, relatively dispersed population. These factors together combine to produce a spatial dispersion with lower homogeneity, especially at the Ward level. It is also noteworthy that the NONW variable has, in general, higher IACs than for the publication geography. Seven of the new zonal systems demonstrate higher IACs, which suggests that there will be higher scale effect in statistical analysis for these zonal systems. However, the level of the NONW IACs relative to the other variables is not the same as the relative position of the AEs. Therefore, the IACs appear lower in magnitude relative to the other variables, than the equivalent AEs.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
minimum	0.001	0.0001	0.0004	0.0003	0.0007	0.0064	0.0021	0.0094
maximum	0.178	0.4814	0.0780	0.0526	0.0420	0.4631	0.7230	0.9583
mean	0.016	0.0388	0.0100	0.0065	0.0065	0.0677	0.1136	0.1455
Median	0.011	0.0088	0.0069	0.0046	0.0049	0.0128	0.0873	0.1135

Table 5.8: Minimum, maximum mean and median IACs for the UK SAR Districts.

Table 5.8 reviews the maximum, minimum, mean and median IAC values for all the SAR Districts. As the IAC measure is directly comparable due to the population size adjustment in the calculations the values observed in the UK publication geography can be directly compared to not only the Reigate publication data but also the Pseudo Ward systems. For all the variables under consideration the values observed in the Pseudo geographies are below the mean, and with the exception of the CAR0 variable the median values for the full UK Census distribution. This implies that the scale effect for the Reigate SAR is relatively low in comparison with the UK as a whole. For instance, the NONW variable the IAC achieved with the Pseudo Geography IACs is around half that observed for the median. This demonstrates that they are in the bottom half of the IAC distribution, and therefore the analysis of LLTI in Reigate will exhibit more stable statistical results with using the Pseudo zonal system. Moreover, the level of within-area homogeneity for the LLTI variable is greater in the publication geography than in the Pseudo Geographies. This is despite the fact that the aggregation process sought to maximise the level of homogeneity in the LLTI variable.

5.4.1.4. Correlation Analysis

In order that it is possible to assess the ability of the measures explored above to predict and describe the scale effect observed in statistical analysis, it is necessary to compare the predicted out comes using these measures to some incidences of statistical analysis. This is done below using correlation coefficients and assessing the nature of their change by the expected change given the measure of the scale effect from the aggregation effect and the IAC. The analysis is dealt with by considering each variable in turn, and determining the level of the scale effect expected, and then the level and nature of the scale effect observed. Finally, the findings from all eight variables are considered together for a comparative analysis. An important point to note is the fact that there are differences in the relationships between the variables when the data are presented in different geographies. This is a demonstration of the scale effect.

5.4.1.4.1 A60P

The A60P variable does not tend to exhibit high level of scale effect according to the Aggregation Effects and the IACs. They demonstrate that there is likely to be limited incidence of the scale effect in this data. However, with correlation analysis at least two variables are used. In this case the aggregation effect and IACs from the other variable has to be included in the analysis. Thus, although one variable may have limited scale effect, another with which it is analysed may and this would increase the incidence of the scale effect in the correlation coefficient.

The Aggregation Effects between the individual and the Ward level are the fourth highest of the eight variables. The NONW, EMP, UNEMP and LLTI all have Aggregation Effects lower than A60P, and so the correlation coefficients for these variables would be expected to have low incidence of the scale effect. This would result in the correlation coefficients staying relatively stable and not exhibiting elements of the scale effect such as changing significance or sign swapping. Table 5.9 demonstrates that this is the case. There are some differences between the lower levels of aggregation for all the variables. Only the EMP variable when correlated with the A60P variable displays the scale effect in terms of a sign swap at the ED level. For most of the variables, the correlation coefficients for the Pseudo geographies are relatively consistent, demonstrating that there are also zonation effects present within the data. However, for these data in this configuration they are not as severe as the scale effects.

	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
SAR	-0.026	-0.331	-0.075	0.378	0.295	-0.103	0.092
ED	-0.200	-0.589	-0.457	0.740	0.545	-0.115	0.206
Ward	-0.221	0.031	-0.254	0.525	0.268	-0.094	0.199
PWard1	-0.344	-0.725	-0.272	0.613	0.243	-0.101	0.225
PWard2	-0.283	-0.773	-0.103	0.627	0.328	-0.164	0.245
PWard3	-0.416	-0.805	-0.178	0.614	0.184	-0.134	0.257
PWard4	-0.355	-0.741	-0.150	0.632	0.302	-0.154	0.288
PWard5	-0.409	-0.810	-0.243	0.605	0.220	-0.091	0.175
PWard6	-0.288	-0.716	-0.154	0.692	0.342	-0.223	0.283
PWard7	-0.372	-0.788	-0.177	0.618	0.284	-0.099	0.202
PWard8	-0.392	-0.755	-0.200	0.661	0.214	-0.077	0.232
PWard9	-0.423	-0.926	-0.285	0.578	0.214	-0.093	0.183
PWard10	-0.381	-0.916	-0.367	0.475	0.023	-0.051	0.034

Table 5.9: Correlation coefficients for publication geography and the Pseudo geographies of the Reigate SAR district with A60P.

The other 3 variables CAR0, OO and RLA have higher Aggregation Effects than the A60P variable. Therefore, when combined it would be expected that they would have greater incidence of the scale effect in the correlation coefficients. When comparing the Ward level geographies both the publication and Pseudo Ward with the lower level publication geographies it is apparent that there is more scale effect. Furthermore, the differences between the transformed correlation coefficients at the individual and Pseudo Ward level are not consistent, revealing that the magnitudes of the scale effect for these data are changeable resulting in unpredictable relationships. Moreover, unlike the previously discussed variables, the zonation effect appears greater, as there is greater instability in the correlation coefficients between the different Pseudo Wards.

The variable used for the homogeneity in the aggregation process demonstrates slightly higher correlation coefficient change than the publication ward, suggesting that the scale effect is worse in this data. This is despite recording a lower Aggregation Effect, which in turn would suggest that it would be likely that a lower level of scale effect would be observed in that data.

	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Ward	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard1	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard2	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard3	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard4	Sig	Sig	Sig	Sig	Not	Sig	Sig
PWard5	Sig	Sig	Sig	Sig	Sig	Not	Sig
PWard6	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard7	Sig	Sig	Sig	Sig	Not	Sig	Sig
PWard8	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard9	Sig	Sig	Sig	Sig	Sig	Not	Sig
PWard10	Sig	Sig	Sig	Sig	Sig	Not	Sig

Table 5.10: Highlighting the significant changes in correlation coefficients for the relationships with A60P between the individual and Pseudo Ward levels of analysis. (Shaded cells highlight the significant changes).

The other measure of the scale effect is the IAC. As with the Aggregation Effects these are relatively low for A60P, although it is not the lowest variable. The pattern between the IACs and the correlation coefficients are similar to those with the Aggregation Effects. This is to be expected as the IACs can be seen as correlation coefficients that have been adjusted for the populations of the area. As the base population is the same in all the cases used here, it is unlikely that there would be large changes in the trends. Therefore, the highest IACs are observed for the tenure variables such as OO and RLA. These are the variables that also exhibit the largest level of scale effect in the differences between the correlation coefficients recording the relationships present at the different levels of aggregation. The CAR0 variable also exhibits large IACs and relatively large differences. Again, the IACs for the homogeneity variable LLTI are not relatively great in magnitude, and the correlation coefficients reflect this.

Using the Fisher Transformation (Fisher, 1921), and testing for significance, it is apparent that the scale effect in the correlation coefficients between A60P and the other variables are significantly changeable (see table 5.10). Out of the 80 relationships described, only 5 of them do not exhibit a significant change between the individual and Pseudo Ward levels. It is notable that these five occur in the CAR0 and OO variable, which are variables that have exhibited relatively high measures for the AE and IACs.

5.4.1.4.2 NONW

The NONW variable has relatively high AEs but relatively low IACs, thus indicating that the relative magnitude of the scale effect should not be excessive, and that there is low within-area homogeneity in the Pseudo Wards. There is not, therefore a large level of clustering in the distribution of NONW variable. The correlation coefficients are shown in table 5.11. It would be expected that the correlation coefficients would be relatively stable given the magnitudes of the AE and IACs. It is likely that this stability will be greater than observed in the other variables, as the magnitudes of the AE and IACs are the lowest for all the variables observed

The relationship with the A60P variable is relatively consistent. At all times the relationship maintains its negative sign. Moreover the magnitude of the relationship, once at aggregate level either at the ED, Ward or Pseudo Ward level, is relatively constant. This result is surprising, as the Aggregation Effects for the A60P variable are the fourth highest, which would suggest that a greater degree of scale effect would be present. The IACs are also relatively high for both variables, again suggesting that a greater degree of variability would be observed in the relationships. Indeed, this is the only pair of variables in this section where such stability is observed. The other variables that exhibit high scale measures, such as CAR0, OO and RLA demonstrate severe differences in correlation coefficient at different levels, and within the same aggregation level as different boundary definitions are employed. For the RLA variable it is not only the magnitude of the variable that changes as the boundary and aggregation level changes, but also the sign of the relationship. Using the NONW relationships it is not directly possible to outline generalisations relating the size of the scale effect to the magnitude of the measures.

	A60P	EMP	UNEMP	LLTI	CAR0	OO	RLA
SAR	-0.026	0.063	0.038	-0.030	0.037	-0.007	0.005
ED	-0.200	0.159	0.050	-0.016	0.156	-0.047	-0.004
Ward	-0.221	-0.150	0.218	0.161	0.372	-0.025	0.14
PWard1	-0.344	0.234	0.286	0.043	0.274	0.029	-0.060
PWard2	-0.283	0.396	0.265	0.111	0.367	-0.062	0.013
PWard 3	-0.412	0.400	0.178	0.053	0.268	0.067	-0.078
PWard 4	-0.355	0.326	0.109	0.128	0.326	0.011	-0.047
PWard5	-0.409	0.389	0.229	-0.015	0.283	0.029	-0.012
PWard6	-0.288	0.308	0.288	0.146	0.292	-0.023	0.002
PWard7	-0.372	0.365	0.149	0.041	0.207	0.054	-0.21
PWard8	-0.396	0.450	0.186	-0.008	0.302	0.043	-0.107
PWard9	-0.423	0.426	0.281	-0.010	0.283	0.023	-0.003
PWard10	-0.381	0.405	0.240	0.194	0.478	-0.081	0.041

Table 5.11: Correlation coefficients for publication geography and the Pseudo geographies of the Reigate SAR district with NONW.

The other variables, of EMP, UNEMP, and LLTI have Aggregation Effects and IACs that are lower than those of the NONW variable. The LLTI variable was the variable upon which the zonal systems for the Pseudo Wards were constructed. The correlation coefficients for LLTI are the most variable of the set of low scale effect measures. The individual and ED level relationships demonstrate a negative slope. However, for the publication geography and 8 of the Pseudo Ward geographies the relationship is positive. However, for Pseudo Ward 5 and 8 the relationship is negative as observed for the lower aggregations. This suggests that for these constructions the zonal system reflects the individual level relationships. The employment variables exhibit relatively low variability in the correlation coefficients, although there is still evidence of the scale effect in this data.

Table 5.12 presents the results of the significance test after the Fisher Transformation. As before, the majority of the differences are significant. However, 8 of the relationships are not significant. Three of them are between NONW and LLTI (Pseudo Wards 5, 8 and 9), one between NONW and OO (6) and the last four between NONW and RLA (4, 5, 6 and 9). Of these, both the OO and RLA variables have higher scale effect measures, although this is not the case for the LLTI variable.

	A60P	EMP	UNEMP	LLTI	CAR0	OO	RLA
Ward	Sig	Sig	Sig	**Sig**	Sig	**Sig**	**Sig**
PWard1	Sig	Sig	Sig	**Sig**	Sig	**Sig**	**Sig**
PWard2	Sig	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard3	Sig	Sig	Sig	**Sig**	Sig	**Sig**	**Sig**
PWard4	Sig	Sig	Sig	**Sig**	Sig	**Sig**	**Not**
PWard5	Sig	Sig	Sig	**Not**	Sig	**Sig**	**Not**
PWard6	Sig	Sig	Sig	**Sig**	Sig	Not	Not
PWard7	Sig	Sig	Sig	**Sig**	Sig	**Sig**	**Sig**
PWard8	Sig	Sig	Sig	**Not**	Sig	**Sig**	**Sig**
PWard9	Sig	Sig	Sig	**Not**	Sig	**Sig**	**Not**
PWard10	Sig	Sig	Sig	**Sig**	Sig	Sig	Sig

Table 5.12: Highlighting the significant changes in correlation coefficients for the relationships with NONW between the individual and Pseudo Ward levels of analysis. (Shaded cells highlight the significant changes, whilst bold text denotes a change in direction).

5.4.1.4.3 EMP

As has been noted in the above sections, the EMP variable does not exhibit high levels of scale effect using the scale effect measures. Therefore, it would be expected that the correlation coefficients for the relationships with the EMP variable would be more stable than relationships with other variables, such as the tenure variables or NONW where the scale effect measures are higher. Table 5.13 contains the correlation coefficients for the relationships between the EMP variable and the other seven variables under consideration.

The OO variable shows the most scale effect of the variables considered. The publication geography has a high correlation coefficient, of 0.815. This is much greater than the correlation coefficients observed at either the SAR or ED levels. The correlation coefficients observed for the Pseudo Wards demonstrate a reasonable degree of scale effect. The relationship appears negative for Pseudo Wards 2, 6, 9 and 10. This is in contrast to Pseudo Wards 1, 3, 4, 5, 7, and 8 which reflect the positive relationship between OO and EMP observed at the SAR and ED levels. The variability is predicted by the scale effect measures, which are among the highest for the OO variable. Similar variability is observed for the RLA variable, where magnitudes and direction of the relationship change with different scales and realisations. The other high scale effect measure variable, CAR0 also demonstrates changing relationships, with changing magnitudes and directions. However, it is not as severe as that observed in the OO and RLA data. Therefore, those variables that have higher scale effect measures also have higher scale effect in the correlation coefficients.

	A60P	NONW	UNEMP	LLTI	CAR0	OO	RLA
SAR	-0.331	0.063	-0.161	-0.236	-0.187	0.101	-0.088
ED	-0.589	0.159	0.198	-0.521	-0.438	0.303	-0.406
Ward	0.031	-0.150	-0.965	-0.544	-0.696	0.815	-0.795
PWard1	-0.725	0.234	0.256	-0.496	-0.148	0.230	-0.353
PWard2	-0.773	0.396	0.142	-0.562	-0.247	-0.271	-0.384
PWard 3	-0.805	0.400	0.167	-0.518	-0.149	0.224	-0.339
PWard 4	-0.741	0.326	0.074	-0.553	-0.241	0.317	-0.459
PWard5	-0.810	0.389	0.256	-0.505	-0.155	0.218	-0.323
PWard6	-0.716	0.308	0.146	-0.538	-0.253	-0.330	-0.436
PWard7	-0.788	0.365	0.191	-0.510	-0.175	0.257	-0.339
PWard8	-0.755	0.450	0.155	-0.529	-0.154	0.236	-0.404
PWard9	-0.926	0.426	0.313	-0.494	-0.149	0.131	-0.227
PWard10	-0.916	0.405	0.337	-0.402	0.038	-0.022	-0.077

Table 5.13: Correlation coefficients for publication geography and the Pseudo geographies of the Reigate SAR district with EMP.

The A60P variable, NONW and UNEM variable with lower measures of the scale effect, have lower variability in their correlation coefficients. There is still a degree of scale effect movement present in the correlation coefficients, although it is not as severe as in the variables discussed above. There is also some change in direction of the relationships. It is interesting to note that the most stable relationship with the EMP variable is that of LLTI. The LLTI variable, despite being the aggregation variable, has relatively low Aggregation Effects and IACs, lending to the expectation that the relationships including LLTI would be more stable. Moreover, this provides limited evidence that aggregating using one variable in an analysis is potentially a useful tool that can lead to the realisation of more stable results from statistical analysis. In the case the EMP variable, the scale effect measures provide reasonably reliable indications of the scale effect.

	A60P	NONW	UNEMP	LLTI	CAR0	OO	RLA
Ward	Sig	Sig	**Sig**	Sig	Sig	Sig	Sig
PWard1	Sig	Sig	**Sig**	Sig	Sig	Sig	Sig
PWard2	Sig	Sig	**Sig**	Sig	Sig	**Sig**	Sig
PWard3	Sig	Sig	**Sig**	Sig	Sig	Sig	Sig
PWard4	Sig	Sig	**Sig**	Sig	Sig	Sig	Sig
PWard5	Sig	Sig	**Sig**	Sig	Sig	Sig	Sig
PWard6	Sig	Sig	**Sig**	Sig	Sig	**Sig**	Sig
PWard7	Sig	Sig	**Sig**	Sig	Not	Sig	Sig
PWard8	Sig	Sig	**Sig**	Sig	Sig	Sig	Sig
PWard9	Sig	Sig	**Sig**	Sig	Sig	Sig	Sig
PWard10	Sig	Sig	**Sig**	Sig	**Sig**	**Sig**	Not

Table 5.14: Highlighting the significant changes in correlation coefficients for the relationships with EMP between the individual and Pseudo Ward levels of analysis. (Shaded cells highlight the significant changes whilst bold text denotes a change in direction).

Table 5.14 relates to the results of the significance testing. In comparison to the results shown previously, a higher proportion of the variables and relationships demonstrate significant changes in correlation coefficients, with only the EMP to CAR0 relationship for Pseudo Ward 7 and the EMP to RLA relationship for Pseudo

Ward 10 demonstrating non-significance. Therefore, although all the relationships presented so far have mostly demonstrated significant changes in correlation coefficients, the EMP relationships appear to be the most severely affected.

5.4.1.4.4 UNEMP

As with EMP, the unemployment variable (UNEMP) demonstrates low incidence of the scale effect using the Aggregation Effects and IACs as scale effect measures. It would be expected that the variability of the correlation coefficients relating to the UNEMP variable would be the lowest shown in this section, as the IACs for UNEMP are the lowest observed in this analysis, for all zonal constructions. The correlation coefficients for this analysis are shown in table 5.15.

	A60P	NONW	EMP	LLTI	CAR0	OO	RLA
SAR	-0.075	0.038	-0.161	-0.028	0.013	-0.020	0.031
ED	-0.457	0.050	0.198	-0.445	0.282	-0.014	-0.059
Ward	-0.254	0.218	-0.965	0.419	0.645	-0.754	0.707
PWard1	-0.272	0.286	0.256	0.270	0.549	-0.595	0.545
PWard2	-0.030	0.265	0.142	0.413	0.626	-0.599	0.590
PWard 3	-0.178	0.178	0.167	0.300	0.633	-0.632	0.559
PWard 4	-0.150	0.109	0.074	0.267	0.523	-0.667	0.565
PWard5	-0.243	0.229	0.256	0.305	0.602	-0.645	0.616
PWard6	-0.154	0.288	0.146	0.367	0.637	-0.613	0.558
PWard7	-0.177	0.146	0.191	0.363	0.594	-0.423	0.385
PWard8	-0.200	0.186	0.155	0.310	0.621	-0.651	0.584
PWard9	-0.285	0.281	0.313	0.324	0.620	-0.696	0.622
PWard10	-0.367	0.240	0.337	0.325	0.632	-0.668	0.655

Table 5.15: Correlation coefficients for publication geography and the Pseudo geographies of the Reigate SAR district with UNEMP.

For the variables that exhibit low Aggregation Effects, such as A60P, NONW, and EMP, the correlation coefficients are reasonable stable. The A60P variable demonstrates directional consistency for all areas, although the magnitude of the relationship actually falls as aggregation increases, with the Ward and Pseudo Ward aggregations having relationships closer in magnitude to the individual than the relationship observed at the ED level. This observation is not typical for the MAUP, and the scale effect in particular, where it is assumed that as aggregation increases, so the strength of the relationship also increases. The NONW variable also demonstrates stability, and the direction of the relationship remains constant. This again supports the proposition that when all variables in an analysis have low predicted incidences of the scale effect, then the observed scale effect in the statistical analysis is likely to be lower.

	A60P	NONW	EMP	LLTI	CAR0	OO	RLA
Ward	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard1	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard2	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard3	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard4	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard5	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard6	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard7	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard8	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard9	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig
PWard10	Sig	Sig	**Sig**	**Sig**	Sig	Sig	Sig

Table 5.16: Highlighting the significant changes in correlation coefficients for the relationships with UNEMP between the individual and Pseudo Ward levels of analysis. (Shaded cells highlight the significant changes whilst bold text denotes a change in direction).

The remaining variables of LLTI, OO and RLA demonstrate higher Aggregation Effects and IACs than the variables discussed above. Therefore, they should exhibit greater instability in the correlation coefficients demonstrating the scale effect. The LLTI variable demonstrates relative stability at the Ward and Pseudo Ward level. However, for the lower levels of aggregation, the ED and individual, the relationship is negative, which is the reverse direction of the relationship exhibited at the higher levels of aggregation. There is also a more instability in the relationships demonstrated by the correlation coefficients for the OO and RLA variables, where-by magnitude and direction of the relationship changes. These variables have higher scale effect measures, in the Aggregation Effects and the IACs, and therefore it was predicted that the correlation coefficients would be more unstable. Therefore, the generalisation suggested above, that low scale effect measures when correlated with variables also exhibiting low scale effect measures is supported, as low scale effect measures correlated against higher scale effect measures tends to result in more unstable relationships.

From table 5.16 is possible to conclude that all the changes in correlation coefficients between the individual level and the Pseudo Ward level are significant, demonstrating pervasive scale effect in the relationships with the UNMEP variable. This suggests that the UNEMP variable is more scale dependent.

5.4.1.4.5 LLTI

LLTI was the variable used as the homogeneity maximisation variable for the construction of the Pseudo Wards. However, in comparison to some of the other variables used the scale effect measures of Aggregation Effects and IACs are not relatively high. Thus, the LLTI variable can be considered as a low scale effect variable. Therefore, it is expected that there will be less scale effect present in the correlation coefficients, summarised in table 5.17.

It is expected that the variables A60P, EMP and UNEMP would display relative stability. Both the A60P and EMP variables exhibit consistency of direction, although there is scale effect present in the magnitude of the correlation coefficients. The UNEMP variable shows less stability, as the magnitude of the correlation coefficients change. However, the negative relationships are present at the individual and ED level, whilst all the Ward and Pseudo Ward level coefficients are positive and demonstrate relative stability. The NONW variable has low IACs, although the Aggregation Effects are relatively high in comparison to the other variables discussed above. It would therefore be expect that there would be a greater degree of scale effect present in the correlation coefficients. This is the case as there are changes in the magnitude of the correlation coefficients and in their direction. This is evidence of more severe scale effect. The changes in direction do not only occur as the scale of analysis changes, for instance between individual and Ward, but also between the

Pseudo Wards areal units. Pseudo Ward 5 and 8 exhibit negative correlation coefficients similar to those observed at the ED and individual levels, and as such are areal unit systems that provide a better representation of the NONW data as the relationships are more stable between the different levels of aggregation.

	A60P	NONW	EMP	UNEMP	CAR0	OO	RLA
SAR	0.378	-0.030	-0.236	-0.028	0.226	-0.216	0.100
ED	0.740	-0.016	-0.521	-0.445	0.782	-0.444	0.520
Ward	0.525	0.161	-0.544	0.419	0.805	-0.579	0.631
PWard1	0.613	0.043	-0.496	0.270	0.770	-0.590	0.657
PWard2	0.627	0.111	-0.562	0.413	0.824	-0.614	0.652
PWard 3	0.614	0.053	-0.518	0.300	0.737	-0.525	0.593
PWard 4	0.632	0.128	-0.553	0.267	0.794	-0.560	0.640
PWard5	0.605	-0.015	-0.505	0.305	0.763	-0.571	0.609
PWard6	0.692	0.146	-0.538	0.367	0.805	-0.643	0.675
PWard7	0.618	0.041	-0.510	0.363	0.773	-0.429	0.505
PWard8	0.661	-0.008	-0.529	0.310	0.763	-0.575	0.655
PWard9	0.578	-0.010	-0.494	0.324	0.781	-0.583	0.632
PWard10	0.475	0.194	-0.402	0.325	0.753	-0.533	0.561

Table 5.17: Correlation coefficients for publication geography and the Pseudo geographies of the Reigate SAR district with LLTI.

The variables with higher incidence of the scale effect, as indicated by the Aggregation Effects and the IACs, CAR0, OO and RLA, actually exhibit relatively stable results. Although there is a clear increase in the strength of the correlation coefficients as the scale of analysis increases, the direction of the coefficient does not change. This relative stability in these correlation coefficients is not expected due to the magnitude of the scale effect measures. However, as has been noted above, the LLTI variable has a low aggregation effect and IAC, and so is less susceptible to the scale effect. For the correlation coefficients of these variables, it is likely that the lower susceptibility of the LLTI variable, is resulting in the correlation coefficients of more susceptible variables becoming more stable.

	A60P	NONW	EMP	UNEMP	CAR0	OO	RLA
Ward	Sig	**Sig**	Sig	**Sig**	Sig	Sig	Sig
PWard1	Sig	**Sig**	Sig	**Sig**	Sig	Sig	Sig
PWard2	Sig	**Sig**	Sig	**Sig**	Sig	Sig	Sig
PWard3	Sig	**Sig**	Sig	**Sig**	Sig	Sig	Sig
PWard4	Sig	**Sig**	Sig	**Sig**	Sig	Sig	Sig
PWard5	Sig	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard6	Sig	**Sig**	Sig	**Sig**	Sig	Sig	Sig
PWard7	Sig	**Not**	Sig	**Sig**	Sig	Sig	Sig
PWard8	Sig	Not	Sig	**Sig**	Sig	Sig	Sig
PWard9	Sig	Not	Sig	**Sig**	Sig	Sig	Sig
PWard10	Sig	**Sig**	Sig	**Sig**	Sig	Sig	Sig

Table 5.18: Highlighting the significant changes in correlation coefficients for the relationships with LLTI between the individual and Pseudo Ward levels of analysis. (Shaded cells highlight the significant changes whilst bold text denotes a change in direction).

Table 5.18 presents the significance test results for the relationships with the LLTI variable. As with the other variables, the majority of the changes in the magnitude of the relationships are positive. However, the exception to this is the relationship between the LLTI and NONW variables, where Pseudo Wards 7, 8 and 9 all exhibit non-significant changes in the correlation coefficients. This means that, there is a lower incidence of the scale effect in this relationship at this scale for those three Pseudo Geographies. Therefore it is possible to be more confident over these results. However, it is a surprising finding as, although the LLTI variable has low AE and IAC values, the NONW has high scale effect measures, suggesting that there would be more variability in the relationships observed with that variable.

5.4.1.4.6 CAR0

The percentage of the population without a car is represented by the CAR0 variable. It is a variable that has exhibited relatively high scale effect in terms of the Aggregation Effects and the IACs. It is the third highest scale effect variable in these terms, where only the OO and RLA variables have measures that are greater. Therefore, it would be expected that the scale effect observed in the correlation coefficients would be greater than has been observed in some of the other variables, such as A60P, or EMP where the scale effect measures were relatively low. Table 5.19 presents the correlation coefficients.

	A60P	NONW	EMP	UNEMP	LLTI	OO	RLA
SAR	0.295	0.037	-0.187	0.013	0.226	-0.289	0.319
ED	0.740	-0.017	-0.512	-0.445	0.782	-0.444	0.520
Ward	0.268	0.372	-0.696	0.645	0.805	-0.710	0.693
PWard1	0.243	0.274	-0.148	0.549	0.770	-0.706	0.689
PWard2	0.328	0.367	-0.247	0.626	0.824	-0.773	0.752
PWard 3	0.184	0.268	-0.149	0.633	0.737	-0.710	0.681
PWard 4	0.302	0.326	-0.241	0.523	0.794	-0.713	0.699
PWard5	0.220	0.283	-0.155	0.602	0.763	-0.719	0.708
PWard6	0.342	0.292	-0.253	0.637	0.805	-0.766	0.748
PWard7	0.284	0.207	-0.175	0.594	0.773	-0.729	0.695
PWard8	0.214	0.302	-0.154	0.621	0.763	-0.779	0.747
PWard9	0.214	0.283	-0.149	0.620	0.781	-0.715	0.707
PWard10	0.023	0.478	0.038	0.632	0.753	-0.763	0.708

Table 5.19: Correlation coefficients for publication geography and the Pseudo geographies of the Reigate SAR district with CAR0.

In comparison with the correlation coefficients observed for the variables with less scale effect, such as A60P, EMP and UNEMP there is more scale effect present in the relationships presented in Table 5.20. In general, there is more instability, demonstrated by the wider variation in magnitude of the coefficients between different scales and within the Pseudo Wards. Furthermore, there is also a greater degree of direction change of the coefficients, with the three low scale effect variables identified above actually demonstrating direction change. The high scale effect variables, OO, RLA, and exhibit stability in the direction of the correlation coefficients.

With the CAR0 variable, it is not possible to generalise and propose that if a variable in an analysis has a high scale effect in terms of the aggregation effect or IAC that it will follow that the statistical results from the analysis will be highly susceptible to the scale effect. It is clear that there is more scale effect present in the CAR0 correlation coefficients, and that the scale effect is more variable than in some of the correlation coefficients presented above such as A60P or EMP.

	A60P	NONW	EMP	UNEMP	LLTI	OO	RLA
Ward	Sig	Sig	Sig	Sig	Sig	Sig	Sig
Pward1	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard2	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard3	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard4	Not	Sig	Sig	Sig	Sig	Sig	Sig
PWard5	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard6	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard7	Not	Sig	Not	Sig	Sig	Sig	Sig
PWard8	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard9	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard10	Sig	Sig	**Sig**	Sig	Sig	Sig	Sig

Table 5.20: Highlighting the significant changes in correlation coefficients for the relationships with CAR0 between the individual and Pseudo Ward levels of analysis. (Shaded cells highlight the significant changes whilst bold text denotes a change in direction).

5.4.1.4.7 OO

The last two variables considered are both tenure variables. Previous studies, see for instance Tranmer and Steel (2001), have identified that the tenure variables tend to have high incidences of the scale effect. This may be in part due to the nature of tenure as highly clustered variables. The first of the tenure variables considered is OO, the percentage of the population that live in owner occupied properties. The correlation coefficients for OO are presented in table 5.21.

In terms of the direction of the variables, there is relative stability in the correlation coefficients. The NONW variable, which has relative high Aggregation Effects, demonstrates the most severe scale effect in terms of this measure. The EMP variable has correlation coefficients that are stable in comparison to the others in the analysis.

Indeed, the correlation coefficients from the zones constructed maximising the homogeneity of the LLTI variable provide a better areal unit system in terms of stable correlation coefficients than the publication Ward level geography. This is because the correlation coefficients are much closer to those observed at the lower levels (ED and Individual), than those obtained in from the statistical analysis of the publication data. This is true of the A60P variable as well, where the correlation coefficients are very stable at all levels and for all geographies. As the OO variable has a high degree of scale effect present, according to the scale effect measures it is surprising that there are variables in this section that do not exhibit relatively high incidents of the scale effect. However, it was noted above, that a variable with relatively high levels of the scale effect, when correlated against a variable with low incidence of the scale effect tends to have correlation coefficients that are relatively stable. This evidence supports this argument.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	RLA
SAR	-0.103	-0.007	0.101	-0.020	-0.216	-0.289	-0.656
ED	-0.115	-0.047	0.303	-0.014	-0.444	-0.583	-0.857
Ward	-0.094	-0.025	0.443	-0.754	-0.579	-0.710	-0.957
PWard1	-0.101	0.029	0.230	-0.595	-0.590	-0.706	-0.957
PWard2	-0.165	-0.062	0.270	-0.599	-0.614	-0.773	-0.932
PWard3	-0.134	0.067	0.224	-0.632	-.0525	-0.710	-0.932
PWard4	-0.154	0.011	0.317	-0.667	-0.560	-0.713	-0.937
PWard5	-0.091	0.029	0.218	-0.695	-0.571	-0.719	-0.944
PWard6	-0.223	-0.023	0.330	-0.613	-0.643	-0.766	-0.949
PWard7	-0.099	0.054	0.257	-0.423	-0.429	-0.729	-0.949
PWard8	-0.077	0.043	0.236	-0.651	-0.575	-0.779	-0.938
PWard9	-0.093	0.023	0.131	-0.696	-0.583	-0.715	-0.942
PWard10	0.051	-0.081	-0.022	-0.668	-0.533	-0.763	-0.935

Table 5.21: Correlation coefficients for publication geography and the Pseudo geographies of the Reigate SAR district with OO.

The variables with relatively high scale effect measures, such as the other tenure variable, and CAR0 demonstrate high scale effect as the magnitude of the correlation coefficients changes as the level of aggregation increases. Moreover, as aggregation increases, so the correlation coefficient increases, as expected in scale effect analysis. Therefore the combination of two variables with high predicted scale effect, in the case of the OO variable leads to correlation coefficients that exhibit higher levels of the scale effect.

	A60P	NONW	EMP	UNEMP	LLTI	OO	RLA
Ward	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard1	Not	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard2	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard3	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard4	Sig	**Not**	Sig	Sig	Sig	Sig	Sig
PWard5	Not	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard6	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard7	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard8	Not	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard9	Not	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard10	Sig	Sig	Sig	Sig	Sig	Sig	Sig

Table 5.22: Highlighting the significant changes in correlation coefficients for the relationships with OO between the individual and Pseudo Ward levels of analysis. (Shaded cells highlight the significant changes whilst bold text denotes a change in direction).

The changes in the magnitudes of the relationships are again significant for most of the variables and Pseudo Wards. However, there are a number of relationships that do not change significantly. These occur in the OO to NONE relationship (Pseudo Ward 4) and between A60P and OO for Pseudo Wards 1, 5, 8 and 9. It is surprising that any of the NONW and OO relationships appear not significant, as both the OO and NONW variable exhibit large AEs and IACs for all the Pseudo Wards. However, it is notable that for Pseudo Ward 4, both the AEs and the IACs for the NONW variable are the lowest for the reaggregations.

5.4.1.4.8 RLA

The last of the 8 variables under consideration is the second of the two tenure variables, the percentage of people living in accommodation rented from local authorities (RLA). The RLA variable has, along with OO, been identified as a variable that exhibits a high level of scale effect. This is reinforced by the aggregation effect and IACs in tables 4 and 10 above. Table 5.23 shows the correlation coefficients for the RLA relationships.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO
SAR	0.092	0.005	-0.088	0.031	0.100	0.319	-0.656
ED	0.206	-0.004	-0.406	-0.059	0.520	0.594	-0.857
Ward	0.199	0.014	-0.795	0.707	0.631	0.693	-0.957
PWard1	0.225	-0.060	-0.353	0.545	0.657	0.689	-0.957
PWard2	0.245	0.013	-0.384	0.590	0.652	0.752	-0.932
PWard3	0.257	-0.078	-0.339	0.559	0.593	0.681	-0.932
PWard4	0.288	-0.047	-0.459	0.565	0.640	0.699	-0.937
PWard5	0.175	-0.012	-0.323	0.616	0.609	0.708	-0.944
PWard6	0.283	0.002	-0.436	0.558	0.675	0.748	-0.949
PWard7	0.202	-0.021	-0.339	0.385	0.505	0.695	-0.949
PWard8	0.232	-0.107	-0.404	0.584	0.655	0.747	-0.938
PWard9	0.183	-0.003	-0.227	0.622	0.632	0.707	-0.942
PWard10	0.034	0.041	-0.077	0.655	0.561	0.708	-0.935

Table 5.23: Correlation coefficients for publication geography and the Pseudo geographies of the Reigate SAR district with RLA.

The variables that are predicted to have high levels of scale effect in the correlation coefficients, OO, CARO and NONW from the Aggregation Effects and IACs demonstrate unstable correlation coefficients, in terms of the magnitude changes in the coefficients, and in the case of the NONW variable, the direction of the relationships. However, although the NONW relationships change direction, they are all relatively similar in demonstrating that the relationship between RLA and NONW is virtually zero.

Of the variables that are predicted to have lower scale effect present in the correlation coefficients, the UNEMP variable is the least stable. The relationship for UNEMP not only changes magnitude but it also changes direction depending upon the scale (negative at the ED level). The aggregation variable, a low scale effect variable, has relatively stable correlation coefficients, between the aggregated levels, although there is a marked difference between the individual level and areal level correlation coefficients. The differing Pseudo Ward structures do not appear to be highly susceptible to the scale effect for the LLTI variable.

	A60P	NONW	EMP	UNEMP	LLTI	OO	RLA
Ward	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard1	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard2	Sig	Sig	Sig	Sig	Sig	Sig	Sig
PWard3	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard4	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard5	Sig	**Not**	Sig	Sig	Sig	Sig	Sig
PWard6	Sig	Not	Sig	Sig	Sig	Sig	Sig
PWard7	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard8	Sig	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard9	Sig	**Not**	Sig	Sig	Sig	Sig	Sig
PWard10	Sig	Sig	Not	Sig	Sig	Sig	Sig

Table 5.24 Highlighting the significant changes in correlation coefficients for the relationships with RLA between the individual and Pseudo Ward levels of analysis. (Shaded cells highlight the significant changes whilst bold text denotes a change in direction).

Table 5.24 presents the significant changes in magnitude of the relationships between RLA and the other variables. As with the other tenure variable, OO, the relationships with NONW are non-significant for Pseudo Wards 5, 6 and 9. Although the NONW and RLA variables both exhibit high AEs and IACs, the Pseudo Wards that are identified as non-significant are those that have the lowest magnitudes of the scale effect measures. Nevertheless, it is still surprising that any of the changes in relationships are non-significant for these variables. The fourth non-significant change in relationship with the RLA variable is with EMP for Pseudo Ward 10. The EMP variable has relatively low AEs and IACs, and therefore is less likely to be affected by the scale effect in to the same degree as the other variables.

Again, the results obtained for the correlation coefficients of the RLA variable support the theory proposed above, that the combination of two high scale effect variables tends to result in coefficients highly susceptible to the scale effect. In bivariate analysis, the inclusion of a variable that has relatively low predicted incidence of the scale effect tends to lead to more stable coefficients. The combination of two relatively scale effect free variable has tended to result in coefficients that are highly stable in comparison to the other coefficients in the analysis.

5.4.2 Comparative Analysis

The previous sections have considered the variables individually investigating whether they are susceptible to the scale effect, and whether or not the Aggregation Effects and IACs provide reliable predictors of the scale effect. It is also potentially useful to consider if the Pseudo Ward geographies provide better areal unit systems than the publication geography, in terms of having more stable correlation coefficients in comparison to the individual and ED level results. For instance, in most cases, the Pseudo Ward areal units, demonstrate lower scale effect in the correlation coefficients of the EMP variable when it is correlated against all other variables. Therefore, in terms of reducing the scale effect in data analyses, the Pseudo Ward systems used here are, from a scale effect perspective, better than the publication geography for analysing the EMP variable. For other variables, such as the two tenure variables OO and RLA, the Pseudo geographies exhibit as much scale effect as the publication Ward geography. This suggests that aggregation based on the LLTI variable does not provide areal units more suitable than the publication geography units for scale free, or scale reduced, analysis. The Pseudo geographies do not provide reliable areal units for the LLTI itself either. In all cases, although the LLTI is a low scale effect variable, the correlation coefficients are relatively unstable, and do not provide a consistent analysis.

It is possible to note that the other factor of the MAUP is also observable in this analysis. The zonation effect is present in the 10 Pseudo Ward units, and the publication Ward geography, as between the different areal unit systems the correlation coefficients change. This highlights the complex nature of the MAUP phenomenon, and highlights the inter-related nature of the issue. The zonation problem occurs most in the NONW variable, as this not only exhibits changing magnitude of correlation coefficients, but also exhibits the highest incidence of directional change in the correlation coefficients. As was noted above, the EMP variable exhibits the least scale effect when comparing between the different scales. Within the zonal structures investigating here it also demonstrates the lowest incidence of the zonation effect. However, there are still statistically significant differences between the correlation coefficients caused by the scale effect. Table 5.13 demonstrates that there is less change between the Pseudo Wards themselves, suggesting that the zonation effect is less significant in the EMP variable. Thus, it is likely that the pattern of LLTI is closely related to the pattern of EMP, however, as those members of the population with LLTI are unlikely to be employed, especially in Reigate which is an area of affluence. Therefore, there will be a similarity in the distribution of the variables. Moreover, as those members of the population with LLTI are likely to live in areas of less affluence, also a characteristic of unemployed areas, then the clustering of LLTI through homogeneity maximisation is likely to reflect the pattern of employment.

5.4.3 Discussion

The above analysis has tested a number of potentially useful concepts for MAUP, and specifically scale analysis. Firstly, that the scale effect is highly visible in many variables of the British Census. Even when only using the publication geography, there is still scale effect. The addition of the alternative pseudo coverages demonstrates how variable the relationships are at a given scale. Despite this, there tends to be a relative stability in the relationships seen in the pseudo wards. There are exceptions to this rule, notable with the NONW variable where the relationships change magnitude and direction. The main focus of this section is to examine whether or not the Aggregation Effects and IACs provide an indication of the level of the scale effect in a given set of variables. It was designed to examine whether or not high values of the aggregation effect and IACs indicated high presence of the scale effect. Thus, the greater the aggregation effect or IAC the greater the uncertainty of the accuracy of the relationships viewed.

The AEs and IACs are more successful at predicting some variables than others. For instance, the variables that have relatively low AEs and IACs, such as A60P, EMP and UNEMP tend to demonstrate less scale effect in the correlation coefficients. Those variables with higher measures, such as OO, RLA and CAR0 have correlation coefficients that vary more widely. The NONW variable is one of the most unstable of the variables considered. The AEs and IACs are not excessively high between the Individual and Ward data. However, it has the highest Aggregation Effects for all variables between the ED and Ward level. As the aggregation process for the pseudo coverages sought to aggregate EDs to the Ward level, then it is not surprising that the scale effect is severe in this variable.

There appear to be a number of trends that appear within the data. When two variables with low measures are correlated, then the scale effect tends to be low (see for instance the A60P and EMP relationships). When a low and high scale effect variable are combined in analysis, the resulting scale effect appears to be relatively with stable coefficients. This can be seen with the relationships such as EMP and CAR0, where the instability present in some of the other CAR0 relationships is not present. When two variables with high measures are combined, then the resulting scale effect appears to be stronger, with more movement in the correlation coefficients. These relationships are to be expected, and provide evidence that the scale effect measures can be used to gauge the likely incidence of the scale effect in analysis.

5.5. Bradford

Above, Pseudo Geographies for Reigate were created using the LLTI variable for homogeneous grouping. However, the results did not provide substantial evidence either to assess the ability of the aggregation measures to predict the magnitude of the scale effect, or to provide evidence of the impact of excessive homogeneity in a given variable. Therefore, the method of aggregating a given SAR Region with a target homogeneity variable is repeated. However, LLTI is not used as a homogeneity target variable, as the potential ability of an aggregation system to provide homogeneous areal units for a variable with low incidence is limited. Furthermore, the SAR Region of Reigate is not used as a larger Region with greater urban to rural contrast is required. Of the high incidence variables, those relating to tenure were rejected, as they are considered to have potentially too many processes operating in their location (see the analysis in Chapter 4), as they would not just reflect the decisions of where people wished to live, but also a host of socio-economic effects. Whilst this may not be a problem for the construction of the Output Areas for the 2001 UK Census which were based on, amongst other considerations, the homogeneity in the tenure variables, notably RLA (see Martin, 2003b), it was not deemed appropriate here as it was sought to minimise potential confounding effects in the data through the selection of less related variables from the set. The CAR0 variable, shown to have the third greatest scale effect, is used for the homogeneity in the aggregation process. The SAR Region selected is Bradford SAR, West Yorkshire. This SAR Region has a large urban centre, the City of Bradford, as well as a large rural extent outside the city. Moreover it is an old industry city of the north and there are, therefore, likely to be a number of contrasting processes operating within the area that could impact on the structure of the spatial data in the areal units. The ED distribution of the CAR0 variable which is to be aggregated is described in figure 5.2. From this it is clear to see that there are areas of clustering with high and low incidence of CAR0.

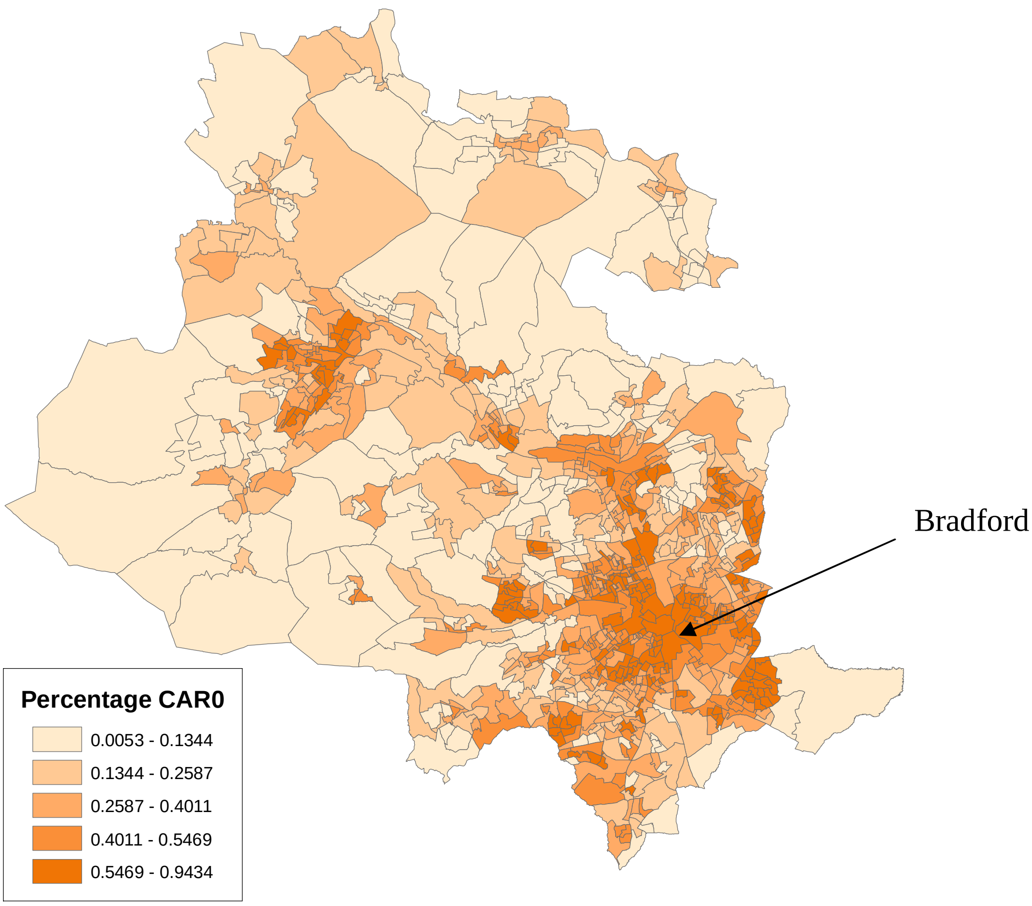


Figure 5.2: Percentage of CAR0 at the ED level in the Bradford SAR District.

The analysis is as described previously. The Enumeration Districts of the Bradford SAR were aggregated into ten Pseudo Ward Coverages. These all have the same number of areal units as the publication Ward Coverage, and are all unique. The Pseudo Ward Coverages are compared to the publication geographies of the Individual, ED and Ward levels in terms of the Weighted Variances, Aggregation Effects and IACs. The Scale Effect is then measured using correlation coefficient analysis, specifically relating the differences in correlation coefficients between the different aggregations. The greater the difference in correlation coefficient, the greater the scale effect. These differences will be related to the scale effect measures such as the Aggregation Effects and IACs.

5.5.1. Bradford Results.

Below, the results for Bradford are presented. They take the same form as section 5.4.1 where the results for Reigate were presented and discussed, with the weighted variance, AEs and IACs forming the initial part of the discussion. These findings are then used to support the results of the correlation coefficient analysis.

5.5.1.1 Weighted Variance

The weighted variances provide a rough statistic to describe the amount of variation between areal units within a group. Therefore, the greater the value of the weighted variance, the greater the amount of variation between the areal units in the zonal system. Table 5.25 presents the publication geography weighted variances in the top section and the Pseudo geographies in the lower section. The Pseudo Geographies are equivalent to the Ward level publication geography. Consequently the Weighted Variances for the Pseudo Geography are comparable with those of the Ward Level publication geography. For all the variables except the CAR0 aggregation variable, the weighted variance of the Pseudo Wards are, with one exception, lower than those observed in the Publication Ward coverage. For the A60P variable, Pward 2 has the lowest weighted variance, whilst Pward 3 has the highest. For the NONW variable the lowest weighted variance is Pward 7 whilst the highest is Pward 8. For the employment variables the lowest are Pward 7 for both EMP and UNEMP, whilst the highest are Pward 10 and Pward 1 respectively. The LLTI variable Pward 5 and

Individual	0.153	0.130	0.242	0.048	0.110	0.220	0.183	0.122
ED	3.330	40.229	6.834	0.599	1.190	20.229	27.211	24.455
WARD	15.232	563.824	91.382	7.809	3.249	240.380	188.946	162.797
	A60P	**NONW**	**EMP**	**UNEMP**	**LLTI**	**CAR0**	**OO**	**RLA**
Pward 1	14.898	529.442	83.192	7.750	2.340	217.851	157.795	130.524
Pward 2	12.646	447.847	67.607	6.275	2.314	197.643	140.273	113.971
Pward 3	14.771	501.963	84.306	7.440	2.457	215.819	171.671	144.126
Pward 4	13.389	558.142	85.207	7.661	2.122	212.870	150.254	128.379
Pward 5	13.770	525.349	81.929	7.159	1.985	196.121	127.422	116.423
Pward 6	13.056	460.667	82.623	7.695	2.146	220.551	162.309	107.567
Pward 7	13.991	438.130	64.098	5.788	2.871	184.439	142.455	146.149
Pward 8	14.134	559.529	80.767	7.007	2.933	210.185	135.890	141.777
Pward 9	13.442	443.584	69.655	6.212	2.427	188.236	143.101	115.218
Pward 10	14.718	534.636	85.313	7.026	2.084	202.003	193.199	165.429

Table 5.25: Weighted Variance results for Publication Geography and Pseudo Coverages for Bradford SAR.

Pward 8 exhibiting the highest and lowest weighted variances. The tenure variables Pward 5 and Pward 6 are the lowest for OO and RLA respective, whilst both have Pward 10 as the highest Pseudo Ward. For both the OO and RLA variables PWard 10 is the only Pseudo Ward coverage with an observed weighted variances that are higher than in the Publication geographies, within this group. The final variable presented in figure 5.25 is CAR0. As with the other variables, the weighted variance is below that observed in the publication geography. However, it was not discussed with the other variables as the CAR0 variable was used in the aggregation process as the homogeneity maximising variable. Despite this, the highest level of weighted variance is lower than that achieved in the publication geography. This demonstrates, therefore, that there is less internal homogeneity in the Pseudo Wards than in the Publication Wards, with the exception of Pward 10 in the OO and RLA variables. This conclusion is surprising given that this is the inverse of the objective that was sought.

Table 5.26 presents an overview of the weighted variance results for the UK as a whole. For the A60P, NONW, EMP and LLTI the weighted variances for Bradford are relatively low, closer to the minimum than the maximum, although A60P, NONW, EMP are all above the mean measure, and the median measure. The UNEMP variable is substantially greater than the mean and median. This confirms that the weighted variance for UNEMP is relatively high in the Pseudo Geographies.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
minimum	1.444	0.009	0.612	0.083	0.539	5.806	13.352	3.354
maximum	90.325	1271.79	129.798	18.711	19.455	505.572	692.932	700.93
Mean	12.775	35.284	14.409	1.831	3.777	71.748	129.156	125.12
Median	10.321	1.136	8.239	0.935	2.956	41.713	82.930	81.865

Table 5.26: Maximum, minimum and mean weighted variances for the whole UK SAR Districts at the Ward level.

The LLTI variable has weighted variance measures close to those of the median for the publication geographies. The CAR0 variable has weighted variances approximately half way between the minimum and maximum values observed in the UK. However, the Weighted Variances of the CAR0 variable is above the mean and median, although it does not tend to the upper limits of the distribution. The CAR0 variable in Bradford, therefore, has relatively high weighted variance, although there are some Districts, such as Birmingham or Leeds, in the UK that have greater values. The tenure variables of OO and RLA both have weighted variances close to the mean value of the UK distributions, but greater than the median values of the UK data. Despite this, it is far lower than the maximum values observed in the UK dataset. It is notable that those variables that exhibit the higher Weighted Variances are those that are related to the CAR0 variable. For instance, the UNEMP variable is likely to be related strongly to the CAR0 variable, and therefore it is not surprising that the Weighted Variance for this variable is high.

5.5.1.2 Aggregation Effects

A simple measure of the scale effect is the Aggregation Effect. These have been calculated for the ten Pseudo Geographies of Bradford, and will be compared to the Aggregation Effects for the publication geographies. There are two different measures of the Aggregation Effect discussed below. These are the Aggregation Effect between individual level data and the Ward and Pseudo Ward geographies, and the Aggregation Effect between ED level and the Ward and Pseudo Ward geographies.

5.5.1.2.1 Individual to Ward Aggregation Effects

Table 5.27 presents the Aggregation Effects for the Bradford SAR, with the publication geography results in the top section, and the Pseudo Geography results below. The trend is similar to that observed from the weighted variances, which as they are a calculation from the weighted variances is to be expected. As before, the discussion is based around each variable in turn, relative to the publication geography and then relative to the overall UK results.

ED	21.713	309.40	28.296	12.460	10.84	92.129	149.03	199.8
WARD	99.323	4336.4	378.36	162.36	29.60	1094.738	1034.8	1330.4
	A60P	**NONW**	**EMP**	**UNEMP**	**LLTI**	**CAR0**	**OO**	**RLA**
Pward 1	97.146	4071.971	344.453	161.138	21.324	992.138	864.206	1066.632
Pward 2	82.466	3444.421	279.925	130.481	21.094	900.103	768.243	931.360
Pward 3	96.322	3860.626	349.069	154.700	22.395	982.880	940.202	1177.781
Pward 4	87.310	4292.707	352.797	159.279	19.342	969.449	822.911	1049.106
Pward 5	89.792	4040.495	339.225	148.844	18.093	893.195	697.866	951.400
Pward 6	85.138	3543.016	342.100	159.998	19.561	1004.429	888.933	879.027
Pward 7	91.237	3369.687	265.396	120.340	26.171	839.970	780.195	1194.321
Pward 8	92.165	4303.375	334.413	145.689	26.730	957.225	744.238	1158.593
Pward 9	87.652	3411.635	288.403	129.151	22.118	857.263	783.732	941.549
Pward 10	95.974	4111.917	353.237	146.092	18.996	919.963	1058.106	1351.874

Table 5.27: Aggregation Effects for the Publication and Pseudo Geographies for the Bradford SAR.

All the weighted variances observed for the Pseudo Geographies are lower than those observed in the Publication Wards, with the exception of the OO and RLA AEs for Pward 10. They demonstrate that it would be expected that there would be less scale effect in the Pseudo Wards than in the Publication Wards, and that consequently, statistical analysis would be more likely to be stable. However, the difference between the Publication and Pseudo geographies is not great. Therefore, although the above is correct, the actual differences in the magnitude of the scale effect is not likely to be very significant. The A60P, NONW and EMP variables all have similar Aggregation Effects to those observed in the publication geography. Although they are all lower than observed in the publication geography. The overall pattern is similar to that described with the weighted variances.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Minimum	10.169	1.6413	2.4481	3.6388	5.2980	57.686	25.317	87.335
Maximum	514.99	7623.1	542.91	305.61	147.98	2313.962	3094.7	4252.25
Mean	77.583	358.83	58.961	37.897	34.212	365.594	622.11	780.96
Median	66.125	48.276	33.186	23.689	27.388	261.293	445.48	587.09

Table 5.28: Maximum, minimum and mean Aggregation Effects between Individual level data and Wards for all UK SAR Districts using publication geography.

Table 5.28 presents a description of the distribution of the Aggregation Effects for the whole of the UK. In the case of the first variable, A60P, the observed Aggregation Effects are greater than either the mean or the median values for the UK dataset. In the case of the next three variables NONW and the employment variables (EMP and UNEMP) they are significantly greater than the mean and median measures. Therefore, the scale effect in these variables is likely to be severe relative, to the scale effect observed elsewhere. The LLTI variable has Aggregation Effects lower than the means and medians for the UK data. The CAR0 variable has Aggregation Effects above the minimum, median and mean observed values, and below the maximum for the publication geography. Again, although above the average measures for the variable, which would suggest relatively high scale effects for the CAR0 variable, the results obtained here do not extend to the high tail values. The two tenure variables of OO and RLA both have Aggregation Effects greater than the average (median and mean) AEs observed in the UK dataset. Therefore, it would be expected that the scale effect would be relatively severe in the Bradford data in comparison to the scale effect observed in many of the other Districts in the UK.

5.5.1.2.2 ED to Ward Aggregation Effects

The second measure to be discussed considers the Aggregation Effect between the ED level data and the Pseudo Ward level data. In general it would be expected that this would be lower in magnitude than the Aggregation Effects between the Individual and Pseudo Ward as the change in scale of aggregation is less.

Table 5.29 presents the Publication and Pseudo Geography measures. As expected, the Aggregation Effects presented in this table are lower than those presented in table 5.30. This demonstrates that there is less scale effect present between the ED and Ward levels than between the Individual and Ward levels. The first six variables of A60P, NONW, EMP, UNEMP, LLTI and CAR0 all demonstrate Aggregation Effects lower than those observed in the Publication Geography. The A60P variable has Aggregation Effects that are around the same as those of the Publication Geography. Similarly, NONW has Aggregation Effects below the Publication Geography as do the employment variables of EMP and UNEMP. The LLTI variable has Aggregation Effects below those of the publication, and has the lowest of the set of variable discussed here. It is expected that the LLTI variable will not display a relative large scale effect in analysis when compared to the scale effect present in the other variables with high Aggregation Effects, such as A60P or UNEMP. These patterns are to be expected and reflect the patterns observed in the scale effect measures discussed above.

WARD	4.574	14.015	13.372	13.031	2.730	11.883	6.944	6.657
	A60P	**NONW**	**EMP**	**UNEMP**	**LLTI**	**CAR0**	**OO**	**RLA**
Pward 1	4.474	13.161	12.173	12.933	1.967	10.769	5.799	5.337
Pward 2	3.798	11.132	9.893	10.472	1.945	9.770	5.155	4.660
Pward 3	4.436	12.478	12.336	12.416	2.066	10.669	6.309	5.893
Pward 4	4.021	13.874	12.468	12.784	1.784	10.523	5.522	5.250
Pward 5	4.135	13.059	11.988	11.946	1.669	9.695	4.683	4.761
Pward 6	3.921	11.451	12.090	12.841	1.804	10.902	5.965	4.399
Pward 7	4.202	10.891	9.379	9.658	2.414	9.117	5.235	5.976
Pward 8	4.245	13.909	11.818	11.693	2.465	10.390	4.994	5.797
Pward 9	4.037	11.027	10.192	10.366	2.040	9.305	5.259	4.711
Pward 10	4.420	13.290	12.484	11.725	1.752	9.986	7.100	6.765

Table 5.29: Aggregation Effects for the Publication and Pseudo Geographies for the Bradford SAR.

The tenure variables of OO and RLA also have AEs below those observed from the Publication Geography, with the exception of Pward 10. The AEs for the variable in Pward 10 are greater than those observed in the Publication Geography describing an areal unit system that will have greater scale effect present. The other Pseudo Wards have AEs that are lower than observed with the Publication Geography. In the case of Pward 5 they are substantially lower than observed, suggesting that the aggregation system of Pward 5 is less susceptible to the scale effect. It would be expected that the level of homogeneity in Pward 5 will be lower than observed in the Pward 10. This is considered in the section below.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Minimum	0.8037	0.8832	0.6280	1.1111	0.735	0.294	1.2767	1.2237
Maximum	16.141	562.63	23.981	24.125	15.190	12.118	25.348	25.431
Mean	3.6331	7.9186	4.5472	5.8826	3.5983	1.721	5.3187	5.2301
Median	3.1703	4.8782	3.5375	4.7432	3.0559	1.455	3.8823	3.9464

Table 5.30: Maximum, minimum and mean Aggregation Effects between Enumeration Districts and Wards for all UK SAR Districts using publication geography.

Table 5.29 describes the distribution of the Aggregation Effects for the whole of the UK. The A60P, NONW EMP and UNEMP variables are above the mean and median measures of their distributions, suggesting that the scale effects to be observed in analysis using these two variables is likely to be relatively sever compared to other Districts within the UK. It is clear from table 5.29 that the results for the LLTI variable in the Pseudo Geographies should result in relatively low incidences of the scale effect as the Pseudo Geography has Aggregation Effects below the media and mean measures and close to the minimum observed in the UK dataset. The CAR0 variable used for the aggregation process has Aggregation Effects above the minimum observed for the UK. However, they Aggregation Effects are below those observed for the average measures of the mean and the median. This suggests that the statistical results for CAR0 when the scale of analysis changes should be more stable than has been observed previously and that there is less scale effect when aggregation changes between the EDs and Pseudo Wards than between the EDs and Publication Wards. As with the results discussed above, the tenure variables exhibit Aggregation Effects below that of the minimum observed for the UK dataset. The OO and RLA results are greater than the median measure, but virtually the same as the mean Aggregation Effects for the UK data. This suggests that the scale effects observed for this variable would be around average.

5.5.1.2.3. Intra-Area Correlations

The last scale effect measure considered here is that of Intra-Area Correlation, or IAC. This presents a population adjusted measure of the scale effect. The IACs range between 1 and 0, where 1 suggests complete homogeneity while 0 is complete heterogeneity. It is possible to get values slight beyond the maximums (see section 3.3 of the Methodology), although this rarely occurs in practice. It is expected that the overall pattern of the distribution of the IACs will be similar to that observed in the Aggregation Effects, as the population adjustment will be the same for all the variables. Therefore the A60P, NONW, EMP, UNEMP and LLTI variables appear to have similar IACs to those observed in the Publication Geography (see table 5.31). The A60P variable has IACs that are the always slightly lower than observed in the publication geography. This demonstrates that the within-area homogeneity of the A60P variable is the always slightly lower than for the publication geography than observed in the publication geography. The NONW has IACs that are both greater than publication (Pwards 3, 4 and 8) and lower than the publication geography (Pwards 1, 2, 5, 6, 7, 9 and 10). This demonstrates that a greater level of within-area homogeneity has been achieved in the Pwards that have higher IACs. For these Pwards, the scale effect would be expected to be greater, and reference back to the AEs suggests that this will be the case. The other variables, EMP, UNEMP, LLTI and CAR0 all have IACs that are lower than those observed for the publication geography, demonstrating lower within-area homogeneity, and therefore, lower incidence of the scale effect. This is consistent with the other results discussed above. However, the reduction in within-area homogeneity in the CAR0 variable, as measured by the IACs, is surprising, given that the aggregation process used to create the Pwards sought to maximise the level of within-area homogeneity in the CAR0 variable.

Similarly, for the OO and RLA variables, the IACs are very low. The OO has lower IACs than found in the publication geography, which suggests that the internal homogeneity of the variable is lower, and that the scale effect will be limited. The RLA variable also has lower Aggregation Effects than the publication geography, suggesting that the scale effect will be limited in that variable. It also has one of the greatest ranges for the IACs, with values between 0.0531 and 0.0791 which is larger than all the other variables suggesting that the scale effect for RLA is highly dependent on the areal unit system selected as well as the scale at which the analysis is conducted.

ED	0.040	0.597	0.0528	0.0221	0.019	0.176	0.286	0.384
WARD	0.0066	0.288	0.0251	0.0107	0.001	0.072	0.068	0.088
	A60P	**NONW**	**EMP**	**UNEMP**	**LLTI**	**CAR0**	**OO**	**RLA**
Pward 1	0.0066	0.2799	0.0236	0.0110	0.0014	0.0681	0.0593	0.0733
Pward 2	0.0056	0.2367	0.0192	0.0089	0.0014	0.0618	0.0527	0.0640
Pward 3	0.0066	0.2653	0.0239	0.0106	0.0015	0.0675	0.0646	0.0809
Pward 4	0.0059	0.2950	0.0242	0.0109	0.0013	0.0666	0.0565	0.0721
Pward 5	0.0061	0.2777	0.0233	0.0102	0.0012	0.0613	0.0479	0.0653
Pward 6	0.0058	0.2435	0.0234	0.0109	0.0013	0.0690	0.0610	0.0604
Pward 7	0.0062	0.2316	0.0182	0.0082	0.0017	0.0577	0.0536	0.0820
Pward 8	0.0063	0.2958	0.0229	0.0099	0.0018	0.0657	0.0511	0.0796
Pward 9	0.0060	0.2345	0.0198	0.0088	0.0015	0.0589	0.0538	0.0647
Pward 10	0.0065	0.2826	0.0242	0.0100	0.0012	0.0632	0.0727	0.0929

Table 5.31: IACs for the Publication and Pseudo Geographies for the Bradford SAR.

Table 5.32 describes the distribution of the IACs for the whole of the UK using Publication Geography. The distribution of the Pseudo Geography variables in comparison to the Publication Geography results is similar to the distributions that have been observed. The Tenure variables OO and RLA both have IACs lower than the means and medians of their respective distributions. This is as expected, given the value of the IAC and the above discussion. The CAR0 IAC is close to the median observed in the publication data, again suggesting that it is unlikely that there will be an extreme scale effect observed in the correlation coefficients using that data. As with the AEs discussed above, the results from the Pseudo Geographies are below the average measures of the mean and median. This again suggests that there should be relatively low scale effect present in the CAR0 variable. The LLTI statistics are below the mean and median measures observed, suggesting that statistical analysis using the LLTI variable should be relatively stable and free from the scale effect. Moreover, it demonstrates that, as with the Reigate analysis, that there is relatively low homogeneity in the LLTI variable. The employment variable of UNEMP has a range of IACs for the Pseudo Geographies that are above the mean and median of the publication distribution, suggesting greater than average homogeneity and scale effect for that variable. The other employment variable of EMP has a lower than average IAC. There is clear homogeneity in the NONW variable as it is greater than the average values for the UK distribution, and close to the maximum observed for the publication data. The last variable, A60P, has an IAC that is lower than the mean and median for the UK data, suggesting lower than average scale effects and homogeneity.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Minimum	0.001	0.0001	0.0004	0.0003	0.0007	0.0064	0.0021	0.0094
Maximum	0.178	0.4814	0.0780	0.0526	0.0420	0.4631	0.7230	0.9583
Mean	0.016	0.0388	0.0100	0.0065	0.0065	0.0677	0.1136	0.1455
Median	0.011	0.0088	0.0069	0.0046	0.0049	0.0534	0.0873	0.1135

Table 5.32: Minimum, maximum and mean IACs for the UK SAR Districts at the Ward level.

Therefore, in terms of the scale effect, it would be expected that A60P, EMP, LLTI, CAR0, OO and RLA will exhibit lower than average scale effects and the correlation coefficients relating to these variables should be relatively stable. The other two variables, NONW, and UNEMP are likely to display more severe scale effect in the correlation coefficients according to this analysis.

5.5.1.3. Correlation Analysis

The scale effect can be observed in the changing nature of the statistical relationships in analysis. One of the simplest statistical relationships is the correlation coefficient. Therefore, below the correlation coefficient is used, and the scale effect is taken as the difference between the correlation coefficients obtained at two different levels. The greater the difference, the greater the magnitude of the scale effect. Below, each variable is discussed in turn, with reference to the measure of the scale effect presented above.

5.5.1.3.1 A60P

Table 5.33 presents the raw correlation coefficients between the A60P and the other variables at the three publication geographies, SAR, ED and Ward as well as at the 10 Pseudo Ward levels. It is clear that the scale effect is evident in the correlation coefficients, as the magnitude and in some cases the direction, of the coefficients change through aggregation.

	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
SAR	-0.046	-0.316	-0.088	0.405	0.174	-0.105	0.045
ED	-0.4289	0.1249	-0.3632	0.6682	-0.0195	-0.0863	0.0803
Ward	-0.7256	0.6721	-0.7943	-0.1535	-0.6554	0.3793	-0.1655
Pward 1	-0.7953	0.7871	-0.8058	-0.1627	-0.7305	0.4352	-0.0956
Pward 2	-0.7436	0.6799	-0.7682	-0.0493	-0.6542	0.3057	-0.0788
Pward 3	-0.7432	0.6692	-0.7678	-0.1537	-0.6632	0.3298	-0.0945
Pward 4	-0.7408	0.7764	-0.8590	-0.1798	-0.7583	0.5005	-0.1977
Pward 5	-0.7064	0.7182	-0.8106	-0.1375	-0.7545	0.5020	-0.1809
Pward 6	-0.8049	0.7592	-0.8301	-0.2441	-0.7358	0.4539	-0.1588
Pward 7	-0.6736	0.6069	-0.7439	0.0608	-0.5934	0.3367	-0.1641
Pward 8	-0.7969	0.7381	-0.7805	-0.0905	-0.6496	0.2690	0.0711
Pward 9	-0.7003	0.6147	-0.7689	-0.0939	-0.6454	0.3976	-0.1224
Pward 10	-0.7255	0.6850	-0.7844	-0.1300	-0.7141	0.3882	-0.1557

Table 5.33: Correlation coefficients for Publication Geographies and the Pseudo Geographies of the Bradford SAR District with A60P.

A60P had relatively low AEs and IACs, with only the LLTI variable exhibiting values that are lower. Therefore, it is likely that the scale effect will be lower in the relationships with the other variables. For instance, the relationship between A60P and LLTI, the two variables with the lowest AE and IAC would be expected to exhibit the least scale effect, through coefficients that remain relatively similar at the different levels of aggregation. The results in table 5.33 demonstrate that this is the case, although there is a change in the direction of the relationship. The tenure variables of OO and RLA exhibit much greater AEs and IACs, and the relationships with those variables would therefore, be expected to be more susceptible to the scale effect. In both cases, there is a change in the direction of the relationship between the SAR and the aggregation level. Moreover, the magnitude of the coefficients is also highly variable. In terms of magnitude the greatest change in coefficients between the individual and aggregate levels occurs in the relationships with the employment variables. Both EMP and UNEMP exhibit directional change in the coefficients, and also large absolute magnitude change, suggesting that the coefficients for these relationships are the most susceptible to the scale effect.

	NONW	EMP	UNEMP	LLTI	CAR0	OO	RLA
Ward	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**
PWard1	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**
PWard2	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**
PWard3	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**
PWard4	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**
PWard5	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**
PWard6	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**
PWard7	Sig	**Sig**	Sig	Sig	**Sig**	**Sig**	**Sig**
PWard8	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**
PWard9	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**
PWard10	Sig	**Sig**	Sig	**Sig**	**Sig**	**Sig**	**Sig**

Table 5.34: Highlighting the significant changes in correlation coefficients for the relationships with A60P between the individual and Pseudo Ward levels of analysis. (shaded cells highlight the significant changes, whilst bold text demonstrates direction change).

Table 5.34 presents a schematic table demonstrating the significance of the changes. Significance is as defined in the Methodology, section 3.4. It is clear from the table, the all the changes through the scales are significant. Those relationships where there is also a swap in the direction of the coefficient between the individual and Ward and Pseudo Ward levels are indicated using bold lettering. It is clear that all the changes in correlation coefficients are significant. Moreover, half of the coefficients presented change direction. Therefore, even if it was argued that coefficients that change magnitude but maintain direction are not overly influenced by the scale effect, and can still be used in analysis, there is a substantial proportion of coefficients that also change direction, and therefore are not sufficiently stable to be dismissed in such a manner. In general, those that change direction of the coefficient change for all of the Pwards used. The exception to this is Pward 7 for the A60P/LLTI coefficient, where the sign of the coefficient remains stable.

5.5.1.3.2 NONW

Table 5.35 presents the correlation coefficients between the NONW variable and the other seven variables in the analysis. As with the relationships highlighted above, there is clear evidence of the scale effect. The NONW variable has the greatest AEs observed in the analysis, and therefore, it would be expected that the relationships observed would have a high incidence of the scale effect. As with the relationships with the A60P variable, the greatest change is observed with the employment variables, EMP and UNEMP. As before there is an observed change in direction of the coefficients, although only between NONW and EMP. The NONW UNEMP relationship maintains the same direction through all levels of aggregation. The tenure variables, although high AE and IAC, do not exhibit such high levels of scale effect through the change in coefficients. However, there is a change in the direction of the NONW and OO relationship, highlighting the incidence of the scale effect. As before, the relationship with LLTI, the variable with the least evidence of the scale effect, using the AE and IAC measures displays relatively stable coefficients, although there is still evidence of the scale effect present in the change magnitude of the relationships.

	A60P	EMP	UNEMP	LLTI	CAR0	OO	RLA
SAR	-0.046	0.035	0.154	0.028	0.058	0.013	-0.041
ED	-0.4289	-0.7047	0.5485	-0.0418	0.3921	-0.0239	-0.1790
Ward	-0.7256	-0.8881	0.7754	0.2218	0.6173	-0.1537	-0.1906
Pward1	-0.7953	-0.9256	0.7987	0.2577	0.7080	-0.2233	-0.2144
Pward 2	-0.7436	-0.8925	0.7773	0.1600	0.6488	-0.1349	-0.1916
Pward 3	-0.7432	-0.8778	0.7939	0.3004	0.6557	-0.1993	-0.1963
Pward 4	-0.7408	-0.9100	0.8109	0.2515	0.6639	-0.1751	-0.2241
Pward 5	-0.7064	-0.9147	0.8095	0.2995	0.7137	-0.1952	-0.2692
Pward 6	-0.8049	-0.9052	0.8237	0.3472	0.7201	-0.2888	-0.0988
Pward 7	-0.6736	-0.8605	0.7356	0.1190	0.6085	-0.0784	-0.2217
Pward 8	-0.7969	-0.9204	0.7964	0.1513	0.6326	-0.1058	-0.3090
Pward 9	-0.7003	-0.9159	0.8123	0.2334	0.6792	-0.2037	-0.1991
Pward 10	-0.7255	-0.8957	0.7987	0.2310	0.6692	-0.1951	-0.2045

Table 5.35: Correlation coefficients for Publication Geographies and the Pseudo Geographies of the Bradford SAR District with NONW.

	A60P	NONW	UNEMP	LLTI	CAR0	OO	RLA
Ward	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard1	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard2	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard3	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard4	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard5	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard6	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard7	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard8	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard9	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard10	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig

Table 5.36: Highlighting the significant changes in correlation coefficients for the relationships with NONW between the individual and Pseudo Ward levels of analysis. (shaded cells highlight the significant changes, whilst bold text demonstrates direction change).

This is supplemented by Table 5.36, which presents those relationships that demonstrate significant change between the different scales. For all the relationships, the differences between the correlation coefficients at the individual and Ward and Pseudo Ward levels are significant. Furthermore, the relationships between NONW and EMP and between NONW and OO demonstrate not only significant changes in magnitude, but also changes in the direction of the relationships.

5.5.1.3.3 EMP

Table 5.37 presents the correlation coefficients between the EMP variable and the others in the analysis. As with the previous discussions, there is clear evidence of the scale effect in the coefficients, as they change depending upon the level of aggregation. The pattern established by the previous two sections is continued with the relationships presented in table 5.37. In comparison with the relationship identified in table 5.33 and 5.35, the relationships in table 5.37 are less stable. There is greater evidence of the scale effect through the change in magnitude of the coefficients. As the previous discussion had noted that the employment variables of EMP and UNEMP tend to exhibit the greatest change in coefficients. Despite the fact

	A60P	NONW	UNEMP	LLTI	CAR0	OO	RLA
SAR	-0.3160	0.035	-0.188	-0.239	-0.233	-0.18	-0.144
ED	0.1249	-0.7047	-0.7473	-0.4056	-0.8096	0.6135	-0.4385
Ward	0.6721	-0.8881	-0.9131	-0.5035	-0.8423	0.5267	-0.2143
Pward 1	0.7871	-0.9256	-0.9146	-0.4621	-0.8824	0.5216	-0.1251
Pward 2	0.6799	-0.8925	-0.9187	-0.4605	-0.8651	0.5098	-0.2147
Pward 3	0.6692	-0.8778	-0.9315	-0.5903	-0.8827	0.5954	-0.2458
Pward 4	0.7764	-0.9101	-0.9262	-0.4231	-0.8580	0.5186	-0.1504
Pward 5	0.7182	-0.9147	-0.9145	-0.4617	-0.8830	0.5137	-0.0799
Pward 6	0.7592	-0.9052	-0.9296	-0.5835	-0.8987	0.6201	-0.2817
Pward 7	0.6069	-0.8605	-0.8907	-0.3986	-0.8610	0.5076	-0.2381
Pward 8	0.7381	-0.9204	-0.9312	-0.4057	-0.8405	0.4374	-0.0340
Pward 9	0.6147	-0.9159	-0.9095	-0.4717	-0.8503	0.5110	-0.1254
Pward 10	0.6850	-0.8957	-0.9308	-0.4879	-0.8687	0.5630	-0.1911

Table 5.37: Correlation coefficients for Publication Geographies and the Pseudo Geographies of the Bradford SAR District with EMP.

	A60P	NONW	EMP	LLTI	CAR0	OO	RLA
Ward	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard1	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard2	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard3	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard4	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard5	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard6	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard7	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard8	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard9	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig
PWard10	Sig	**Sig**	Sig	Sig	Sig	**Sig**	Sig

Table 5.38: Highlighting the significant changes in correlation coefficients for the relationships with EMP between the individual and Pseudo Ward levels of analysis. (shaded cells highlight the significant changes, whilst bold text demonstrates direction change).

that the relationships tend to be greater than has been observed previously the overall pattern is similar. The EMP and LLTI relationship has the lowest change in coefficients, along with the RLA tenure variable. The EMP UNEMP relationship on the other hand, has the greatest change in coefficients. These results are consistent with the above discussion.

Table 5.38 presents the significance test results for the correlation coefficients. All the changes in the correlation coefficients between the individual and Ward level aggregations are significant. For the EMP RLA relationship and the EMP OO relationship there are direction changes for all the Ward level aggregations highlighting an extreme incidence of the scale effect. This is not surprising as the NONW and OO have among the greatest AEs and IACs observed in the dataset.

5.5.1.3.4 UNEMP

Table 5.39 presents the correlation coefficients for the relationships with the UNEMP employment variable. The correlation coefficients do not remain stable through the different levels of aggregation, thus demonstrating that there is incidence of the scale effect in the relationships with UNEMP. The pattern of difference is as expected, and reflects the discussions above. UNEMP is the second of the employment variables, and therefore, it is not surprising that the differences between the coefficients at the individual and Ward aggregate levels are relatively high. As would be expected, the difference between the different levels is least for the relationship with the LLTI variable. The EMP relationship is the greatest, as would be expected. The other high AE and IAC variables of RLA and OO also have large differences between the different levels of aggregation, although again the OO relationship exhibits a greater different than the RLA relationship. The NONW UNEMP relationship also has large differences between the levels of aggregation.

Table 5.40 presents the significance test results for the differences between the correlation coefficients, and demonstrates that the differences for the relationships with in each of the difference Pseudo Ward aggregations are significant. The relationships with LLTI and CAR0 are not only significant in terms of the difference between the correlation coefficients, but they also demonstrate a change in the direction of the relationship. This is surprising for the LLTI variable, as it is not a high scale effect variable, according to the AE or IAC, whilst CAR0 has AEs and IACs of a similar magnitude to those observed for tenure in the OO and RLA variables.

	A60P	NONW	EMP	LLTI	CAR0	OO	RLA
SAR	-0.088	0.154	-0.188	-0.02	-0.1	-0.104	0.083
ED	-0.3632	0.5485	-0.7473	0.2375	0.7704	-0.6395	0.4380
Ward	-0.7943	0.7754	-0.9131	0.6045	0.9468	-0.7106	0.4240
Pward 1	-0.8058	0.7987	-0.9146	0.6123	0.9587	-0.7415	0.3451
Pward 2	-0.7682	0.7773	-0.9187	0.5548	0.9477	-0.6927	0.4012
Pward 3	-0.7678	0.7939	-0.9315	0.6437	0.9530	-0.7220	0.3866
Pward 4	-0.8590	0.8109	-0.9262	0.5128	0.9430	-0.6784	0.3218
Pward 5	-0.8106	0.8095	-0.9145	0.5472	0.9562	-0.6988	0.2646
Pward 6	-0.8301	0.8237	-0.9296	0.6393	0.9473	-0.7565	0.4126
Pward 7	-0.7439	0.7356	-0.8907	0.4801	0.9272	-0.6855	0.4050
Pward 8	-0.7805	0.7964	-0.9312	0.5593	0.9495	-0.6614	0.2741
Pward 9	-0.7689	0.8123	-0.9095	0.5370	0.9506	-0.7042	0.3573
Pward 10	-0.7844	0.7987	-0.9308	0.5824	0.9579	-0.7146	0.3654

Table 5.39: Correlation coefficients for Publication Geographies and the Pseudo Geographies of the Bradford SAR District with UNEMP.

	A60P	NONW	EMP	LLTI	CAR0	OO	RLA
Ward	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard1	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard2	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard3	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard4	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard5	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard6	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard7	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard8	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard9	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig
PWard10	Sig	Sig	Sig	**Sig**	**Sig**	Sig	Sig

Table 5.40: Highlighting the significant changes in correlation coefficients for the relationships with UNEMP between the individual and Pseudo Ward levels of analysis. (shaded cells highlight the significant changes, whilst bold text demonstrates direction change).

5.5.1.3.5 LLTI

LLTI has the lowest incidence of scale effect, as described by the AEs and IACs, and therefore, it would be expected that the differences observed in the correlation coefficients for the relationships with this variable should be lower than those observed for some of the other, higher scale effect incidence variables, such as OO and RLA. Table 5.41 presents the results of the coefficients. Those variables that have demonstrated relatively low AEs and IACs, such as A60P demonstrate relatively low incidence of the scale effect in the changes in the correlation coefficients between the different levels of aggregation. The NONW variable, one with the greatest AE and IACs demonstrates lower correlation coefficient change than is observed in the NONW variables with other variables. The greatest change in correlation coefficient occurs with the tenure variables and the CAR0 variable, all of which exhibit higher AEs and IACs. This evidence supports the hypothesis that the great the AE or IAC, the greater the magnitude of the scale effect.

	A60P	NONW	EMP	UNEMP	CAR0	OO	RLA
SAR	0.405	0.028	-0.239	-0.02	0.125	-0.161	0.079
ED	0.6682	-0.0418	-0.4056	0.2375	0.5746	-0.5763	0.4836
Ward	-0.1535	0.2218	-0.5035	0.6045	0.7884	-0.7914	0.6844
Pward 1	-0.1627	0.2577	-0.4621	0.6123	0.7046	-0.7605	0.6004
Pward 2	-0.0493	0.1600	-0.4605	0.5548	0.7189	-0.7557	0.6777
Pward 3	-0.1537	0.3004	-0.5904	0.6437	0.7591	-0.7771	0.6232
Pward 4	-0.1798	0.2515	-0.4231	0.5128	0.6772	-0.6119	0.4689
Pward 5	-0.1375	0.2995	-0.4617	0.5472	0.6543	-0.6056	0.3857
Pward 6	-0.2441	0.3472	-0.5835	0.6393	0.7757	-0.7647	0.6265
Pward 7	0.0608	0.1190	-0.3986	0.4801	0.6739	-0.6506	0.5219
Pward 8	-0.0905	0.1513	-0.4057	0.5593	0.7299	-0.8014	0.6815
Pward 9	-0.0939	0.2334	-0.4717	0.5371	0.6978	-0.6774	0.6234
Pward 10	-0.1301	0.2311	-0.4879	0.5825	0.7008	-0.7445	0.5844

Table 5.41: Correlation coefficients for Publication Geographies and the Pseudo Geographies of the Bradford SAR District with LLTI.

All the differences in correlation coefficients are significant, as shown in table 5.42. The relationships between LLTI and A60P and between LLTI and UNEMP demonstrate a change in the direction. UNEMP is one of the employment variables, which as has already been discussed exhibit high incidence of the scale effect. For A60P it is surprising, as the A60P variable has lower AEs and IACs, and therefore, would be expected to exhibit lower incidence of the scale effect.

	A60P	NONW	EMP	UNEMP	CAR0	OO	RLA
Ward	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard1	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard2	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard3	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard4	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard5	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard6	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard7	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard8	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard9	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard10	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig

Table 5.42: Highlighting the significant changes in correlation coefficients for the relationships with LLTI between the individual and Pseudo Ward levels of analysis. (shaded cells highlight the significant changes, whilst bold text demonstrates direction change).

5.5.1.3.6CAR0

The CAR0 variable exhibits relatively high AEs and IACs. Therefore, it would be expected that the correlation coefficients would demonstrate greater incidence of the scale effect through greater changes in magnitude between the different levels of aggregation. Table 5.43 demonstrates that this is the case, as the differences for all the relationships are relatively large. They are the greatest for the employment variables (EMP and UNEMP). The smallest difference in correlation coefficients is observed for the relationship with the RLA variable. This is surprising as the RLA variable has a high AE and IAC (the second greatest), and therefore would be expected to have relatively large differences in the magnitudes of the correlation coefficients between the levels of aggregation. Table 5.44 presents the significance test results. As with all

	A60P	NONW	EMP	UNEMP	LLTI	OO	RLA
SAR	0.174	0.058	-0.233	-0.1	0.125	-0.365	0.365
ED	-0.0195	0.3921	-0.8096	0.7704	0.5745	-0.8225	0.6614
Ward	-0.6554	0.6173	-0.8423	0.9468	0.7884	-0.8340	0.6050
Pward 1	-0.7305	0.7080	-0.8824	0.9587	0.7046	-0.7967	0.4792
Pward 2	-0.6542	0.6488	-0.8651	0.9477	0.7189	-0.8010	0.5632
Pward 3	-0.6632	0.6557	-0.8827	0.9530	0.7591	-0.8393	0.5539
Pward 4	-0.7583	0.6639	-0.8580	0.9430	0.6772	-0.8015	0.5126
Pward 5	-0.7545	0.7137	-0.8830	0.9562	0.6543	-0.7761	0.4120
Pward 6	-0.7358	0.7201	-0.8987	0.9473	0.7757	-0.8276	0.5729
Pward 7	-0.5934	0.6085	-0.8610	0.9272	0.6739	-0.7997	0.5725
Pward 8	-0.6496	0.6326	-0.8405	0.9495	0.7299	-0.8071	0.4794
Pward 9	-0.6454	0.6792	-0.8503	0.9506	0.6978	-0.7976	0.5273
Pward 10	-0.7141	0.6692	-0.8687	0.9579	0.7008	-0.8151	0.5423

Table 5.43: Correlation coefficients for Publication Geographies and the Pseudo Geographies of the Bradford SAR District with CAR0.

	A60P	NONW	EMP	UNEMP	LLTI	OO	RLA
Ward	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard1	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard2	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard3	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard4	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard5	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard6	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard7	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard8	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard9	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig
PWard10	**Sig**	Sig	Sig	**Sig**	Sig	Sig	Sig

Table 5.44: Highlighting the significant changes in correlation coefficients for the relationships with CAR0 between the individual and Pseudo Ward levels of analysis. (shaded cells highlight the significant changes, whilst bold text demonstrates direction change).

previous relationships presented above, all of the significance tests provide evidence that the differences between the correlation coefficients at the individual and Ward and Pseudo Ward levels are significant. The relationships between CAR0 and A60P, and CAR0 and UNEMP demonstrate that the scale effect is also present in terms of a change in direction of the relationships. This is not surprising for the UNEMP variable, as it has consistently been highlighted as a variable of high incidence of the scale effect. The A60P variable, however, has been noted as a variable with relatively low incidence of the scale effect, and therefore the change in direction of that relationship is more unusual.

5.5.1.3.7 OO

The first of the two tenure variables represents the proportion of household living in owner occupied properties. The previous AE and IAC analysis has indicated that the tenure variables are highly susceptible to the scale effect, as indicated by higher AE and IAC values. Table 5.45 presents the correlation coefficients for the relationships with OO.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	RLA
SAR	-0.105	0.013	0.013	-0.104	-0.161	-0.365	-0.679
ED	-0.0863	-0.0239	0.6135	-0.6395	-0.5763	-0.8225	-0.8366
Ward	0.3793	-0.1537	0.5267	-0.7106	-0.7914	-0.8340	-0.8990
Pward 1	0.4352	-0.2233	0.5216	-0.7415	-0.7605	-0.7967	-0.8481
Pward 2	0.3057	-0.1349	0.5098	-0.6927	-0.7557	-0.8010	-0.9105
Pward 3	0.3298	-0.1993	0.5954	-0.7220	-0.7771	-0.8393	-0.8744
Pward 4	0.5005	-0.1751	0.5186	-0.6784	-0.6119	-0.8015	-0.8814
Pward 5	0.5020	-0.1952	0.5137	-0.6988	-0.6056	-0.7761	-0.8316
Pward 6	0.4539	-0.2888	0.6201	-0.7565	-0.7647	-0.8276	-0.8787
Pward 7	0.3367	-0.0784	0.5076	-0.6855	-0.6506	-0.7996	-0.9163
Pward 8	0.2690	-0.1058	0.4374	-0.6614	-0.8014	-0.8071	-0.8764
Pward 9	0.3976	-0.2037	0.5110	-0.7042	-0.6774	-0.7976	-0.8778
Pward 10	0.3882	-0.1951	0.5630	-0.7146	-0.7445	-0.8151	-0.8664

Table 5.45: Correlation coefficients for Publication Geographies and the Pseudo Geographies of the Bradford SAR District with OO.

As with the previous coefficients that have been presented, the coefficients for the relationships with the OO variable demonstrate the scale effect. There are clear changes in the coefficients at the different levels of aggregation. The NONW and RLA variables exhibit the least change in correlation coefficients between the different levels of aggregation, which is surprising given that both the NONW and RLA variables and the correlation variable, OO, all exhibit high AEs and IACs. However, the absolute difference, discussed here does not provide a full description of the scale effect, and the NONW variable also exhibit a change in the direction of the relationship, which is discussed below. The greatest difference is observed in the relationship with the LLTI and employment variables. This is also surprising given that they do not have relatively high IAC or AE measures.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	RLA
Ward	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard1	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard2	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard3	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard4	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard5	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard6	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard7	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard8	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard9	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig
PWard10	**Sig**	**Sig**	Sig	Sig	Sig	Sig	Sig

Table 5.46: Highlighting the significant changes in correlation coefficients for the relationships with OO between the individual and Pseudo Ward levels of analysis. (shaded cells highlight the significant changes, whilst bold text demonstrates direction change).

Table 5.46 presents the results of the significance test. As with the previous results presented above, all the changes of the correlation coefficients are significant. The relationships between OO and A60P, and OO and NONW also exhibit changes in direction. As before, this is not surprising given the nature of the NONW variable, as high incidence of the scale effect is expected given the magnitude of the AEs and

IACs observed. However, the A60P has low scale effect measures, and would not therefore be expected to exhibit relatively high incidence of the scale effect.

5.5.1.3.8 RLA

The second tenure variable relates to the proportion of people living in accommodation rented from the local authority. The correlation coefficients for the relationships between this and the other variables in the analysis are presented in table 5.47.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO
SAR	0.045	-0.041	-0.041	0.083	0.079	0.365	-0.679
ED	0.0803	-0.1790	-0.4385	0.4380	0.4836	0.6614	-0.8366
Ward	-0.1655	-0.1906	-0.2143	0.4240	0.6844	0.6050	-0.8990
Pward 1	-0.0956	-0.2144	-0.1251	0.3451	0.6004	0.4792	-0.8481
Pward 2	-0.0788	-0.1916	-0.2147	0.4012	0.6777	0.5632	-0.9105
Pward 3	-0.0945	-0.1963	-0.2458	0.3866	0.6232	0.5539	-0.8744
Pward 4	-0.1977	-0.2241	-0.1504	0.3218	0.4689	0.5126	-0.8814
Pward 5	-0.1809	-0.2692	-0.0799	0.2646	0.3857	0.4120	-0.8316
Pward 6	-0.1588	-0.0988	-0.2817	0.4126	0.6265	0.5729	-0.8787
Pward 7	-0.1641	-0.2217	-0.2381	0.4050	0.5219	0.5725	-0.9163
Pward 8	0.0711	-0.3090	-0.0340	0.2740	0.6815	0.4794	-0.8764
Pward 9	-0.1224	-0.1991	-0.1254	0.3573	0.6234	0.5273	-0.8778
Pward 10	-0.1557	-0.2045	-0.1911	0.3654	0.5844	0.5423	-0.8664

Table 5.47: Correlation coefficients for Publication Geographies and the Pseudo Geographies of the Bradford SAR District with RLA.

Despite the fact that the RLA variable exhibits high AE and IAC measures, the differences between the correlation coefficients are relatively small, suggesting that the incidence of the scale effect in the relationships with the RLA data is relatively minor. There are, nevertheless some relationships that exhibit more scale effect than others. For instance, against LLTI, low AE and IAC variable the difference in the correlation coefficients is relatively large, in comparison with the other differences observed in table 5.48. The A60P also has relatively low changes in correlation coefficients, although the scale effect is present in that variable through the change in direction of the coefficients. The employment variables, which have previously been identified as variables with relatively high incidence of the scale effect do not exhibit large differences in the correlation coefficients between the different levels of aggregation.

	A60P	NONW	EMP	UNEMP	LLTI	CAR0	OO
Ward	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard1	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard2	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard3	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard4	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard5	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard6	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard7	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard8	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard9	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig
PWard10	**Sig**	Sig	Sig	Sig	Sig	Sig	Sig

Table 5.48: Highlighting the significant changes in correlation coefficients for the relationships with RLA between the individual and Pseudo Ward levels of analysis. (shaded cells highlight the significant changes, whilst bold text demonstrates direction change).

Despite the fact that all the relationships demonstrate relatively low differences in between the correlation coefficients, the differences are all significant, as highlighted in table 5.48. The only observed change in the direction of the relationship is with the A60P variable.

5.5.2. Comparative Analysis

As with the results presented for the Reigate SAR Pseudo Wards, it is possible to assess the impact of the zonation effect on the Bradford correlation coefficients. Again, no attempt is made to statistically assess the zonation effect as it is not the focus of the work presented here. For the Reigate data, it was possible to suggest that some variables acted better under the Pseudo Ward geography than the publication geography. The A60P, LLTI and tenure variables (OO and RLA) appear stable than in the Reigate SAR, with a greater variation in correlation coefficients.

As with the Reigate data, an overview of the zonation effect is given below. There is only one case where the weighted variances, Aggregation Effects and intra-area correlations appear greater than those observed for the publication Wards. This occurs in Pseudo Ward 10. In all other cases there is a lower incidence of the scale effect, as demonstrated by the AE and IAC, as well as a lower degree of homogeneity, also as demonstrated by the lower IACs. The greatest difference is observed in the NONW variable, which has weighted variances that are up to one fifth less. This demonstrates that the zonation effect can be severe. Conversely, the UNEMP variable weighted variances are very similar to those observed in the publication Ward system. However, the conclusion from this is that, as the AEs and IACs are lower than those observed for the publication geography, the scale effect is less pronounced in the pseudo geography, and that, therefore the alternative zonations are less susceptible to the MAUP. In the case here, the zonation effect is reducing the impact of the MAUP. However, the correlation coefficients are still significantly different in most cases to those observed at the publication Ward level, and as a result it must be concluded that the zonation effect also has an appreciable difference to the results of the statistical analysis of the data presented.

The remaining correlation coefficients, are not stable, and so provide evidence of the zonation effect in the aggregation process. Moreover, as has been demonstrated by the more detailed analysis of the correlation coefficients for the scale effect, it is not necessary to have a large change in correlation coefficient for a significant difference to exist.

5.5.3. Discussion

The above discussion has demonstrated that it is possible to observe the MAUP in a number of variables in the Bradford SAR. Moreover, it is possible to observe both the scale effect and the zonation effect elements of the MAUP, and both are present in the Bradford SAR data. The original intention was to provide a set of Pseudo Wards with relatively high homogeneity in the CAR0 variable. However, both the Aggregation Effects and the IACs confirm that the Pseudo Wards that were the output of the aggregation process did not achieve this, with low values for both these statistics. However, the low values suggest that there was relatively low homogeneity for the

CAR0 variable. With this the case, it was possible to investigate the implication of low homogeneity on a variable. Basing the aggregation process on the distribution of a variable has implications for the other variables under analysis, especially if there is a clear relationship between them. In the aggregation process discussed above, the tenure variables are most clearly related to the CAR0 variable, which is not surprising as they are all related to the income of the population. Therefore, the OO and RLA variables appear to have low incidences of the scale effect. These suppositions were observed in the data presented above. The OO and RLA variables have been observed to have severe incidences of the scale effect were relatively scale effect free in the correlation coefficients presented above. However, those variables that are not so directly related to the CAR0 variable, especially NONW and A60P, have greater Aggregation Effects and Scale effects than have been observed in the publication data, or relative to the data in the UK. The employment variables, EMP and UNEMP are also related to the CAR0 variable. However, the change in correlation coefficient with the relationships for these variables as indicated by the Aggregation Effects and IACs is not low as with the other related variables in tenure. Therefore, it is not possible to conclude that relating variables to those with which the aggregation process is conducted results in low scale effect.

5.6. Conclusions

The work presented in this Chapter has sought to build on the work presented in Chapter 4. Previously, much work has demonstrated the existence of the scale effect in areal unit data, something that Chapter 4 confirmed. The work in Chapter 4 also demonstrated that the scale effect was pervasive across variables and areas. The work here, in Chapter 5 has demonstrated that there is a link between the magnitude of the scale effect, as observed in correlation coefficients, and the magnitude of the AE and IAC as a predictor of the scale effect. This highlights the usefulness of the AE and IAC as tools in analysis, not to prevent the MAUP or more specifically the scale effect, but as a means to gain information about the scale effect in areal unit data.

This Chapter has gone a step further than previous analysis of correlation coefficients and the MAUP (as in, for instance, Openshaw and Taylor, 1979) and shown that the changes in coefficients are almost always statistically significant. It is clear that any changes in coefficient should be of concern to the analyst. However, the fact that these changes are statistically significant, beyond the 99% confidence interval suggests that the severity of the MAUP should not be underplayed. This, above all, provides justification for the continued research into the MAUP, and the scale effect, and the need to continue to highlight the potential pitfalls in the analysis of areal data.

Chapter 6

Factors influencing the scale effect

6.1 Introduction

Chapter 4 demonstrated the MAUP in the Census data of Great Britain. It also illustrated that there were differences between Districts in Great Britain and the amount of scale effect they would exhibit. Developing from the evidence in Chapter 4, Chapter 5 demonstrated the statistical significance of the scale effect using two areas, Bradford and Reigate, and a series of Pseudo Wards. So far, the factors contributing to the magnitudes of the scale effects have not been discussed. This chapter redresses this, by considering a number of the factors that may contribute to the magnitude of the AEs and IACs, and therefore incidence of the scale effect. The purpose of this is to attempt to understand the AEs and IACs in more detail. The relationships that will be investigated are as follows:

With the Aggregation Effect

- Weighted variance
- Proportion of a given variable
- Population Density
- Average number of people in areal units

With the Intra-area Correlation

- Weighted variance
- Proportion of a given variable
- Population Density
- Average number of people in areal units

At all times, the English and Welsh data (represented by diamonds) will be differentiated from the Scottish data (represented by squares) on the scatterplots. On each scatter plot, the measure under discussion will be represented on the *X* axis, whilst the AEs or IACs will be represented on the *Y* axis.

6.2 Aggregation Effects and Weighted Variances

The AE is constructed from weighted variances, and therefore, if one were directly related to the other, then it would be expected that there would be a perfect linear relationship between the two variables. Moreover, as larger weighted variances lead to larger AEs, the linear relationship should also be positive. However, although the relationships are positive in direction, there is not a completely linear trend to the data, as can be observed in figure 6.1. This demonstrates that the AE, and therefore the magnitude of the scale effect are not simply related to the magnitude of the weighted variance alone. Indeed, the definition of the AE also requires lower level weighted variance, either from individual data, or from a lower level of aggregation.

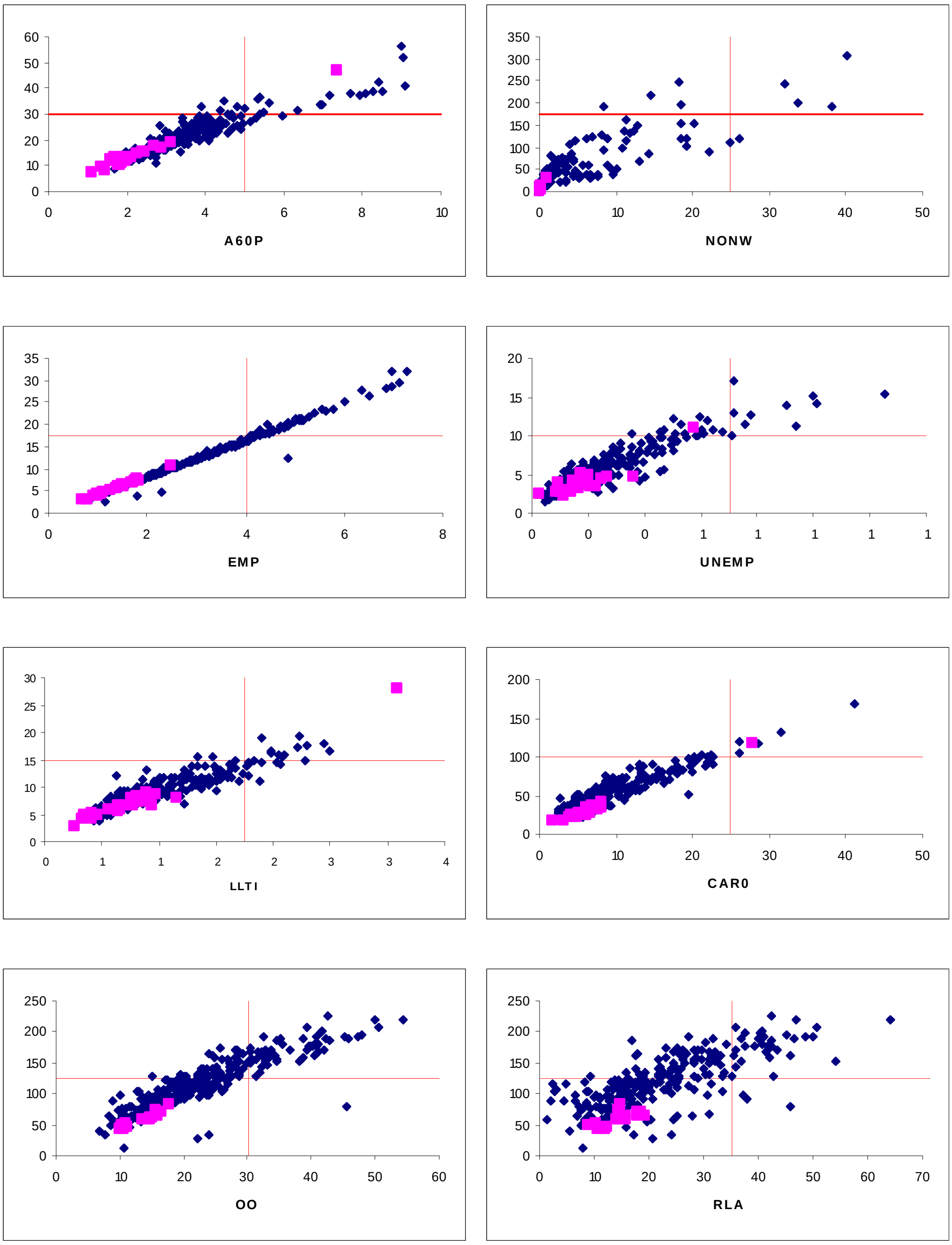


Figure 6.1: AE and weighted variance relationships at the ED level.

Therefore, the AE is comprised of two components, each of which may be capturing at least two different effects. The division of the plots in figure 6.1 demonstrates that the data are positively skewed. There are very few Districts with values in the lower right quadrant of the plot, as the data are concentrated in the lower left, upper left and upper right sections. The Scottish data are almost completely contained in the lower left sector, demonstrating that smaller basic spatial units used in Scotland have lower weighted variances and aggregation effects. This, in turn, suggests lower incidence of the scale effect.

In order that the relationship between AEs and weighted variance can be better understood it is necessary to focus on some of the relationships from figure 6.1 in more detail, to demonstrate that there are major differences in the relationships between the AE and weighted variances in the variables. For instance, the A60P the correlation coefficient is 0.933, while for the RLA variable, the correlation coefficient is 0.785, and for CAR0 the coefficient is lower at 0.302. There is clearly a large range of correlation coefficients for these relationships. However, they are all statistically significant at the 0.01 level.

The RLA, CAR0 and A60P variables are relationships that can be compared. Each has a number of outliers, which were identified in the previous chapter. The differences between the English and Welsh data, and the Scottish data are clear for all three of the variables as the AE values for the Scottish data are below those observed in the English and Welsh data for equivalent weighted variances. As was noted in Chapter 4, there is a marked difference between the population sizes of the areal units at the ED level between these countries. The smaller units in Scotland appear in this analysis to have lower levels of scale effect using the AE as a measure of the scale effect.

Consider the RLA variable. The Scottish data has a lower magnitude of AE relative to the size of the weighted variance than the data from England and Wales. This trend is not evident for the CAR0 or the A60P data. The main difference between the Scottish data is the average size of population for the basic spatial unit (an Output Area) is 154 people, while the equivalent areal unit size for England and Wales, (an Enumeration District), averages 494 people. As Chapter 4 demonstrated, this disparity in size has a clear impact on the magnitude of scale effect. In figures 6.2 and 6.3 there is an outlier in the Scottish data, which fits the pattern of the English and Welsh data better than that of the Scottish data. This is the SAR District of Renfrew, which is on the Western edge of the City of Glasgow, and has been highlighted in Chapter 4 as an outlier in terms of AE and IAC values. The average population for the Output Areas in Renfrew is 131 people, which is below the Scottish average suggesting smaller areas, which may contain more concentrated population in terms of specific variables. Moreover, it has the fourth highest number of areal units in the Scottish dataset, and has more basic level areal units (OAs) than many of the Districts in England and Wales. It is possible that as the number of areal units increases, the overall population of the District is likely to increase. In turn, this can increase the diversity between the areal units of the area. Further information about the characteristics of the Renfrew area could be incorporated at this point, which could be used to model the relationship between the aggregation and weighted variance. Increasing diversity within a district results in higher values for the weighted variance, (increase diversity, increase variation), which in turn will result in higher AEs. Therefore, as well as population size there are additional factors, which could include the number of spatial units, that are causing the Renfrew District to appear as an outlier.

Those areas that exhibit high AEs and high weighted variances are areas that also show high levels of urbanisation. For instance, the highest values for the A60P variable are 51.63 and 9.05 (AE and Weighted Variance respectively), and occur in Poole, an area that exhibits a high urban population, but also high concentrations of older people. On the ED/OA scatterplots (see figure 6.1) there is an outlier, and in each case the outlier area is the same SAR Region of Kingston-Upon-Hull. In general, if a District exhibits a high AE for one variable, it is likely that it will have high values for weighted variance and AEs in the other variables considered. With the exception of the NONW variable this pattern holds. This demonstrates that there are important areal characteristics external to the data under analysis that are causing effects in the results, and also serve to demonstrate the importance of zone construction, as although there is a link between aggregation effects and the weighted variances, there is still a high degree of variation in Districts with similar weighted variances, which should exhibit similar AEs if there were no other factors involved in the scale effect.

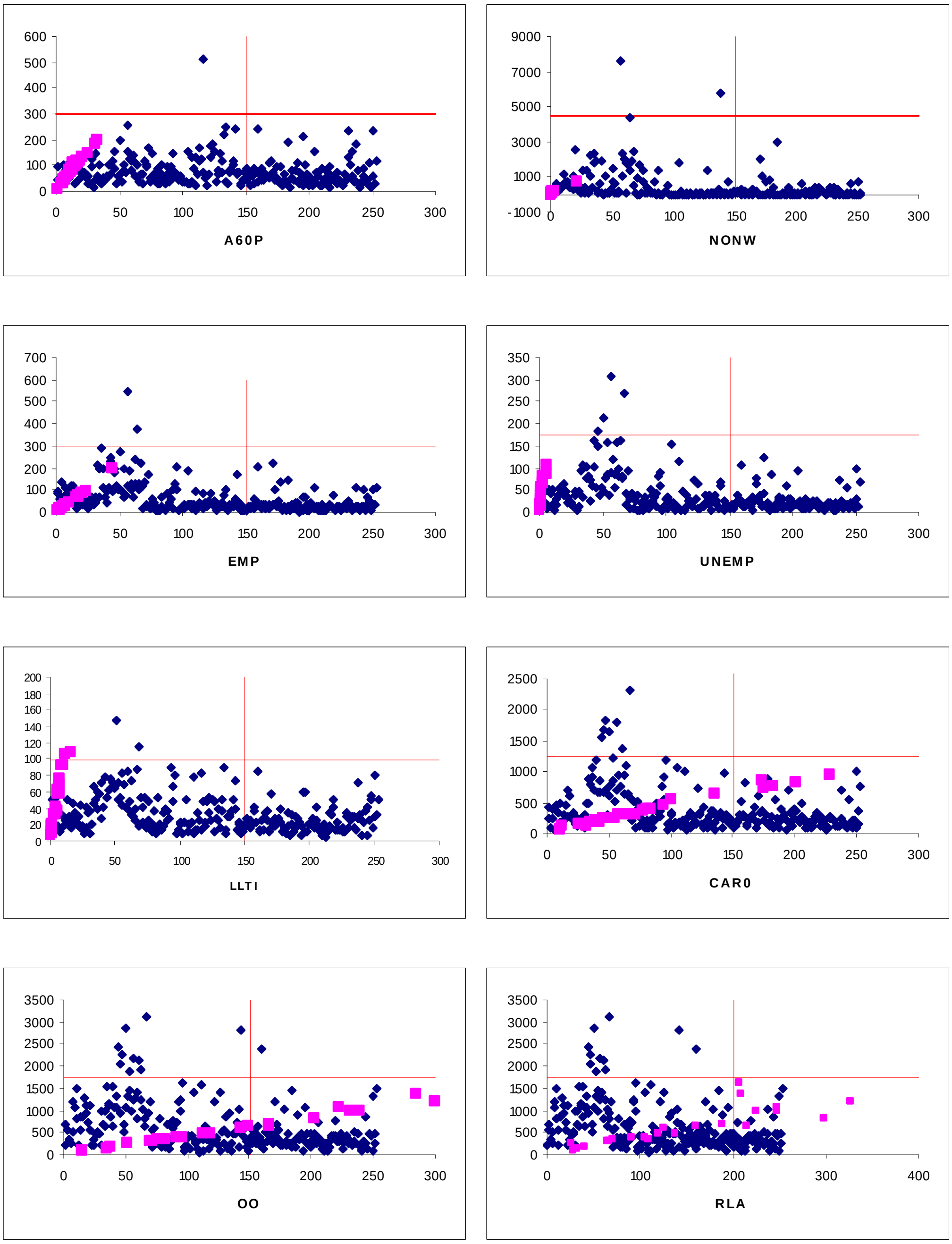


Figure 6.2: The relationship between AE and weighted variance for the eight variables at the Ward level.

Figure 6.2 demonstrates the relationship between the AE and weighted variance when the data are aggregated to the Ward level. For these plots, the relationships for the English and Welsh data are not obviously positive. This is due to the small number of outliers that have relatively high levels of AE, in comparison to the weighted variances recorded for them. In contrast, the Scottish data has a much more obviously positive relationship, similar to that observed in the previous figures at the ED level. From the plots in figure 6.2 it is clear that the data are heteroscedastic, demonstrating that there is unequal variance in the relationships between AE and Weighted Variance at the Ward level. In contrast, the Scottish data demonstrate a linear relationship, with variance that appears to be relatively constant. However, it must be noted that the Scottish data only consist of 25 Districts, whereas the English and Welsh data are a set of 254 Districts.

In all of the plots, there is a concentration of the data in the lower division of the graph. This demonstrates that there is greater variability in the AEs than in the weighted variances. It is possible for two different Districts to have the same AE but different weighted variances, and also vice versa. The Scottish data consistently fall in the lower quadrants of the plot, for the NONW, EMP, and UNEMP variables. For the CAR0, LLTI, OO and RLA variables, the Scottish data are similar to the English and Welsh data, falling in the lower left and right quadrants. The Scottish data for the A60P variable falls with the left hand upper and lower quadrants. The A60P variable has some of the lowest AEs found within the dataset, so the dispersion of the Scottish data is surprising.

For comparison, the three variables that were highlighted at the ED level, are again highlighted below. Despite the differences between the ED and Ward level data, there are still some similarities. For instance, in all cases the relationships are positive. For the three focus variables the correlation coefficients strongly positive, (0.931 (RLA), 0.975 (A60P) and 0.977 (CAR0)) and they are all significant at the 0.01 level. In the case of the Ward/PPS data, the average unit size between Scotland, and England and Wales are much closer (see Chapter 3 for details). This is also reflected in the average population sizes of the areal units in a district of the different aggregations. The average population for the ED levels are 128.6 for Scotland and 432.9 for England and Wales. Whereas, the average areal unit populations for Wards are 4906.4 for Scotland and 4948.1 for England and Wales. Therefore, the degree of aggregation that is required for Scottish data between the ED and Ward level is greater than that on the English and Welsh data. It would, therefore, be expected that the Scottish data would exhibit greater aggregation effects. This is, however, not the case, and the data for Scotland falls within the same trend as the English and Welsh data. It is worth noting that in all cases the Scottish data falls at the lower end of the scale with lower AEs and weighted variances. This might be due to the overall smaller population sizes, although some of the areas such as Renfrew have average population sizes far greater than those found in many of the English and Welsh areas, yet do not exhibit higher magnitudes of weighted variance or AEs as expected. This is also true of areas such as Dunfermline and Glasgow both of which have large average PPS (or Ward) populations of around 6000 people.

It is worth noting that for the Ward data, on both variables the values or the aggregation effect and the weighted variance are greater, implying that as average areal unit population size increases the IAC decreases at a slower rate. As with the ED/OA level data, the higher values relate to the data from urbanised areas, and the outliers include SAR Regions such as Manchester, Birmingham, Poole, and Portsmouth. As with the lower level data, it is these areas that appear as outliers for all the variables.

6.3 Aggregation Effects and Proportions

The AE and the proportion of a variable are very different measures. High proportions of a variable do not imply high AEs, and low proportions of a variable do not imply that a variable will have low AEs. Thus, there is no reason to assume that there is a positive, linear, relationship as observed between AEs and weighted variances will be observed in this instance. Figure 6.3 demonstrates that this is the case. The A60P, EMP, LLTI and OO variables have relationships with the majority of the data contained in the right hand quadrants, whilst the NONW, UNEMP, CAR0 and RLA variables have a greater concentration towards the centre and left quadrants. Overall, there is a clear distinction between the Scottish data, which tend to occur in the lower left of the distribution of Districts and the data for England and Wales.

The evidence in figure 6.3 indicates that it is not sufficient to suggest that, given a known proportion it is possible to determine the aggregation effect of a given SAR District. The correlation coefficient for this data is 0.179, which is not significant at either the 95% or 99% level. There are three outliers highlighted, and these refer to the contrasting Districts of Kingston-upon-Hull, Poole and Renfrew. The outliers in figure 6.4 represent 3 different areas, with little in common with each other: a

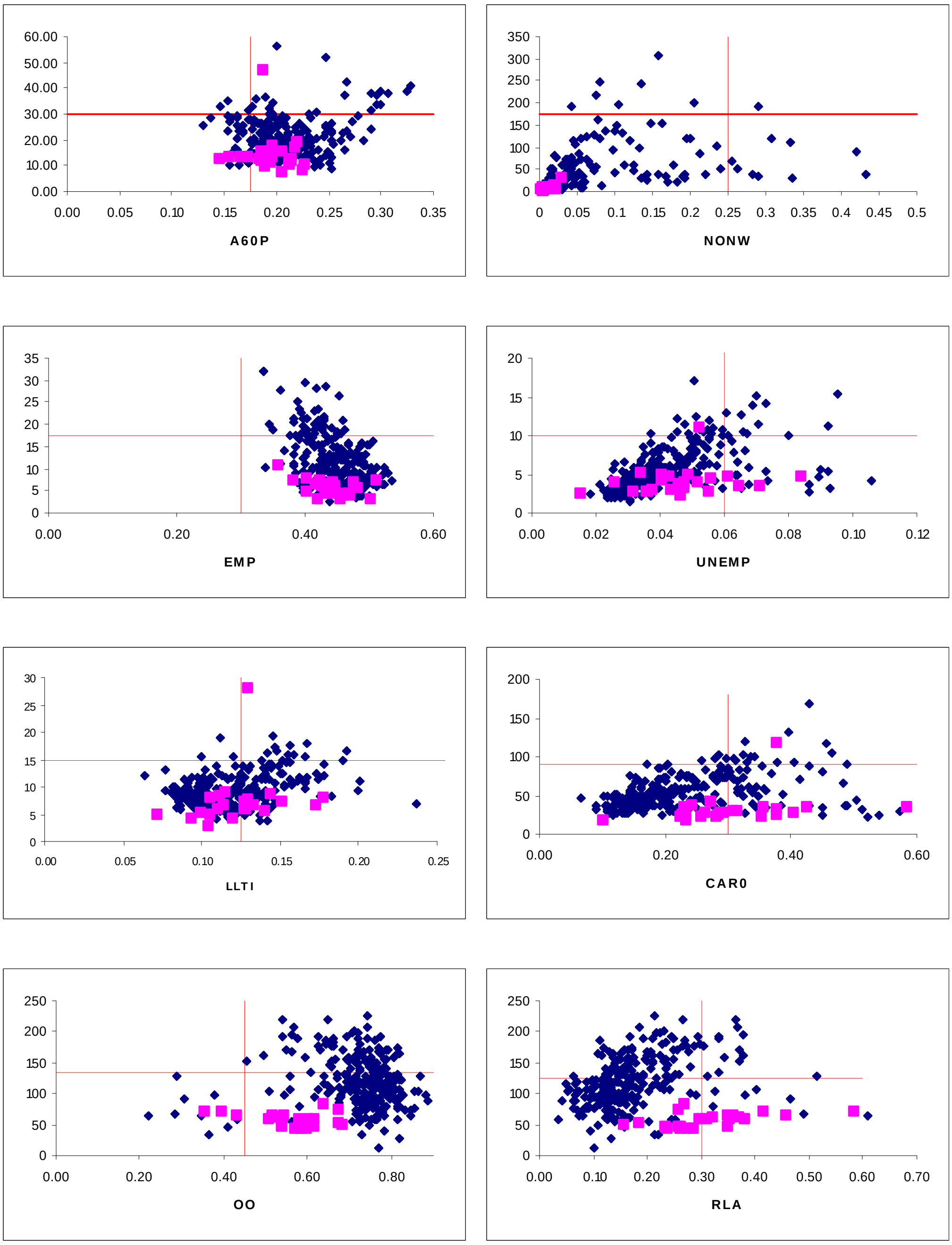


Figure 6.3: Plots demonstrating the relationship between AEs and the proportion of each of the eight variables.

prosperous south coast resort (Poole); old northern industrial area (Kingston-Upon-Hull), and; a Glaswegian suburb with a legacy of old industry (Renfrew). Despite this, they all have characteristics in the population of the older people that results in a large scale effect. However, with the analysis tools presented here, it is not possible to determine whether these processes causing the aggregation effects are the same or not. The tools presented in section 3.5 of the methodology seek to discuss this further, and the results of such an analysis looking at the potential spatial processes within the data are discussed in chapter 7. Conversely, there are also a number of Districts that have the same aggregation effect, but widely different proportions, demonstrating the lack of relationship between the two variables.

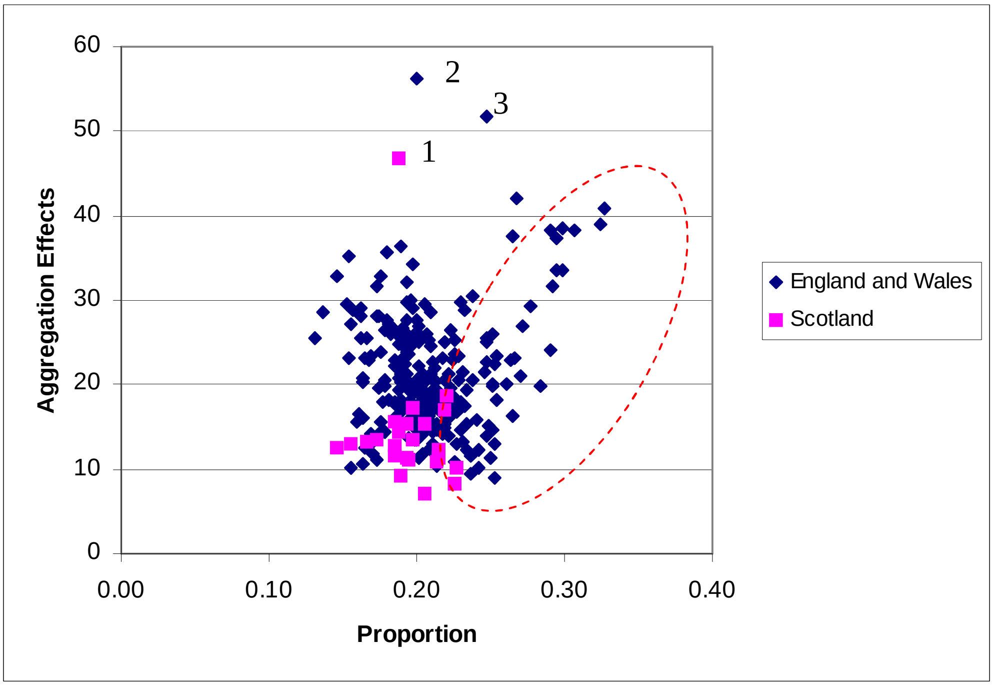


Figure 6.4: Aggregation Effect against proportion, for the A60P variable at the ED level. (1: Renfrew, 2. Kingston upon Hull, 3: Poole, ------ Identifies the coastal grouping).

As well as the general description of this plot, there are a number of interesting patterns that can be identified. Firstly, there are two distinct groupings of Districts on the plot (identified by the dashed line). Each of the Districts identified in this grouping can be considered as coastal, (see figure 6.5 for detail). Not only are they all coastal Districts, but there is also a distinct biased to the south of England in the selected Districts. Almost all of Devon and Cornwall are selected as members of this group. Only Blackpool, Fylde, Northampton, Eden, Craven and, E Yorkshire can be considered northern out of a total of 44 Districts select. The only Scottish District in the group is that of Dumfries and Galloway. Those Districts to the far right of the chart, can be identified as those in the South of England. If 10% of the Districts are chosen, then all 28 of the Districts highlighted are on the South coast, with the exception of Great Yarmouth. This group therefore is distinctly southern in its composition. The overall distinction of the Districts is not overly surprising, as from the chart (figure 6.4) the proportions of the population with ages over 60 is clearly high for this group, and coastal areas along with areas of natural beauty are well known as retirement destinations (see for instance, Law, C. M and Warnes, T. 1976). It is these retirement areas that are likely to have higher concentrations of people recorded in the A60P group, and therefore exhibit higher levels of homogeneity.

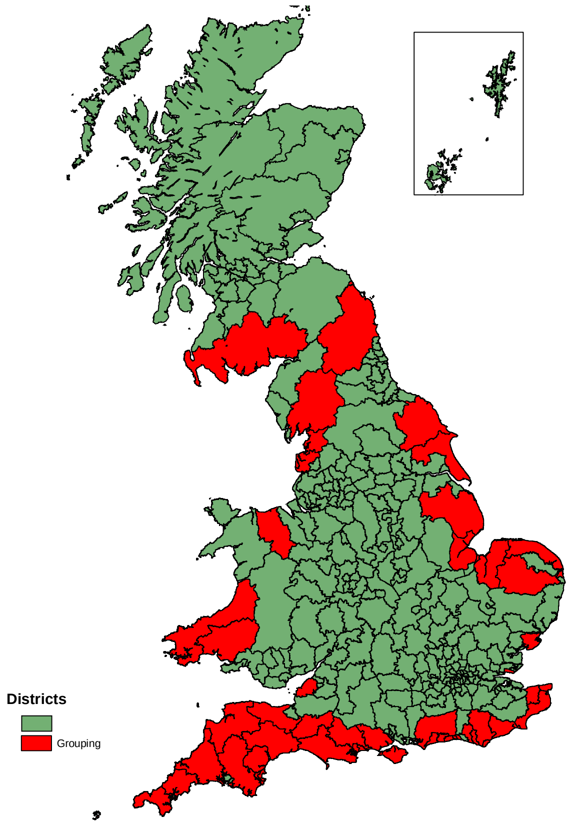


Figure 6.5: Distribution of the cluster in figure 6.4.

It is notable that a full range of aggregation effects are observed for the Districts with higher proportions of A60P. Higher proportions tend to result in more homogeneous populations, which in turn tend to exhibit greater incidence of the scale effect. However, for a number of the Districts identified here, this is not the case. This may occur as the ecological level data would be more closely related to the individual level data when the proportions of a given variable are very high as the construction of the data at the two levels would be more similar. Other groups, include the Scottish data (which are highlighted by square markers), Inner and Outer London, (not identified) as all the Districts in these areas are located at the bottom right of the distribution. Data from Wales is not grouped within the distribution, whilst the Counties with high proportion of urbanisation, such as the West Midlands, West Yorkshire, Merseyside and Manchester are all in the bottom left of the distribution, representing an extension of the London group.

Figure 6.6 demonstrates that there are similar relationships between the AE and proportion at the Ward level to those observed at the ED level. For each of the variables, the overall shape of the data is similar, and there is a clear distinction between the English and Welsh and Scottish data points. However, there are some differences between the two levels of aggregation. The tenure variables of OO and RLA do not have similar relationship patterns. The overall spread of values for the AE is far greater at the Ward level than the ED level, which is as would be expected, as there is likely to be a greater range of scale effects at the higher level of aggregation due to the greater range of levels of homogeneity possible in the data. The majority of the Ward relationships demonstrate that while the proportion of the OO variable remains similar, the aggregation effects tend to be concentrated in the lower section of the graph, below the range mid-point, with a few SAR Districts exhibiting higher aggregation effects than the majority of the country. However, in both the OO and RLA cases, the Scottish data are more similarly distributed with the English and Welsh data than they were at the ED level, as in neither the OO nor the RLA plots can the Scottish data be seen as a distinct group. This is a feature of all the relationships described as the Scottish data are always less concentrated and do not appear as a distinct group. Only the NONW variable does not reflect this relationship. For the LLTI variable the Scottish data are actually greater than the English and Welsh data.

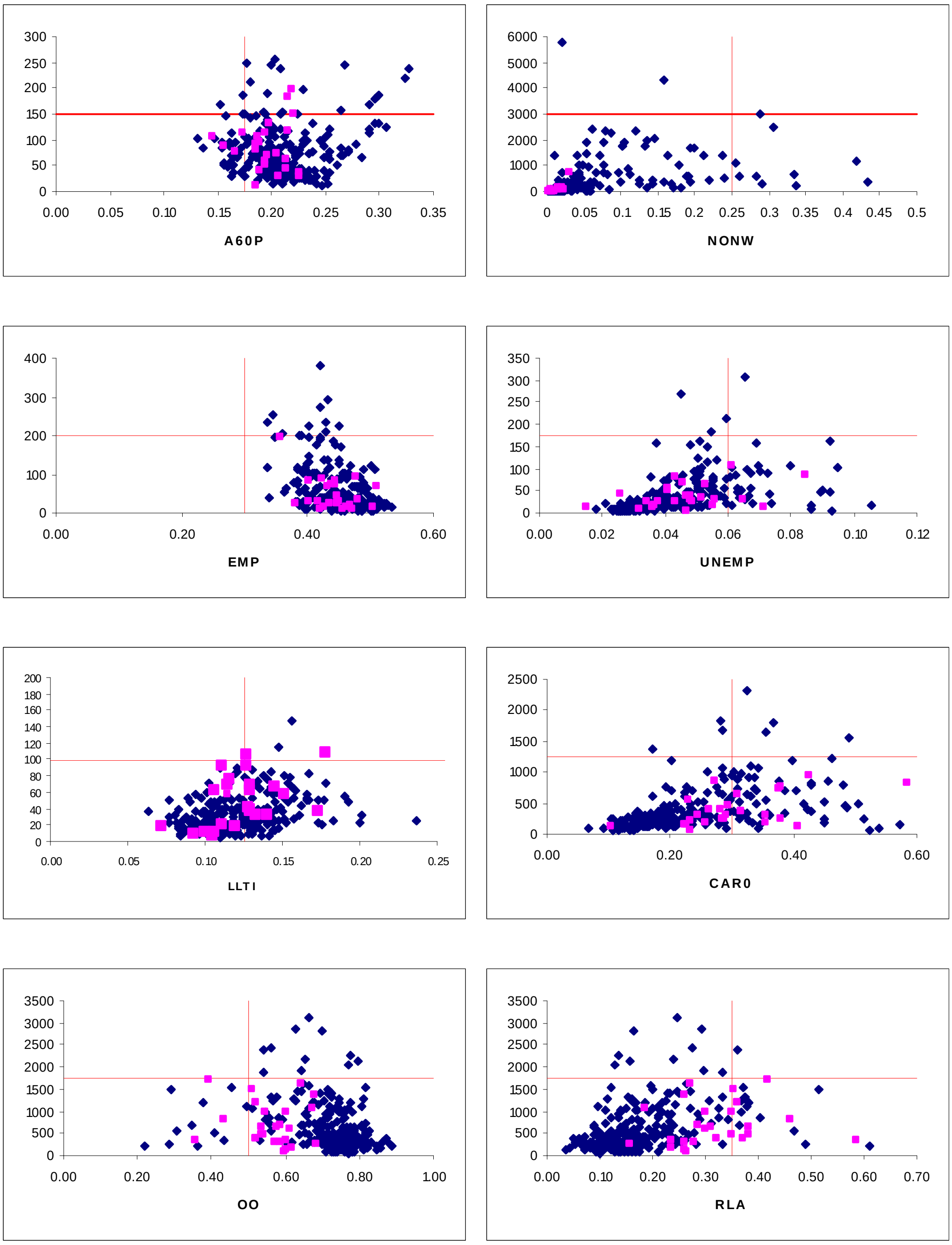


Figure 6.6: AE and Proportions at the Ward level.

The A60P variable provides a case study for the Ward level relationship. There has been an overall reduction in the strength of the relationship, as the correlation coefficient is 0.135, which is statistically significant at 0.05 (although with the Poole outlier removed the correlation coefficient falls to 0.111 and is no longer significant). The other Districts of Renfrew and Kingston-upon-Hull that were previously identified as outliers still have values which result in a plot position on the periphery of the main cluster. However, they are not as extreme as before and they do not appear as outliers.

The A60P relationships again demonstrate groupings of Districts that have similar characteristics. In general, they are similar to those observed in the ED level distribution (figure 6.2). The Districts representing Inner and Outer London are again located in the bottom left of the distribution. Those Districts that have a large proportion of urbanisation in their composition are also located in this part of the distribution. The data from Wales are not clustered within the distribution into an identifiable grouping. This suggests that Wales does not have a population characteristic linked to the scale effect that can be analysed or represented using the proportions of the variables at the levels available here. The coastal Districts discussed above are, again, located on the right of the Distribution, with those Districts in the south of the UK having position in the more extreme part of the distribution.

These observations are not unique to the A60P variable, as the other variables used in this study also demonstrate similar patterns, where there is a concentration of SAR Districts, demonstrating a weak positive relationship between AEs and the proportion of a given variable. With the exception of the A60P relationship, highlighted above, all the relationships are significant at the 0.01 level, suggesting that although the relationship is weak, the proportion of a given variable clearly has an effect on the resulting AE. It is also worth noting that the Districts highlighted as outliers for the A60P variable remain as outliers at the ED level for all variables. This is especially true for Renfrew, which is always the greatest outlier. The process of aggregation reduces these outliers for all variables, as with the A60P plots, so that in general the level of aggregation effect increases, while the clustering increases. Despite this, Renfrew District is still an outlier.

6.4 Aggregation Effects and Population Density

Previous research, such as Steel and Holt (1996b) has suggested that the MAUP occurs partly as a result of the different levels of homogeneity that are exhibited in different areal unit structures. Homogeneity can be measured through spatial autocorrelation, which assesses the degree to which the value of a given variable is related to the value of the same variable in a different spatial location. In general, the closer to instances of a variable are, the more likely they are to be to each other. Thus, in urban areas, there is likely to be a greater degree of similarity, as the population lives in closer proximity to each other, resulting in instances of a given variable being located closer together, and therefore more likely to be similar than in more rural areas. One way of measuring the distance between individuals within an area, when records of an individual's *X*,*Y* location are not available is population density. The greater the population density, the closer the population will be living. Thus, if there is a relationship between the proximity in which people live to each other, the resulting spatial autocorrelation and the magnitude of the scale effect in the MAUP examining the relationship between AEs and the population density could highlight it.

Figure 6.7 demonstrates the relationships between AEs and population density at the ED level. The scatter diagrams in figure 6.7 demonstrate that there is no obvious relationship between the variables. Overall, it would be expected that, if high population densities lead to higher incidence of the scale effect, then there should be positive relationship between the two variables. However, this is not the case for all of the variables, as the EMP variable has a correlation coefficient of -0.053. The relationships observed for the LLTI and CAR0 variables are also negative. However, the A60P variable has a positive relationship with a correlation coefficient of 0.243, and supports the hypothesis.

The Scottish data form a distinct group as they always occurs within the lower half of the scatterplot, and with the exception of the outlier District (Renfrew) for the A60P, and LLTI variables, it is always in the lower left quarter. Moreover, when considering the Scottish data alone, the relationships are all positive, with correlation coefficients ranging from 0.21 (LLTI) to 0.79 (EMP), 0.84 (NONW) and 0.89 (RLA). This suggests that increasing population density, at least in the Scottish Districts, will result in greater AEs.

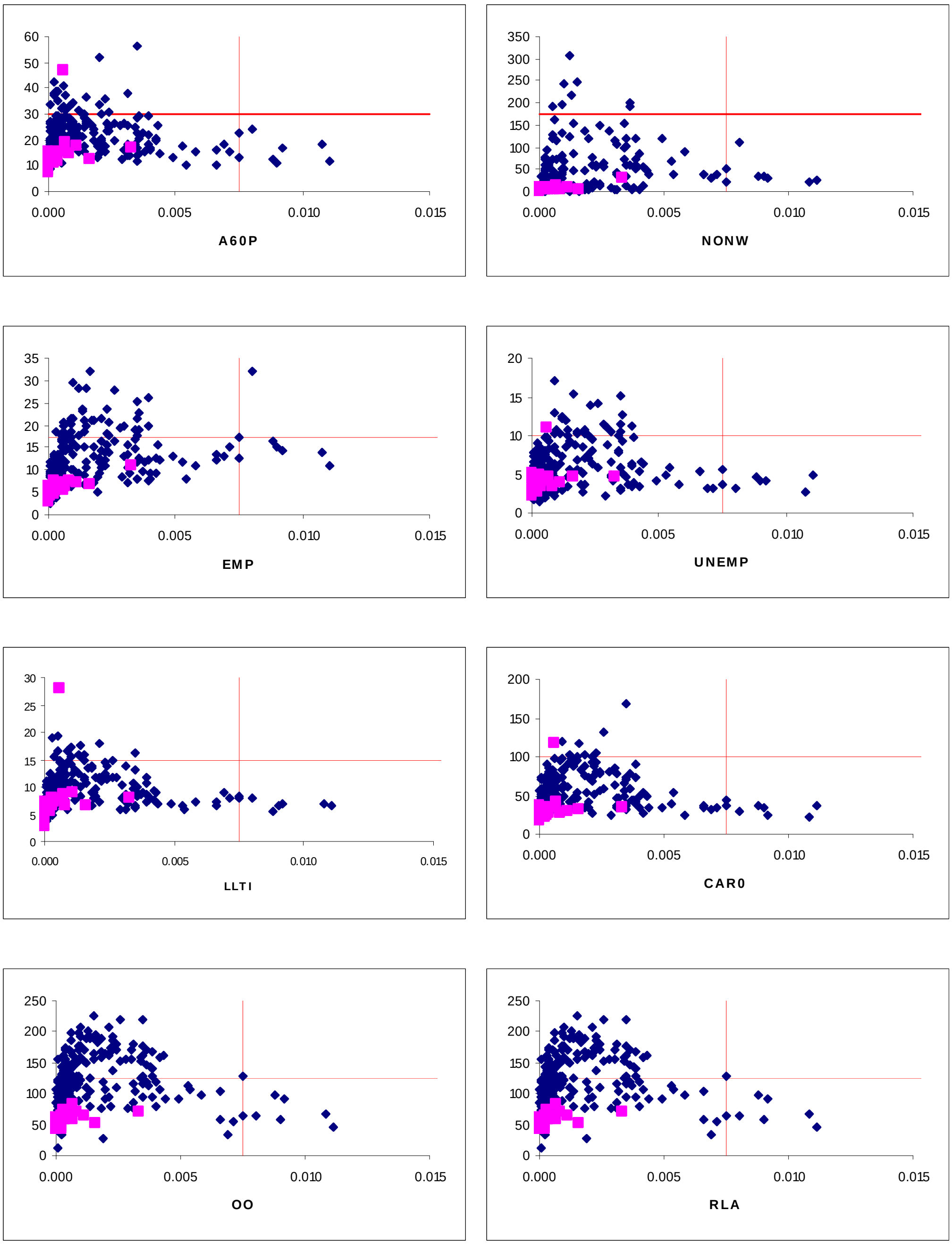


Figure 6.7: Relationship between AEs and Population Density for the eight variables at the ED level.

Figure 6.8 demonstrates the same relationship at the Ward level. When the data are aggregated to the Ward level, all the variables exhibit positive relationships between aggregation effects and the population density (see figure 6.8). This concurs with the hypothesis that as population density increases so the incidence of the scale effect, as measured through the AE will also increase. This supports the supposition that closer things are more related than far things (Tobler's first law of geography, Tober, 1970) and that the incidence of the scale effect is likely to be related to the levels of homogeneity within a given set of areal units. The correlation coefficient for the A60P variable is 0.347 (although it falls to 0.05 with the exclusion of the Birmingham outlier), and the relationship is not statistically significant. Thus, as population density

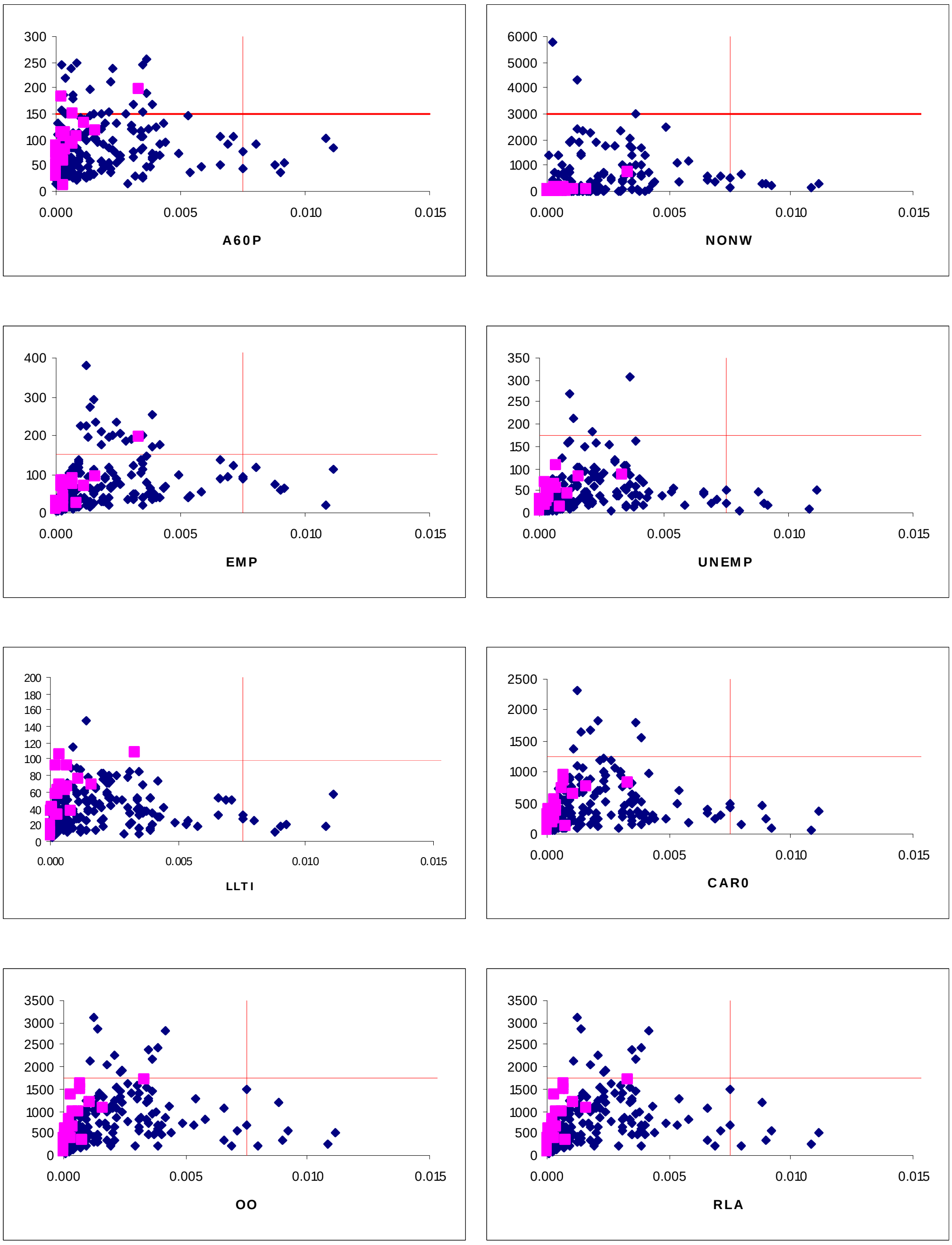


Figure 6.8: Relationships between AEs and Population Density for the eight variables at the Ward level.

increase, so the AE increases. This in turn demonstrates that as population density increases, so incidence of the scale effect increases. This is initially counter intuitive as it would be expected that, with higher population densities the more similar people are likely to be, all other things being equal, thus there would be likely to be a higher level of homogeneity within the areas. However, as aggregation occurs, the level of homogeneity will fall as the population will become less similar the bigger the areal unit system used. Consequently, in zones with high population densities, the fall in homogeneity is greater than in the areas with low population densities. It does not appear that the first of the theories suggested is supported by the data, and as such, must be rejected (see section 4.1.1). Therefore, the second of the two theories proposed, whereby there are processes, which may or may not be represented at the scale of analysis and the areal unit boundaries given, is more likely to be closer to reality. For the other variables in the study, only the NONW, EMP and RLA are significant at the 0.01 level, whilst the UNEMP variable is statistically significant at the 0.05 level. The other variables, A60P, LLTI, CAR0 and 00 are not significant at either of these two levels.

6.5 Aggregation Effects and Average Population

The average population of the areal units in a District could provide a useful indicator of a likely level of scale effect. As with the previous section that sought to identify if the density of population had a strong influence, the average population of an areal also relates to the potential levels of spatial autocorrelation. Areas with high average populations are less likely to have high spatial autocorrelation, as when the number of people in an areal increases the less likely they will be to be similar to each other. Thus, the greater the number of people, the greater the diversity. Because the population sizes of the areal units are so different, it is expected that there will be a clear difference between the Scottish data and the data representing the Districts in England and Wales. If the supposition above is correct, then the Scottish data should exhibit lower aggregation effects than the data from England and Wales.

Figure 6.9 demonstrates the relationship between the average population of the areal units in the Districts and the magnitude of the AEs at the ED level. For all the variables, the Scottish data lies in the bottom left quadrant, with an outlier (Renfrew) in the upper left quadrant for the A60P, UNEMP, LLTI and CAR0 variables. The Scottish data form a small cluster of Districts, demonstrating that the AEs and average populations observed for all of them are relatively similar. The English and Welsh data lies within the right hand quadrants, with the exception of a number of Districts that fall on the left hand side (Kensington and Chelsea, City of London and Camden). The concentration of the English and Welsh Districts is in the lower right quadrant for the A60P, NONW, EMP, UNEMP, LLTI and CAR0 variables, whilst the two tenure variables, OO and RLA are more evenly spread between the two. The average

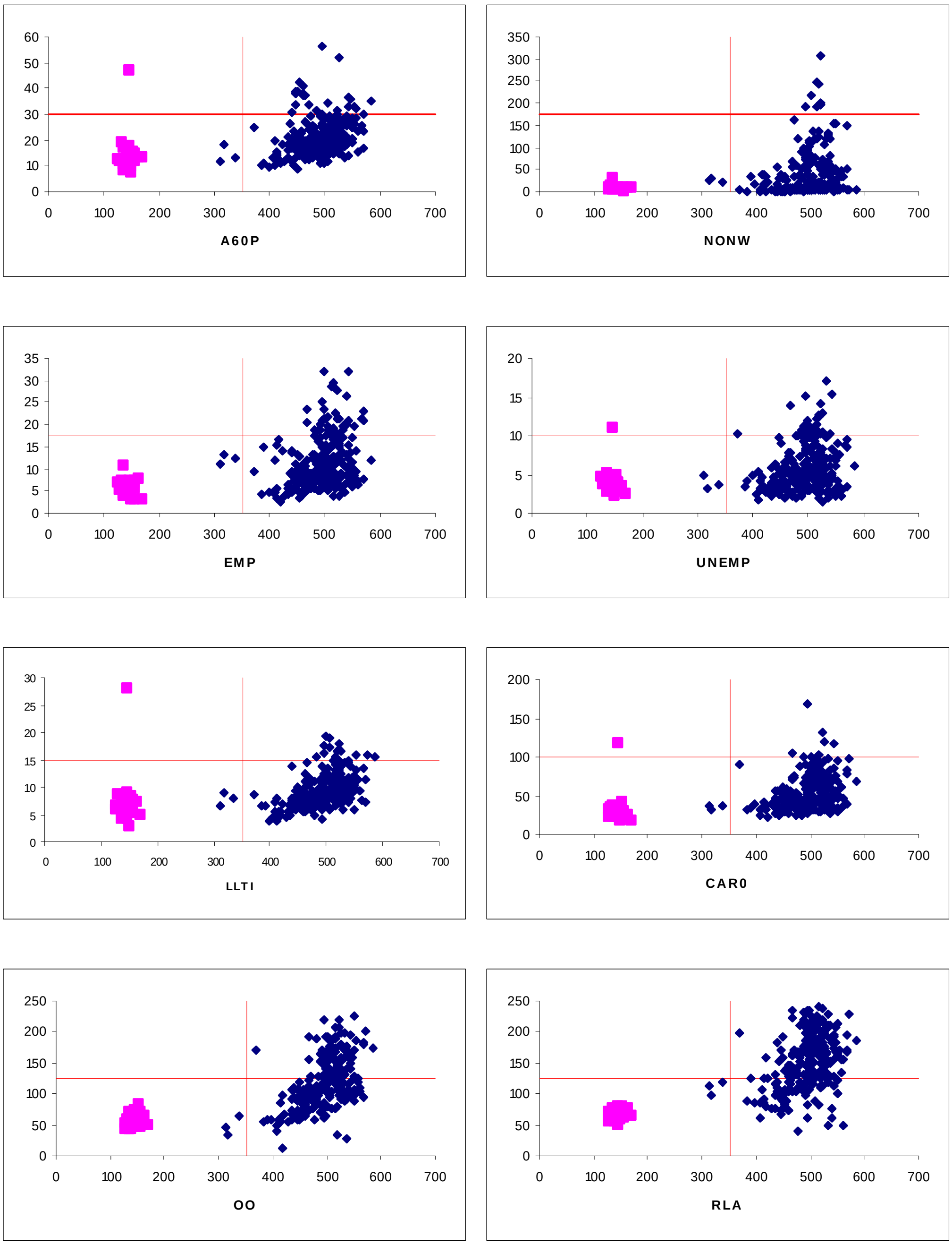


Figure 6.9: Relationships between the AE and average areal unit population by District at the ED level.

population size of the areal units within the English and Welsh Districts are greater than observed with the Scottish data. Overall the correlation coefficients for the data are weak, and all negative. This suggests that as the average population of the areal units within a District increases, so the observed AE will fall. However, the coefficients for this relationship are not significant at either the 0.01 or 0.05 level. However, if the data are correlated by country category (Scotland, and England and Wales), then the coefficients change. For England and Wales, there is a positive relationship between the average population and the AE, which is significant at the 0.01 level for all variables. The coefficients of the correlations range from 0.186 for the NONW variable to 0.406 and 0.538 for RLA and OO respectively. When the Scottish data are correlated as a group then the coefficients are positive except for the two tenure variables, and are not significant.

Figure 6.10 presents the same relationship at the Ward level of aggregation. Unlike the ED level data, there is little distinction between the Scottish data and that from England and Wales. At the Ward level, the average population sizes are the same for both sets of data. However, the Scottish data still exhibit lower average population sizes than the English and Welsh data, as all the Scottish Districts are again located in the lower right quadrant of the plot. This is also true for the English and Welsh data, although there are a small number of Districts that have large average population size. These are Districts that represent large urban centres, such as Birmingham and Manchester. There is clear heteroscedasticity in the data, as the amount of variation that occurs in the relationship between the two variables increases as the average population of the Wards increases. The outlier of Renfrew identified at the ED level in the Scottish data is no longer an outlier.

The data can be considered as a single set this time, as the average population sizes of the Wards are similar. The correlation coefficients for the data demonstrate that there is a strong positive relationship between the average population size of a Ward and the magnitude of the AE. All coefficients are significant at the 0.01 level, and they range from 0.345 for A60P to 0.776 for UNEMP. This confirms the supposition above that increased population size in a given set of areal units is likely to lead to increased incidence of the scale effect, as measured through the AE. As was stated above, one possible cause for this could be the fall in potential spatial autocorrelation, as large average populations are less likely to be as similar as smaller average populations.

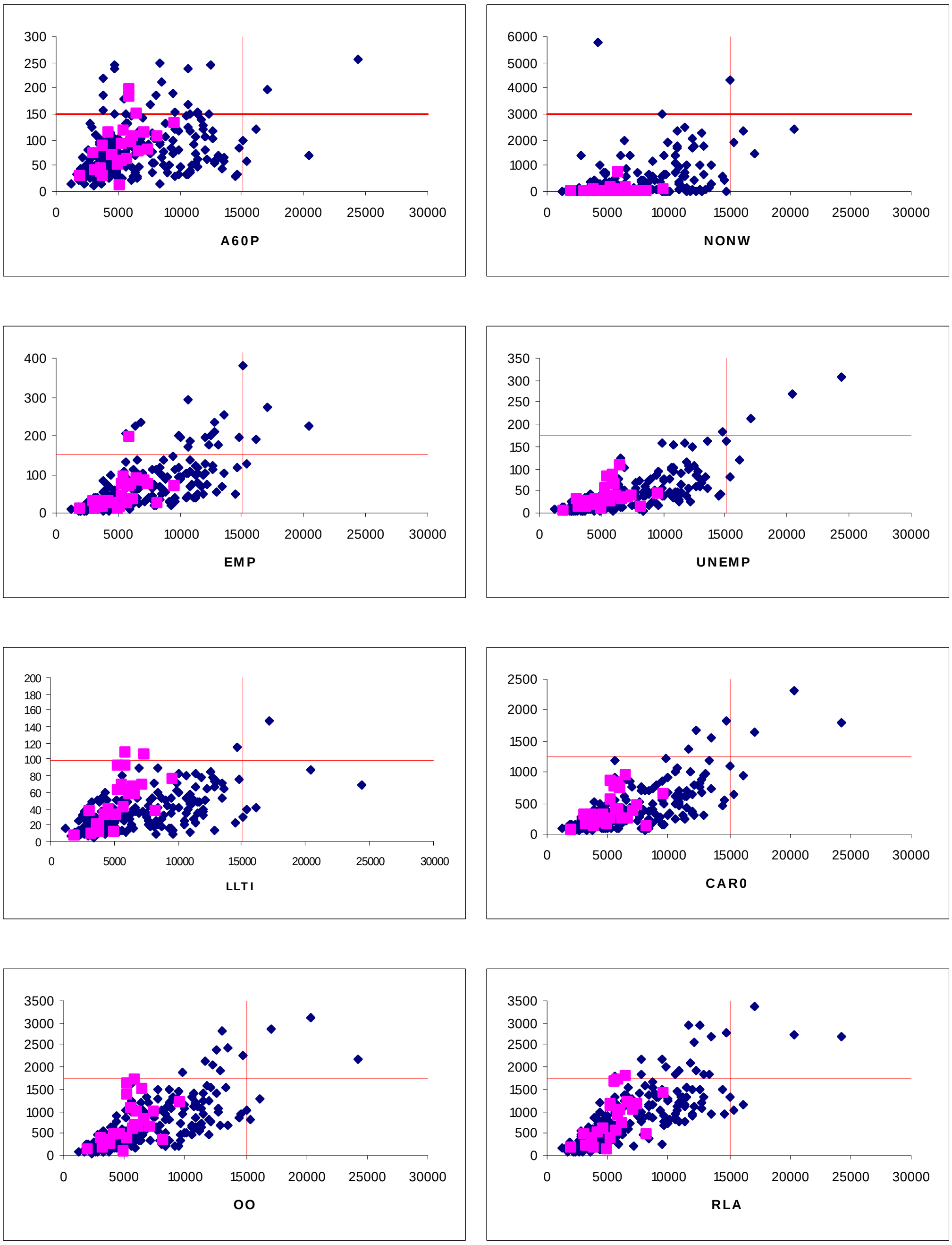


Figure 6.10: Relationships between the average population of the Wards in each District against the AEs.

6.6 IAC and Weighted Variances

The relationships presented above used the Aggregation Effects. This series of relationships considers the same measures as influences on the potential magnitude of the MAUP, but correlates them with the IAC, the measure of within-area homogeneity. As with the AEs, the IACs are constructed using the Weighted Variances. However, the formula is more complex than for the AE, as it also includes the average population of the areal units of the district in the denominator. Thus, there is an extra factor that will influence the magnitude of the IAC. Figure 6.11 presents the relationship between the IACs and Weighted Variances at the ED level. The Scottish data has been distinguished from the English and Welsh data and it is clear that there are differences between the two sets. The Scottish data appear to have consistently greater IACs given a Weighted Variance than is observed in England and Wales. Thus, for Scotland, a given weighted variance will lead to a higher IAC. This

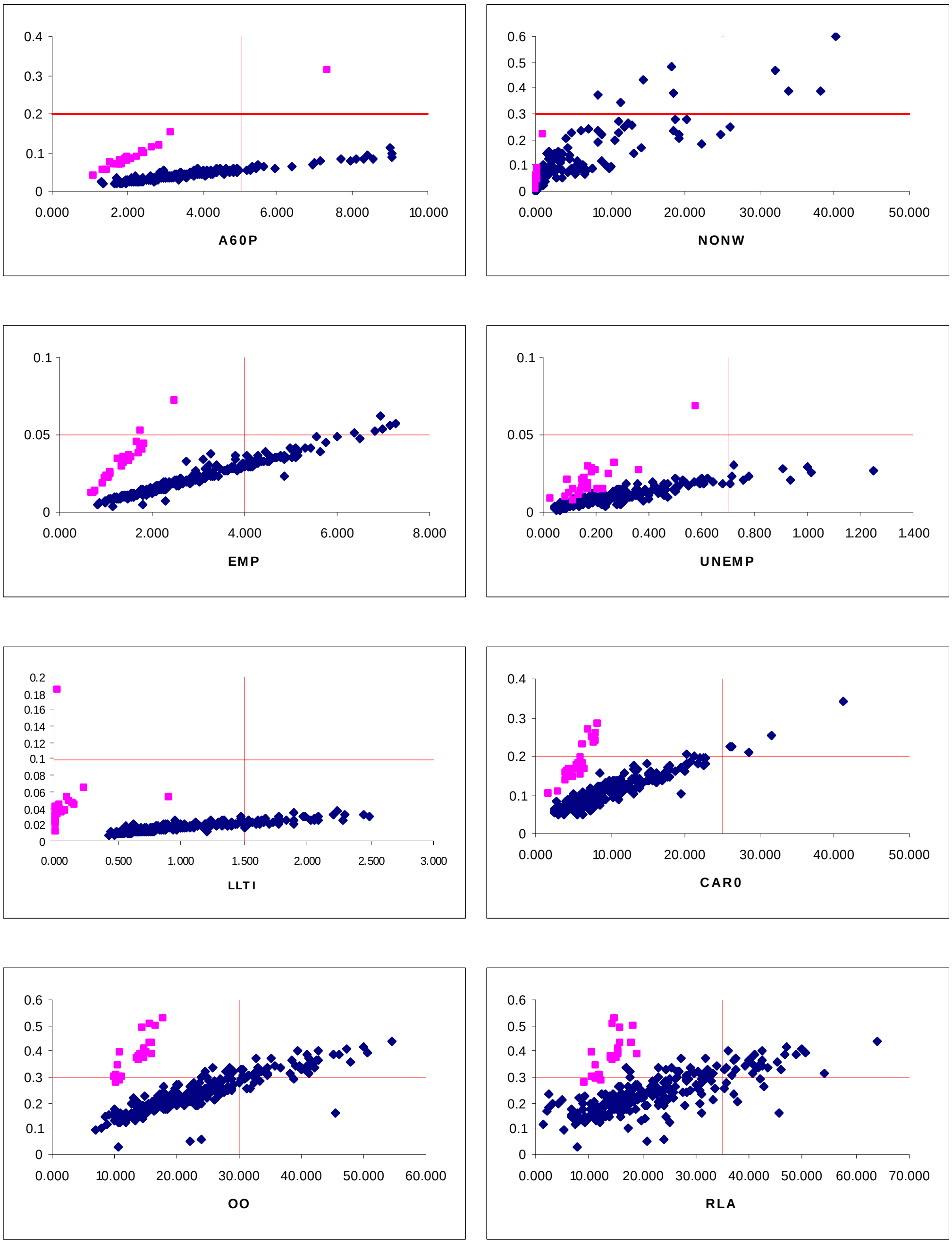


Figure 6.11: Relationships between the Weighted Variances and the IACs at the ED level.

reflects that the within-ED homogeneity of the Scottish data is higher. As the Scottish data units are smaller, in terms of the size of the population that they contain, this is likely. The English and Welsh EDs, which have higher populations, have lower IACs, and thus less within-area homogeneity. A greater degree of variation within the population is required to produce a similar magnitude of IAC in England and Wales in comparison to the level required in Scotland.

It is clear from the scatter diagrams that there is a strong positive relationship between the two measures. The correlation coefficients for the relationships range from 0.478 for A60P to 0.864 for NONW. All the correlation coefficients are significant at the 0.01 level, demonstrating that the relationship between the two measures is significant. If the Scottish data are treated as a completely separate set to the English and Welsh data, then the correlation coefficients for the Scottish data are greater than those for the dataset as a whole with all variables exhibiting coefficients greater than 0.9. Again, they are significant at the 0.01 level. The correlation coefficients for the English and Welsh data remain significant at the 0.01 level, although the strength of the coefficients falls.

Figure 6.12 presents the relationship between the IACs and the Weighted Variances at the Ward level. There is less distinction between the data from Scotland and the data from England and Wales. As the Wards in Scotland are of a similar size to the Wards in England and Wales, the disparity in the relationship observed at the ED level would be less likely to be observed. Thus, at the Ward level, the relationship between the weighted variance and the IAC appears to be similar for all three countries of Great Britain. There are similarities between the relationships observed at the ED level. The main similarity is that the relationship between the two measures is again linear and positive. Again, the data are heteroscedastic. The relationships are relatively strong, although the correlation coefficients are not as high as observed in the ED level data. The coefficients range from 0.508 for CAR0 to 0.739 for A60P. All the coefficients are significant at the 0.01 level.

There are greater differences between the variables than were observed at the ED level. For instance, the CAR0 variable, which has the weakest although still significant relationship, has a wide range of variation in the Weighted Variance measure that can result in similar IAC values. In comparison, the two tenure variables, OO and RLA have relationships that are more obviously linear, with Weighted Variances relating to a lower range of IACs. The NONW data has the greatest range of Weighted Variances. However this is skewed by the presence of a number of fairly large outliers. The majority of the data are plotted in the bottom left quadrant of the scatterplot.

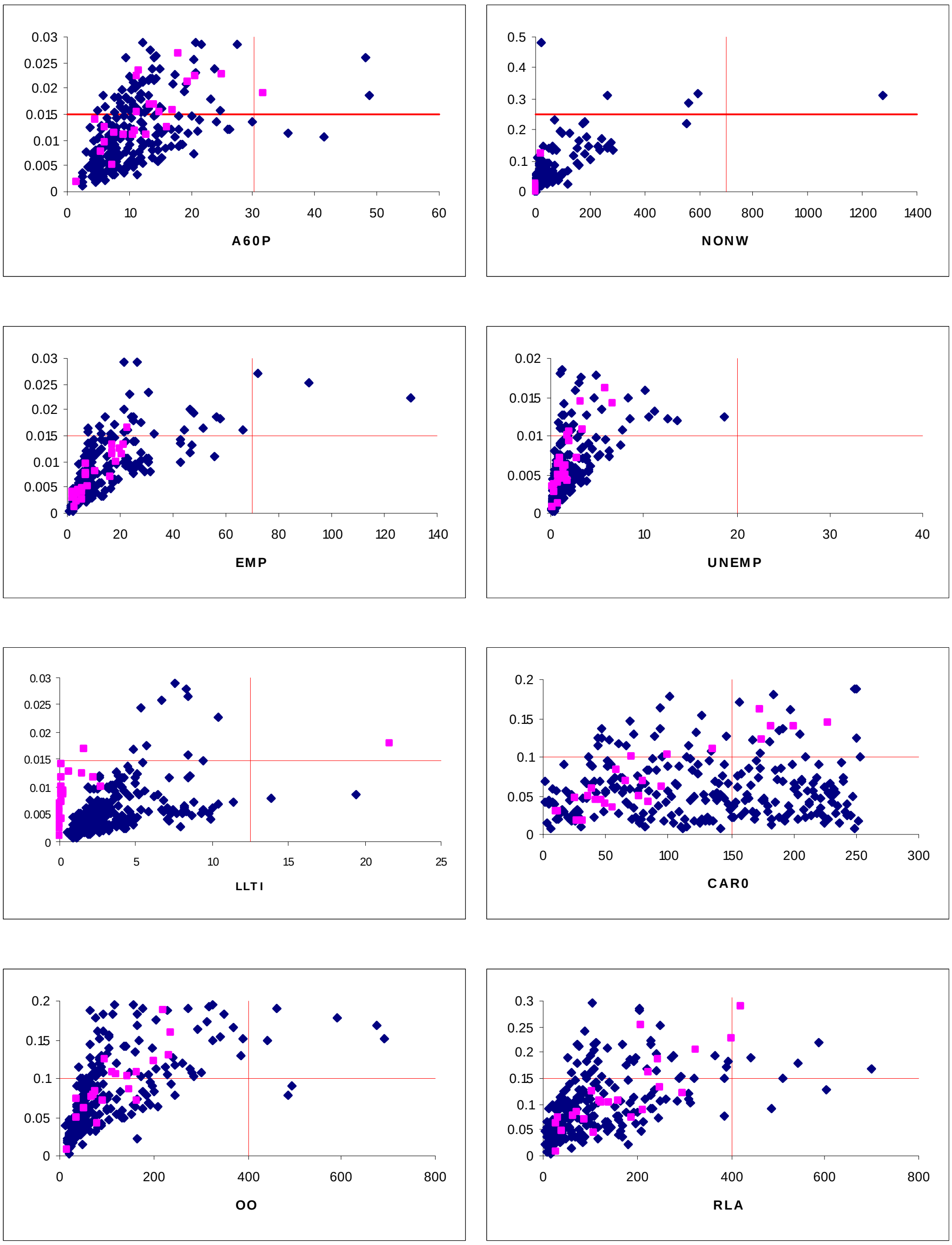


Figure 6.12: Relationship between Weighted Variances and IACs at the Ward level for the eight variables.

6.7 IAC and Proportions

The second IAC relationship to be explored is with the proportion of a variable. As with the AE relationship, there is no reason to suppose that it would be linear, either positively or negatively. Figure 6.13 presents the relationship for the eight variables at the ED level. It is interesting to compare the results to those observed for the AE relationship at the ED level. For instance, with the A60P variable there was a clear

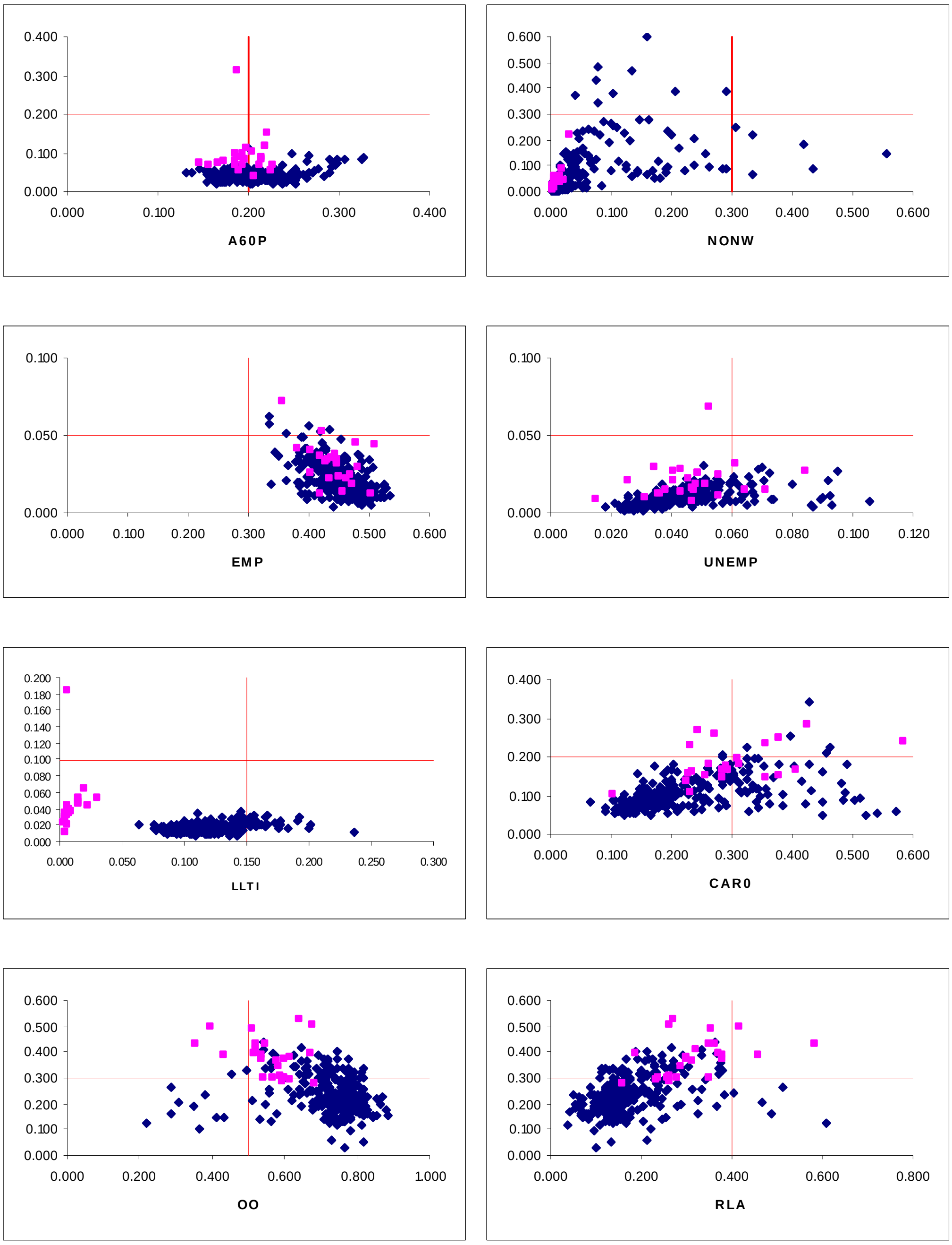


Figure 6.13: Relationship between IAC and proportion for the eight variables at the ED level.

grouping effect between those observed for the high and low proportions of the variables. It is not possible to observe this effect with the A60P variable. However, as with all the variables it is possible to observe a difference between the English and Welsh and the Scottish data. In general, it appears that for any proportion of the variable a District in Scotland have a higher IAC, indicating higher within-area homogeneity. Again, this is likely to be related to the population sizes as smaller populations are more readily capable of exhibiting higher levels of homogeneity than larger ones. There are few generalisable patterns for all the data. The NONW, UNEMP and RLA variables have relationships that result in a linear distribution of the Districts. The A60P variable has a concentration of Districts in the mid-point of the proportion axis, with outliers demonstrating districts with high or low proportions of residents over 60 years of age. The EMP variable has a high concentration in the right quadrants. This is not surprising, given that the majority of people are classified as employed. Likewise the concentration of Districts in the lower left quadrant for the UNEMP variable is also to be expected. Similarly, the differences between the tenure variables, where OO has a high concentration in the right hand quadrants occurs as with RLA variable has lower proportions. These two variables represent opposites, which is not the case with the other variables in the analysis.

The correlation coefficients for the relationships demonstrate that there is a positive relationship between the proportion observed in a District and the IAC for all variables except EMP and OO. These two variables have negative relationships of -0.377 and -0.142 respectively. The positive relationships for the other variables range from 0.121 for A60P to 0.472 for NONW. All the variables exhibit relationships that are significant at the 0.01 level.

6.8 IAC and Population Density

Population density is used as a proxy variable to aid the understanding of spatial autocorrelation and the way in which it its interactions can influence the scale effect. Spatial autocorrelation relates to the similarity of instances of a given variable. In this instance, it refers to the similarity of characteristics of the population. The greater the population density, the more likely people are to be similar to their neighbours. For the IACs, increased similarity to close neighbours will result in greater within-area homogeneity. The greater the within-area homogeneity, the greater the IAC. Thus, it would be expected that there would be a positive relationship between the variables. This is demonstrated in figure 6.14. As would be expected, the Scottish data are located at the lower end of the scale, demonstrating that Scotland has a lower population density. However, this does not lead to lower IACs. Although this does not fit with the initial model suggested, there are other confounding factors, which will influence the magnitude of the IAC. Primary of these is the smaller population size discussed above. The smaller population size increases the within-area homogeneity, and in this case counter acts with the decrease in population density. Thus, it appears logical to consider the Scottish data as a separate dataset to that of England and Wales.

None of the relationships are significant beyond the 0.05 level. For the Scottish data all the variables exhibit positive relationships. The only variables that have significant relationships are NONW, EMP, CAR0 and OO. All other variables have relationships that are not statistically significant. For England and Wales, the NONW, EMP, UNEMP and RLA variables have statistically significant relationships, all of which are positive. The A60P, LLTI and CAR0 relationships are not statistically significant and are also negative in direction. When the data are combined then the correlation coefficients for the A60P, LLTI and CAR0 remain negative, demonstrating the influence of the English and Welsh data over the Scottish relationships, while the only statistically significant relationships at the 0.05 level are those between NONW, EMP and RLA. Thus, there isn't sufficient evidence with this data that there is a direct link between the density of the population in the EDs of a given District and the within-area homogeneity observed.

Figure 6.15 presents the relationship between the IAC and Population Density at the Ward level. The relationships observed are similar to those observed at the ED level. The major difference between the levels of aggregation is within the Scottish data. As with all previous relationships, the difference that exists between the Scottish data and the English and Welsh data at the ED level of aggregation is not observable at the Ward level of aggregation. At the Ward level, the Scottish data lie with the English and Welsh data.

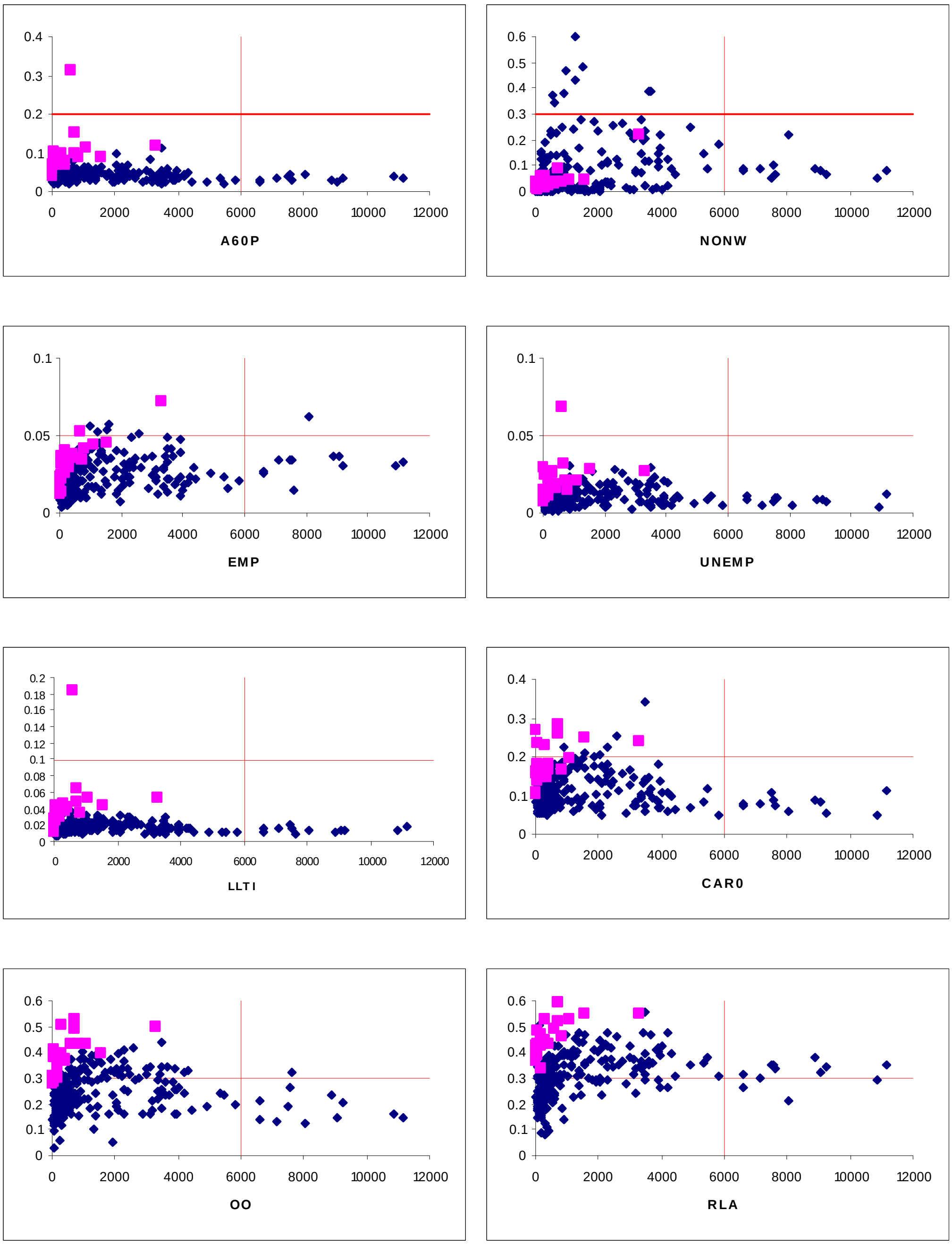


Figure 6.14: Relationship between IACs and Population Density for the eight variables at the Ward level.

As the data plot suggests as a single group they are considered as a single group for the analysis of the coefficient coefficients. Out of the eight variables, the relationships for NOW, EMP, UNEMP, OO and RLA are significant at the 0.05 level. None of the relationships are significant at the 0.01 level. Relationships between A60P and LLTI are negative in direction, whilst all the other relationships are positive, as would be expected. All of the relationships result in scatterplots that appear relatively similar. Although the relationships have been described as positive there are some patterns that do not fit with this generalisation. For instance, although it was suggested that in order to achieve higher within-area homogeneity, observed through a higher IAC, with higher population density, this is not the case. In all variables, the highest IACs occur with the population densities in the lower half of the distribution. Overall, lower population densities result in a wide range of IACs, from low to high, whilst the higher population densities result in low IACs. This is not the relationship that was expected for this data.

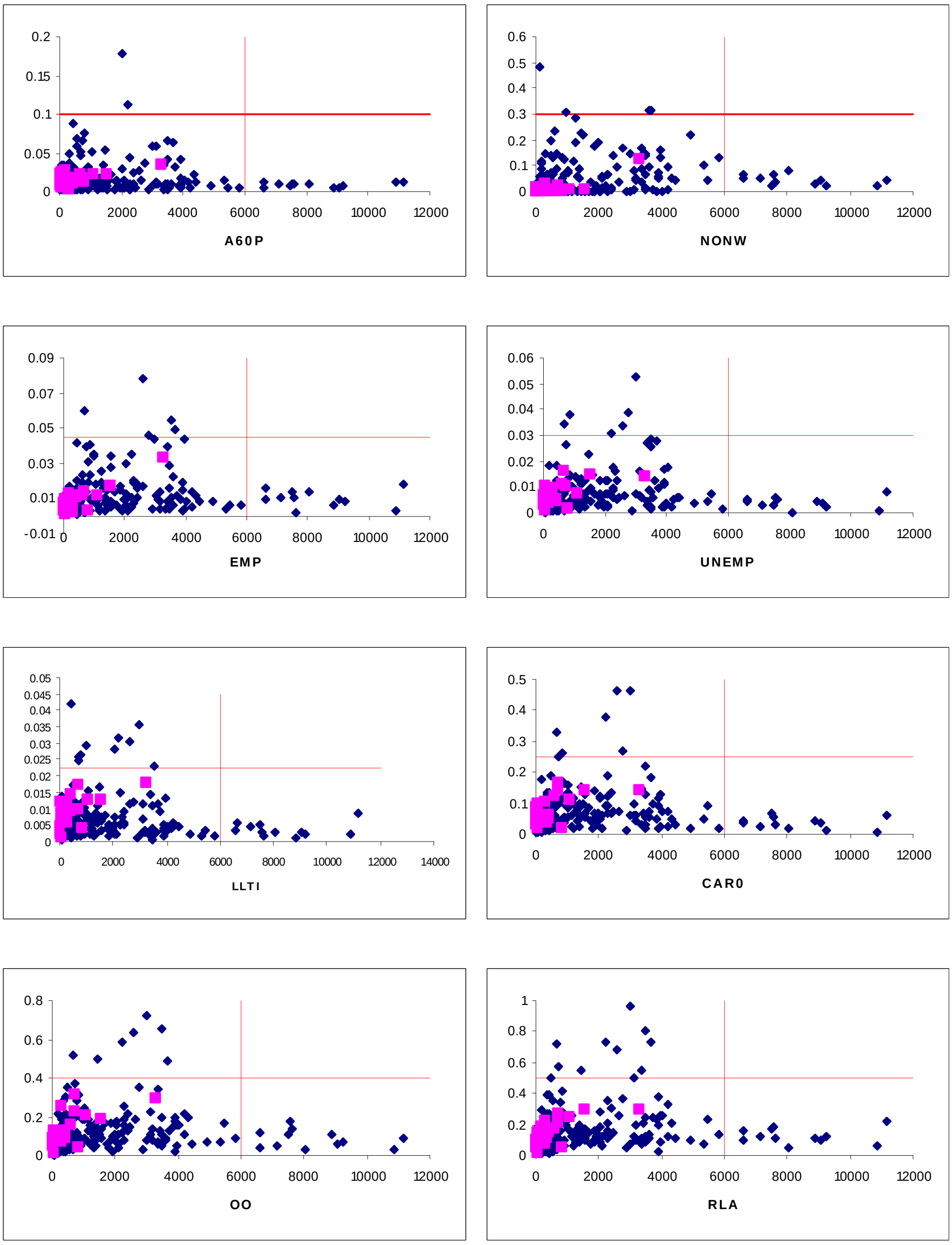


Figure 6.15: Relationship between IACs and Population Densities for the eight variables at the Ward level.

6.9. IAC and Average Population

The final relationship analysed is between the IACs and the Average Population of the areal units in the District. Overall, the greater the population, the wider range of values that are likely to be observed for a given variable. However, greater populations are also likely to relate to areas that have a higher degree of urbanisation, and therefore have a population that live closer together. This relates back to the population density discussed in section 6.7. Therefore, it would be expected that a positive relationship is observed between the IAC and the Average Population.

Figure 6.16 presents the relationship between Average Population and the IAC. As was noted in Chapter 4 there is a distinct difference at the ED between the Scottish data and the data for England and Wales. This highlights the differing composition of the areal units in these areas, and is suspected to be highly influential in the resulting incidences of the scale effect. Therefore, the Scottish data can be treated as a distinct group separate from the data for England and Wales. The Scottish data lie in the left hand quadrants for all the variables, while the data for England and Wales lie within the right hand quadrants. There are very few Districts, which have population densities below the mid point in England and Wales. Those that are below that mid point represent Districts in rural areas of England and Wales, such as Cumbria. These Districts are also more usually Welsh than English, reflecting the more rural nature of Wales.

When analysed as two distinct groups, the correlation coefficients demonstrate that there is little relationship between the two measures. For England and Wales only the NONW and OO variables have coefficients that are significant at the 0.05 level. All other variables have relationships that are not significant. All of the relationships for the England and Wales data are positive. For Scotland, the only statistically significant relationship between the two measures is with the RLA variable, at the 0.01 level. All the other variables have relationships that are not significant. Unlike the relationships observed for the English and Welsh data, the Scottish relationships are all negative, suggesting that greater average population size in the EDs of a district will result in a decrease the IAC observed. When the data are considered as a single group then the significance of the relationships increases, with A60P, EMP, UNEMP, LLTI, CAR0, OO and RLA exhibiting relationships that are significant at the 0.01 level, whilst NONW has a relationship that is significant at the 0.05 level. All the relationships, except that of NONW are negative.

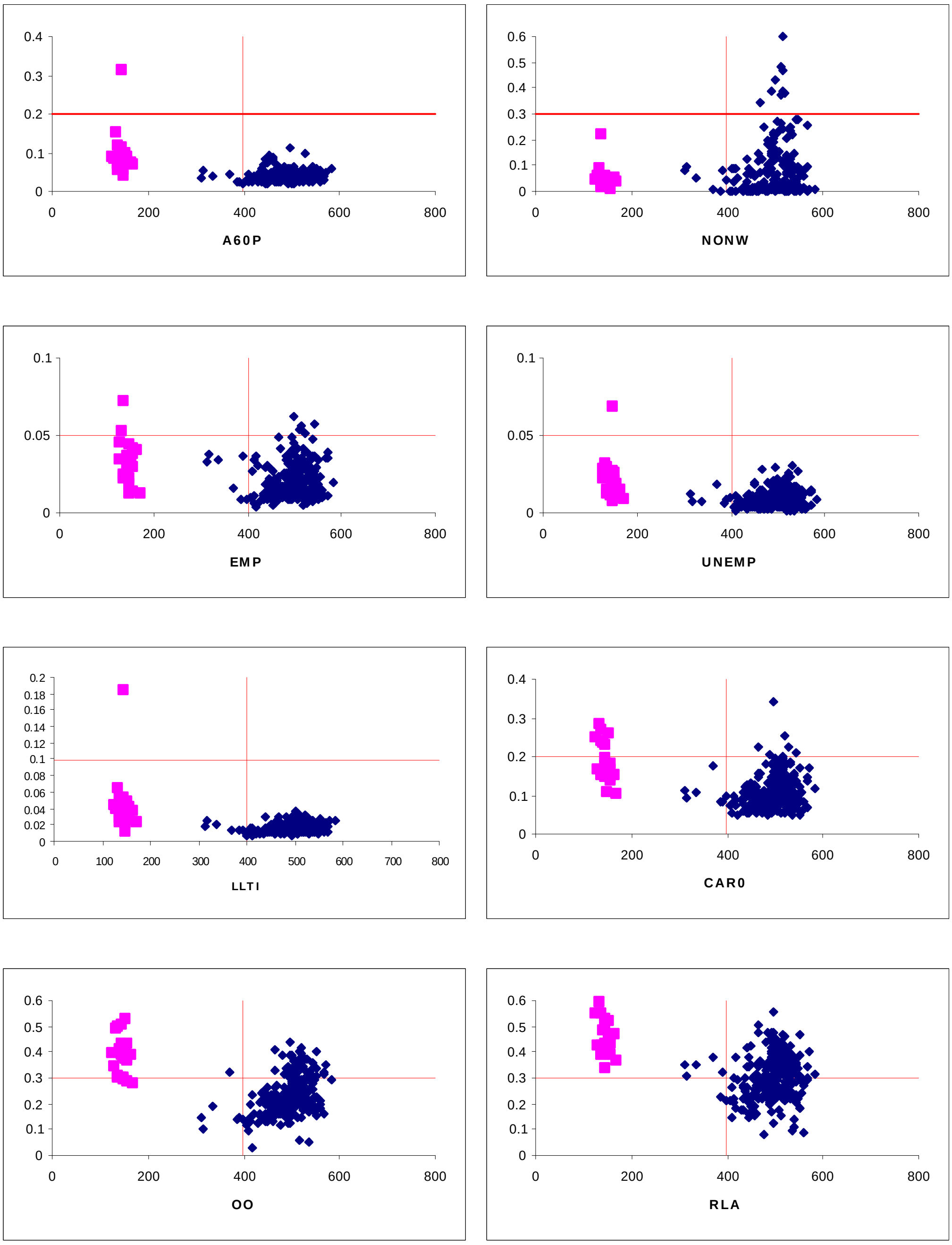


Figure 6.16: Relationship between average population size of the EDs in each District with IACs at the ED level.

Figure 6.17 presents the relationships observed for the eight variables at the Ward level. The distinction between the Scottish data and the data for England and Wales is not present at this level. As the areal units for all three countries are known to be similar, this is not surprising. However, it does mean that the two datasets can be analysed together, rather than treated as two distinct groups as above. It is noticeable, however, that the Scottish data still exhibit lower average population sizes than those in England and Wales, and that the spread of the Scottish data is less than that of the

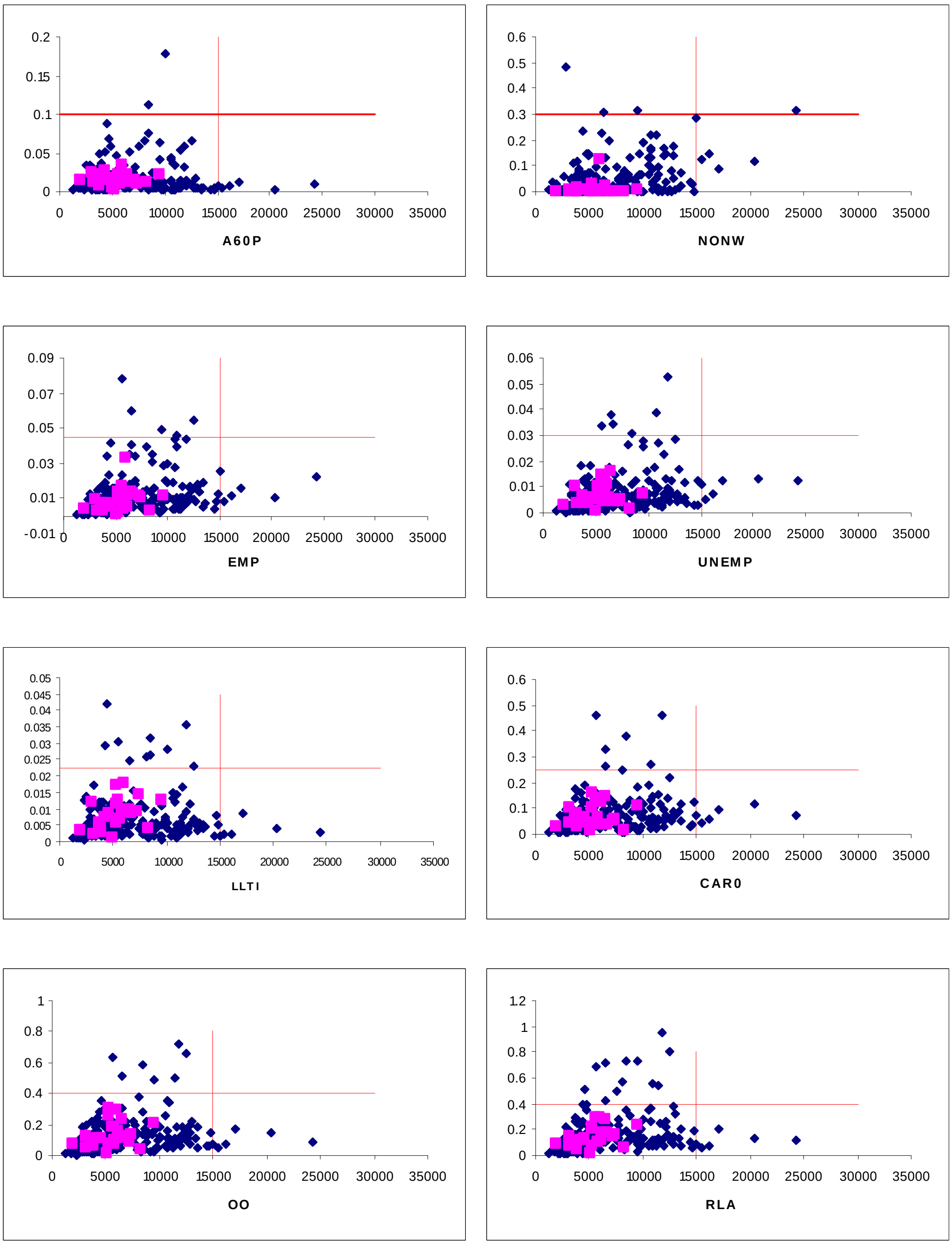


Figure 6.17: Relationship between the average population size of the Wards and IACs at the Ward level.

English and Welsh data. For all the variables, the Scottish data are contained within the bottom left quadrant. The English and Welsh data cover quadrants on both the left and the right hand side. It is noticeable that there is only one instance where there is a District that falls within the upper right quadrant. This is in the NONW variable, and is the District of Birmingham. The other Districts with values falling in the right hand quadrants are also related to highly urbanised areas. The correlation coefficients for the Ward level are all positive, demonstrating that as the average population size increases, so the magnitude of the IAC increases, and there is greater within-area homogeneity. The relationship is demonstrated by the correlation coefficients for the NONW, EMP, UNEMP, LLTI, OO and RLA variables which are all significant at the 0.01 level, with values ranging from 0.23 to 0.53.

6.10. Discussion and Conclusions

Clearly, the Aggregation Effects and the IACs are related to the factors that have been discussed above. However, they do not tell the full story. None of the measures that have been considered above present relationships between the AEs or IACs that can lead to conclusions that the magnitude of either is a direct result of one or more attributes of a District. This is not surprising, as it has been postulated that he scale effect is highly complex (see Openshaw and Taylor 1979, or Fotheringham and Wong 1991 for instance), and that it is unlike to be easily resolve. Nevertheless, there is a case to be made whereby the factors presented show that the scale effect component of the MAUP is related to the size of the areal unit system, in terms of average population, the magnitude of the proportion of a factor and the population density. Even when combined, the variables do not provide sufficient predictive power that it is possible to determine the scale effect from the information presented above. In essence this is because the scale effect is far more complex than this. Indeed, the variables presented above could be acting as proxies for other factors within the areal unit systems that have not yet been considered.

The population density within a District acts as an effective proxy for a level of urbanisation. If this were explicitly considered, then it is possible that relationship may be seen. Other factors that may influence and that have not yet been considered include those that relate to the composition of the population. Whilst tenure variables are used as analytical variables on which the impact of the scale effect is measured, they potentially also provide a source of explanation of the scale effect. This is because the tenure variables will provide a good description of the composition of the likely population of an area. Moreover, it has been demonstrated that the relationships of the AEs and IACs to the average population of the areal units are not linear, and that the relationships are highly complex. This reinforces the notion put forward by Openshaw and Taylor (1979, and 1981) amongst others that as well as being pervasive, the MAUP is highly complex and involves the interactions of many factors, not all of which may be quantifiable. Nevertheless, that relationships were demonstrated between the variables highlights that, although some factors may not be quantifiable, there are links with the size of the population, its density and the amount of variation observed. That this last factor is not linear demonstrates the existence of the other, unidentifiable processes, and leads to the analysis to identify the existence of the processes in Chapter 7. This would enable the interactions between the data to be better understood, as the magnitude of relationships between the areal units in a given system could be presented. This then could provide an additional measure with which the relationship between the magnitude of the scale effect and the areal data can be explored.

Therefore, it is possible to conclude that there is merit in considering these factors when attempting to identify factors that contribute to the magnitude of the scale effect. Clearly, those variables considered here are important, although they do not sufficiently tell the full story. In many cases they will be acting as a proxy for other influences, and the next stage of this research is to better understand what those other variables may be.

Chapter 7

Searching for Spatial Processes in Census Data

7.1. Introduction

Section 3.5 of the methodology set out a technique for the identification of processes within the areal unit data. These processes could be considered as further practical implementations of Green and Flowerdew's (1996) local and regional effects. They sought to identify processes that occurred in area level data, which contributed to the incidence of the scale effect. Below, an analysis is presented that seeks to realise the conceptual local and regional effects, and determine if it is possible to identify them in an area. This analysis also serves to highlight the inconsistencies between processes that may exist within the data and the boundaries within which the data are represented. This is done using multilevel modelling and local spatial autocorrelation tests. The concepts and theory for the analysis are set out in the methodology, section 3.5.

It is necessary to consider what is meant by the term 'spatial processes'. The concept of a spatial process is related to two of the main issues discussed in the literature surrounding the MAUP. These concepts are spatial autocorrelation and the local and regional effects presented by Green and Flowerdew (1996). Thus, a spatial process exists where there are a group of low-level areal units (such as EDs in the UK Census) that have positive spatial autocorrelation between them. These areal units will be very similar and have a high level of between-areal unit homogeneity. This is useful, firstly to assess if when aggregated together they will produce a new areal unit that has high within-areal unit homogeneity. From the perspective of the ecological fallacy, high homogeneity it desirable as people within a given areal unit will be more similar, and the value of a given variable for an areal unit will better reflect the individual population from which the area is constructed. The natural opposite of this is that areal units that are highly dissimilar will be ideal for areal unit boundaries as they could represent breaks in the population processes. Thus areal units can be constructed that reflect the processes within the population under analysis so giving them a meaning with respect to the data that they are used to represent. The second, use of the method is to consider the similarity between the processes that exist between areal units and the published aggregation boundaries at a higher level. The closer the boundary delineations are to the spatial processes, the better the data is reflected by the higher-level aggregations. These concepts are discussed in greater detail in section 3.5.

The analysis is presented below in two sections. The first section explores an implementation of the methodology using four districts from the UK. They represent a number of different areas and include a large city, a semi-rural area and an affluent area. They have been chosen as they provide a wide contrast. In Chapter 4, the proportion of the population who live in accommodation rented from a local authority (denoted as RLA) was identified as having relatively high IACs indicating that there is likely to be high scale effect present. Therefore, the RLA variable is explored in greater detail with these four districts, in an attempt to better understand the processes behind the scale effect. The second section explores the existence of processes in data that have excessive levels of within-Ward homogeneity identified using IACs. For this, the Districts with high IAC values that in Chapter 4 were termed as outliers have been selected. This enables a discussion about the presence of spatial processes and higher levels of within-area homogeneity. This is designed to provide an insight into the potential processes that exist at a given level, and the influence that these processes have on the incidence of the scale effect. Additionally the analysis seeks to provide evidence that processes exist in spatial data organised in areal units, and that their existence and extent is a key factor determining the presence and magnitude of the scale effect.

The first section considers only two variables. The first of these is the RLA variable, as defined in Chapter 3. It is presented here as it has been shown to have high incidence of the scale effect. Moreover, housing estates form natural groupings of people, and therefore it is likely that evidence of spatial processes will be identified from the data as was detailed in the theoretical discussion around the potential nature of spatial processes. A comparison and control will be provided by the introduction of a ninth variable to the analysis. This will be known as FEMALE and represents the proportion of the population that are female. The female variable is used in the analysis to determine effectiveness of the method. It is highly likely that the distribution of females within a given SAR region will be very close to uniform. This is because the presence of a given proportion of females in one Census ED is highly unlikely to have an association with the proportion of females in another Census ED. Finally, the proportion of females is likely to remain relatively constant through the population, at or around 50% in the majority of the EDs. The FEMALE variable therefore provides a control without spatial process.

7.2. Implementing the methodology

An implementation of the methodology is presented below. It considers two variables for four different areas. The areas chosen to contrast are: Glasgow, the largest city in Scotland; Ribble, an affluent, semi-rural, retirement area with old industry in Lancashire; Huntingdonshire, an affluent rural area in the south of England, and; Reigate an outer suburban area used in the original Tramner and Steel (2001) work. Although the method is designed to search for and identify potential processes, which would reflect local and regional effects, the analysis is relatively subjective. A significance test for the Local *I* does not exist as the distribution of the statistic is unknown (see CrimeStat 2003). Thus, a "high *positive* standardised score indicates a clustering of similar values (either high or low) while a high *negative* score indicates a clustering of dissimilar values (high relative to a neighbourhood that is low or, conversely, low relative to a neighbourhood that is high)" (CrimeStat , 2003, p.289, emphasis in original). Therefore, the values of the Local Moran's *I* analysis will be discussed relative to the values observed within other areal units of the same District.

7.2.1 Glasgow SAR

The Glasgow SAR area was chosen to test the methodology outlined in Chapter 3.5, as it was known to be an area in which strong scale effects could be seen (see Chapter 4). It will be contrasted with the Reigate and Ribble SAR Districts that were identified as less susceptible to MAUP (scale) effects (again, see Chapter 4). FEMALE has an IAC value of 0.0007, while RLA has an IAC value of 0.524 (see table 7.1). Clearly, it would be expected that RLA would exhibit larger scale effects than the FEMALE variable, and there is a far greater level of homogeneity in RLA than FEMALE. These values also provide information about the within area relationships, and they can be seen to be very strong in the RLA data, and relatively week in the FEMALE data.

The Global Moran's *I* values are presented to gauge the level of overall spatial autocorrelation. For the FEMALE, the *I* value is 0.011. Although low, it is still significantly different to spatial randomness, as shown by the Z score. Moreover, it is clearly a low value when compared to the Global *I* for RLA which has an *I* value of 0.015, but is considered far more significant, using the normalised significance value, where the value is compared to a normal distribution with a mean of 0 and a variance of 1.

	IAC (ED)	**IAC (Ward)**	**Global *I***	**Z Score**
FEMALE	0.0007	0.00069	0.011	15.99
RLA	0.524	0.290	0.015	78.25

Table 7.1: IAC and Global Moran's *I* values for the Glasgow variables.

When discussing the processes of a District with over 5000 areal units a global measure cannot provide sufficient detail. Thus, it is necessary to identify a more local measure. As the focus of this analysis is the identification of associations between areal units, this is implemented using the concept of an area effect estimate, the $\hat{u}_g$ value, which isolated the area level interactions for each areal unit in the District. These were calculated for these two variables, and the resulting spatial pattern can be seen in figures 7.1 and 7.2. These maps provide confirmatory information that supports the Global Moran's *I* values presented in table 7.1 as it is clearly apparent that there is more grouping (similarity between neighbours) present in the $\hat{u}_g$ values for the RLA variable than in the values for the FEMALE variable. Indeed the FEMALE variable (Figure 7.1) looks similar to spatial independence (see Goodchild, 1986). Local spatial autocorrelation measures will further determine the validity of this conclusion. Originally, the FEMALE data was introduced to provide a control variable within which it would be unlikely that a strong spatial pattern would be found. The interpretation of the Local Moran's *I* analysis suggests that this hypothesis is correct (see figure 7.3). The majority of the *I* values can be seen to be around the zero. Referring back to the description of Moran's *I*, the values of around zero suggest that the distribution of the data is largely random with little or no spatial process present. Despite this there are some extreme values in the representation, with the *I* value ranging from –16 up to over 19, although this is low considering that there are

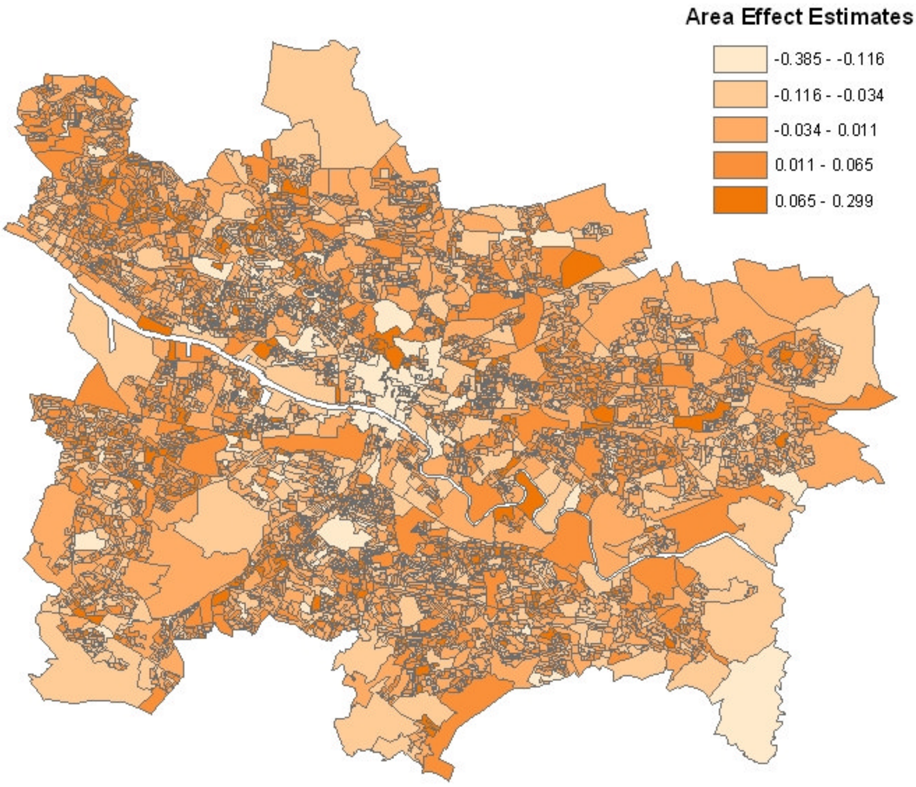


Figure 7.1: The area level effect estimates ($\hat{u}_g$) of the EDs in Glasgow SAR, for the FEMALE variable.

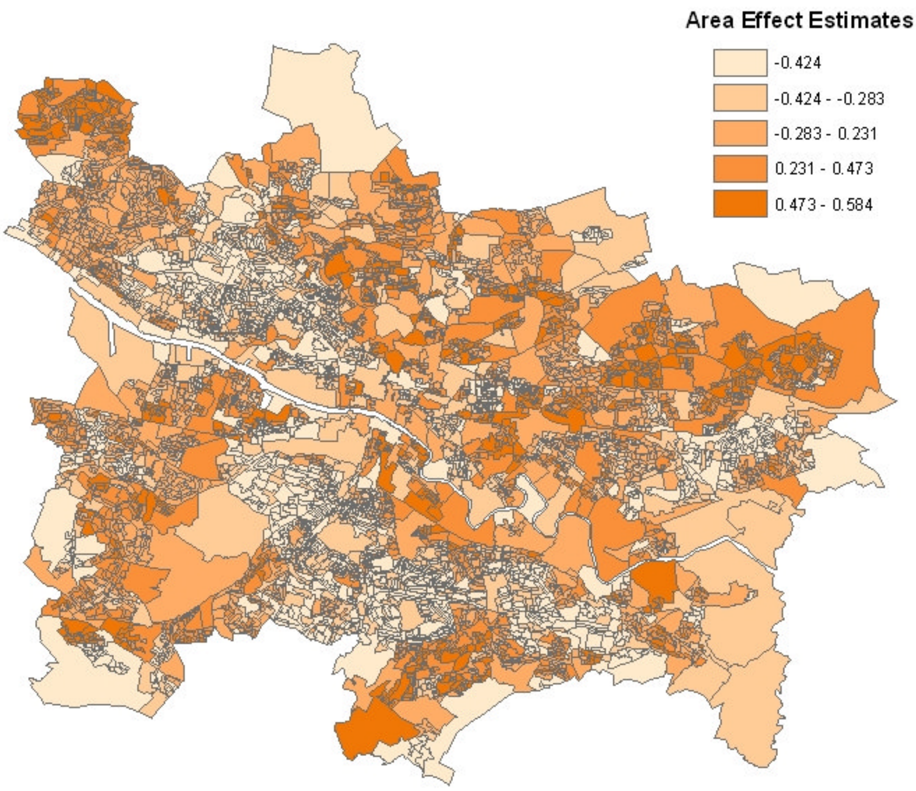


Figure 7.2: The group level effect estimates ($\hat{u}_g$) of the EDs in Glasgow SAR, for the RLA variable.

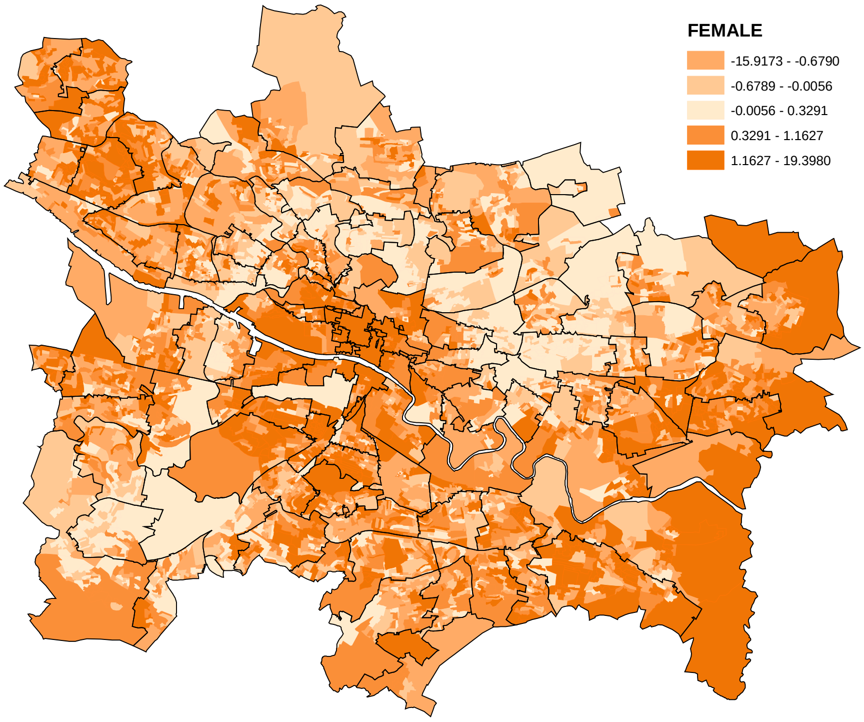


Figure 7.3: Local Moran's *I* showing some central spatial structure in the FEMALE variable at the ED level for Glasgow SAR.

over 5000 observations in the Glasgow dataset (see Methodology, section 3.5.2.2 for more details). However, these areas tend not to be grouped together in large clusters and are, therefore, insignificant for the identification of spatial processes. In terms of areal homogeneity it is possible to determine that there is little between-area autocorrelation above the ED level. Figure 7.4 presents a histogram of the *I* values. This confirms that the distribution is unimodal, and approximately follows a normal curve. Moreover, it is possible to see that the majority of the *I* values fall around the 0 point. This confirms the lack of spatial association for the distribution of the FEMALE variable.

The second variable, RLA, has stronger spatial processes, as is seen in figure 7.5. Firstly, the range of values for the Local Moran's *I* is greater for the RLA data, from below –25 to over 28, indicating more spatial autocorrelation. There are also far fewer areas of the Glasgow SAR that fall close to the zero (spatial independence) value. It is possible to define some areas that exhibit high positive spatial autocorrelation clustering. Therefore, the identification of clustered areas that form spatial processes that demonstrate both local and regional effects is possible.

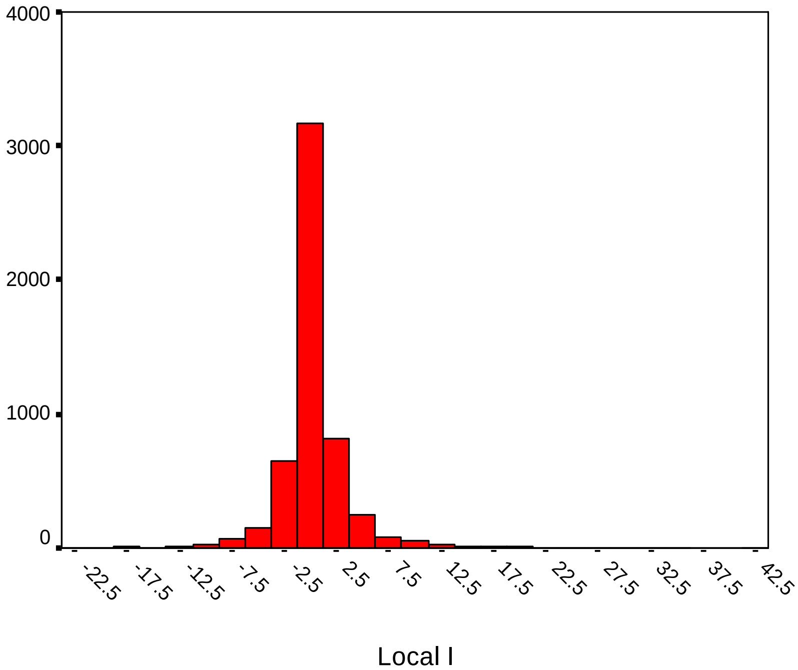


Figure 7.4: Histogram of Local Moran's *I* for the FEMALE variable at the ED level in Glasgow SAR.

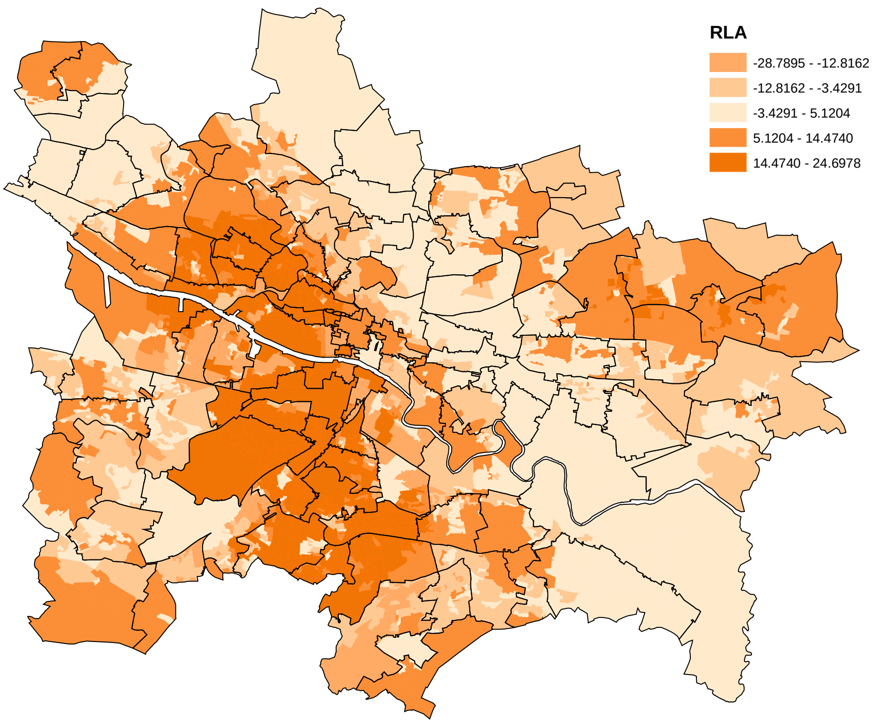


Figure 7.5: Local Moran's *I* showing the spatial process operating above the ED level in the RLA variable.

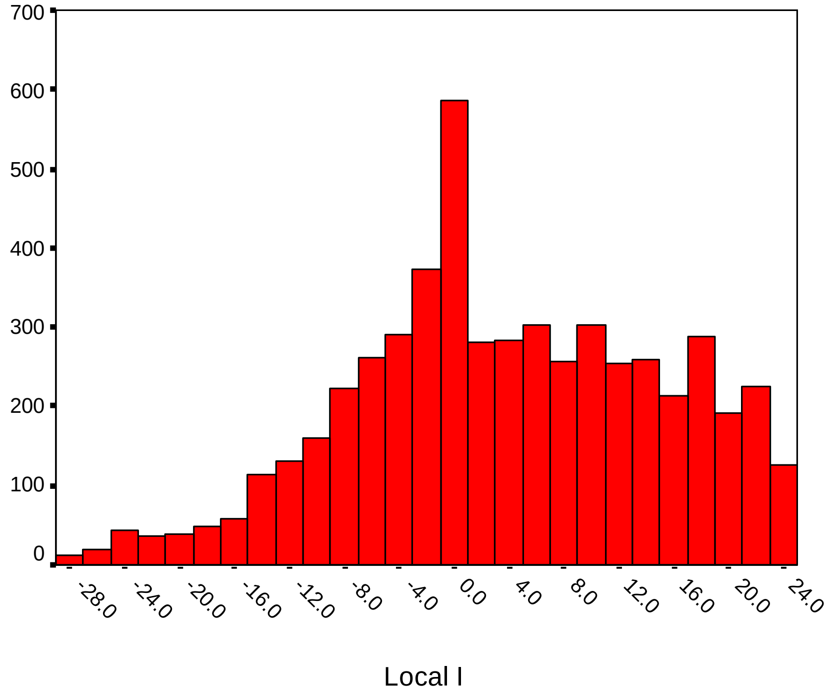


Figure 7.6: Histogram of Local Moran's *I* for the RLA variable at the ED level in Glasgow SAR.

These can be seen in the darker areas around the river area in the western side of the SAR district, and also in the north-eastern edges. These would suggest EDs that could be grouped together to form relatively homogeneous groups at a level above that of the ED. It is also possible to determine groups of areas that exhibit relatively large values of negative spatial autocorrelation. Indeed, the areas immediately surrounding the clusters frequently represent large changes in the process, identified by negative spatial autocorrelation. Figure 7.6 demonstrates the distribution of the *I* values in a histogram. The distribution is similar to that shown in figure 7.4 as it is unimodal. However, it is far more positively skewed, demonstrating that there is a clear presence of positive spatial autocorrelation and therefore spatial association within EDs. This is supported by the description of the data from figure 7.5. Thus, there are spatial processes operating in the Glasgow SAR that contribute to sharp differences in the values of the data. For the creation of higher-level aggregations these results demonstrate that the position of boundaries can, potentially, exacerbate these differences.

The analysis of the area effect estimates ($\hat{u}_g$) of the EDs with the local statistic enables inference about the processes for the Ward level within Glasgow SAR

District. As can be seen in figure 7.7(a) it is possible to demonstrate that some of the Ward areas are composed from zones that reflect the nature of the spatial processes present in the data. These zones could be described as homogeneous. Conversely, figure 7.7(b) demonstrates that other Ward boundaries do not reflect these processes identified above the ED level. For this area, the aggregation to the level of Ward is not representative of the processes that are present in the data, as they appear more local or global than Ward boundaries report. Consequentially, the Wards are relatively dissimilar in composition of EDs. The Wards depicted in figure 7.7(b) could be described as heterogeneous. The fact that Glasgow district is composed of Ward areas that have differing levels of homogeneity, both between and within zones, as demonstrated here, is suggested as a potential cause of the scale effects seen in the MAUP.

a) b)

Figure 7.7: a) Ward boundaries that reflect the spatial processes of RLA, and therefore make homogeneous zones, and; **b)** Ward boundaries that group diverse EDs to make heterogeneous Wards.

7.2.2 Reigate SAR

Reigate provides a comparison to Glasgow. The IACs and Global *I* values to provide supplementary information for the analysis (see table 7.2).

	IAC (ED)	IAC (Ward)	Global *I*	Z Score
FEMALE	0.0001	0.0152	-0.0003	0.78
Reigate RLA	0.277	0.094	-0.0005	0.71

Table 7.2: IAC and Global Moran's *I* values for the Reigate data.

Figure 7.8 presents the results of the analysis for FEMALE. As the analysis presented for Glasgow, they support the hypothesis that the distribution of the variable will be similar to that of random data. The proportions of females (FEMALE) appears similar to a random distribution, with no clear overall pattern in the data (figure 7.8). The

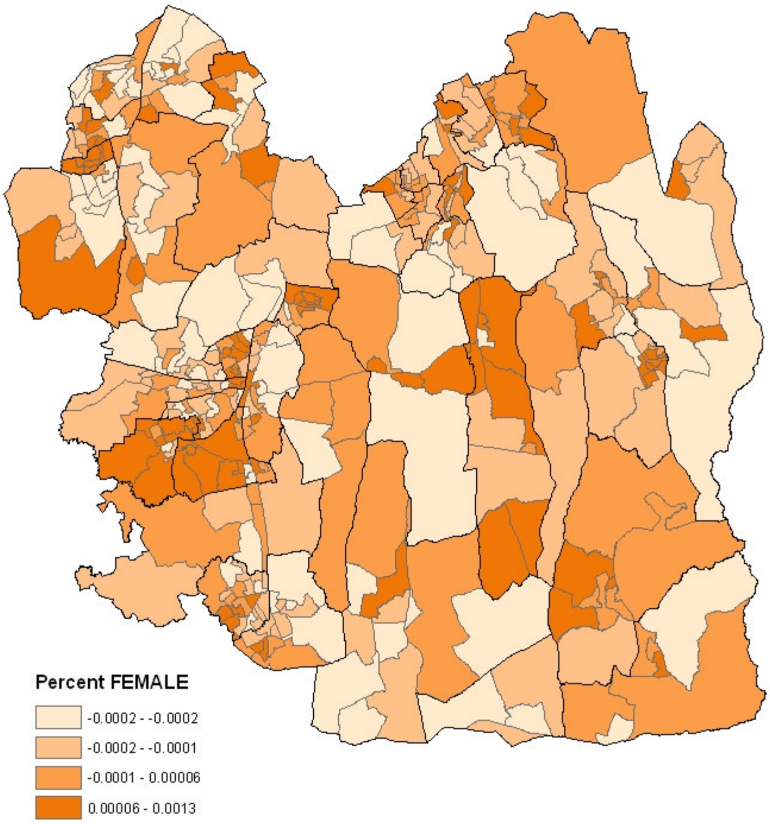


Figure 7.8: Proportion of the population in Reigate who are coded as FEMALE, by ED.

Local *I* values confirm this, with the majority of the area having values around zero, suggesting no spatial association (figure 7.9), which is confirmed by the normal curve approximation shown on the histogram (figure 7.10). The histogram also describes the limited spread of the data, which demonstrates that the FEMALE data has little spatial association (assessed by positive *I* values) or spatial dissimilarity (from negative *I* values). The negative tail is greater than the positive tail, demonstrating that there is some spatial disassociation within the Reigate FEMALE data. However, this may be due to areas where the data were suppressed, and so recorded percentages of zero. Clearly these values do not relate to the surrounding percentages, and therefore do not reflect the processes of the population. However, it is relevant to the analysis as suppressed areas can be used in statistical analysis and, if not acknowledged, influence the results, as their values would represent outliers. Thus, the presence of suppressed areas in an analysis could further exacerbate the MAUP.

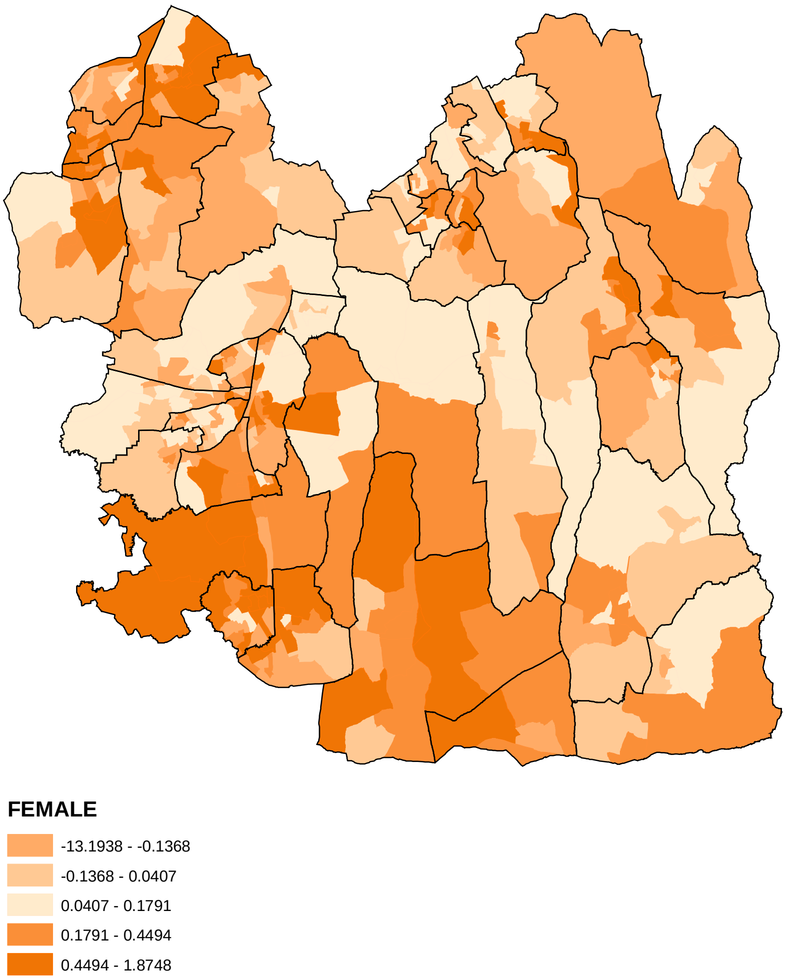


Figure 7.9: Local Moran's *I* values for the FEMALE variable in the Reigate SAR by ED with Ward boundaries imposed.

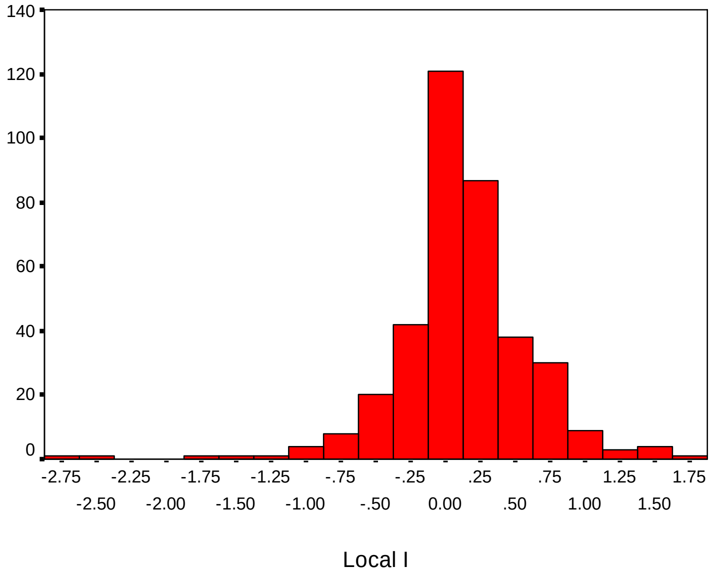


Figure 7.10: Histogram of the FEMALE local *I* values for the Reigate SAR.

The IAC value while stronger for RLA than for FEMALE is lower than observed in the analysis with the Glasgow RLA data. Furthermore, the Global *I* is relatively insignificant for the Reigate SAR. Therefore, it would be expected that RLA data in Reigate is less susceptible to the MAUP (scale) effects than the RLA data in Glasgow, as fewer and weaker spatial processes would identify a lesser degree of spatial autocorrelation and therefore within-area homogeneity, a contributing factor to the presence of the MAUP (see Tranmer and Steel, 2001). Thus, when the Local *I* measure is applied it is likely that there will be fewer processes identified. It is noticeable that the estimates have a far smaller range of values than the estimates for Glasgow. The Local Moran's *I* statistic was also calculated for the RLA variable in the Reigate SAR. Visually it seems that there is comparatively few spatial processes (see figure 7.11). The range of Local Moran's *I* values is lower, as would be expected as the number of observations have fallen from 5000 to around 300. As expected, there is less MAUP (scale) effect in the data, which prior analysis has shown to be the case.

Compared to the Glasgow SAR, RLA has less spatial autocorrelation, which is denoted by the greater prevalence of mid-grey areas. Furthermore, the range of values for Local Moran's *I* is far less than for Glasgow, and unlike in Glasgow where the positive and negative values of *I* are around the same size, the highest positive value of the Reigate SAR is 2, while the largest negative number is almost –8. Indeed, there are very few areas where there are any significant Local *I* values. This trend is supported by the histogram of the *I* values (figure 7.13). Although like the previous histograms it is basically unimodal (refer to figures 7.4 and 7.6), and can still be approximated to the normal curve. The distribution has a large range. The majority of the data is clearly clustered around the zero value, indicating no spatial association. The negative values of spatial autocorrelation exhibit a gradual decline of values whilst the positive slope of spatial association is highly dispersed. This again supports the theory that the RLA variable in Reigate there is a lack of spatial process present from the ED level units that could be used to build homogeneous Ward level units.

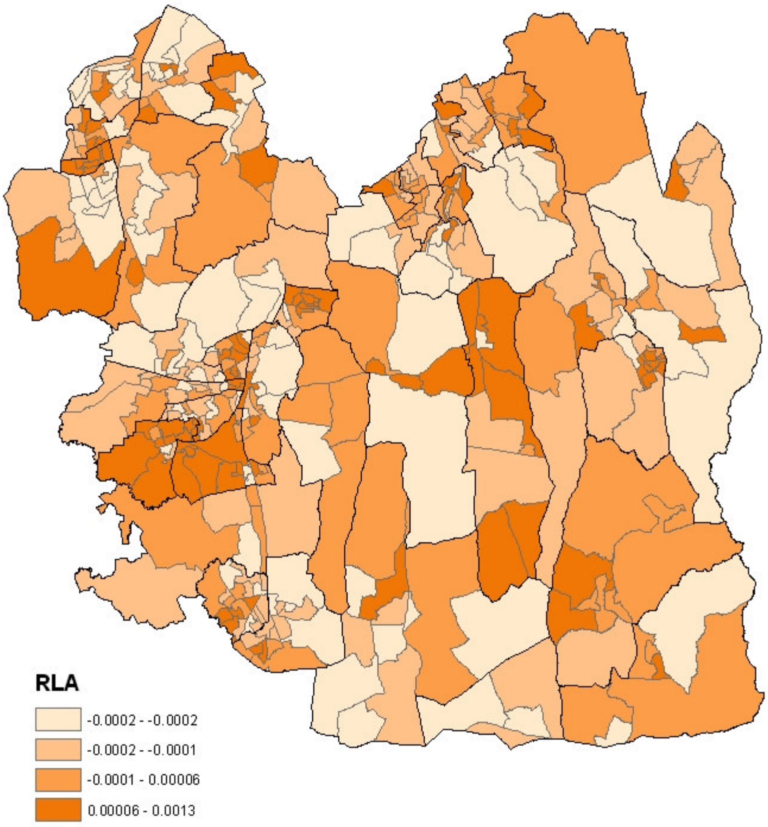


Figure 7.11: The area level effect estimates ($\hat{u}_g$) for the Reigate SAR by ED for the RLA variable.

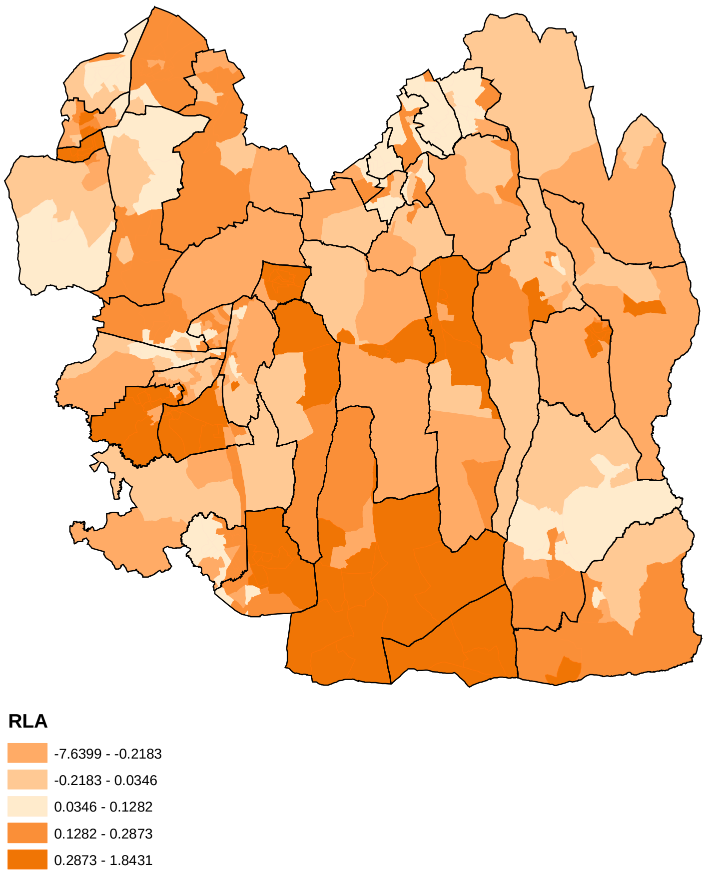


Figure 7.12: Local Moran's *I* for the RLA variable in Reigate, by ED with Ward boundaries imposed.

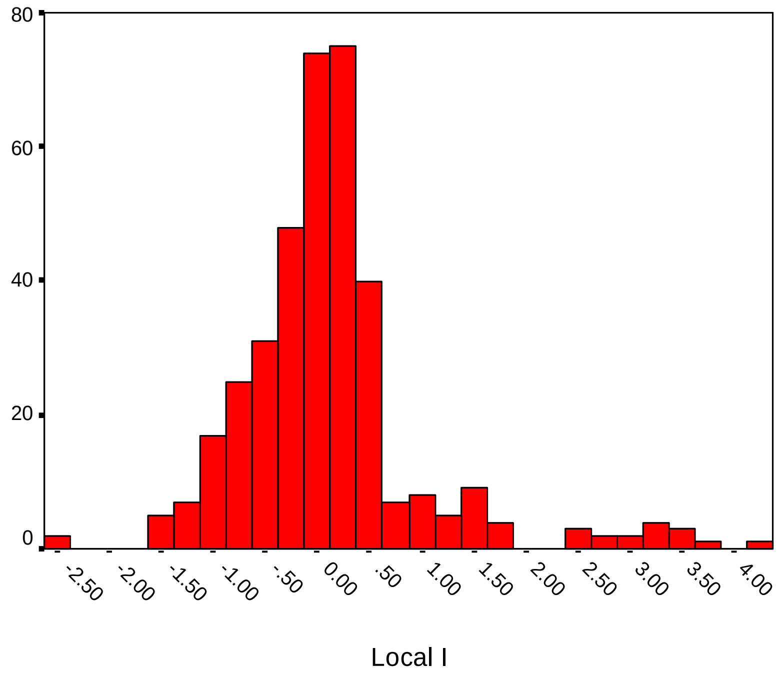


Figure 7.13: Histogram of the RLA local *I* values.

7.2.3 Ribble SAR

The third area of analysis was Ribble, in Lancashire. The IAC value for the RLA data in the Ribble district is between those of Reigate and Glasgow. Therefore, it would be expected that the magnitude of the scale effects would be between the two, as well as the extent of the spatial processes identified by the global and local spatial autocorrelation measures (see table 7.3). Ribble was included as a mainly rural area, which would contrast with urban Glasgow, and affluent suburban Reigate. Again the FEMALE and RLA variables were used to enable comparison.

	IAC ED	IAC Ward	Global *I*	Z Score
FEMALE	-0.00032	0.000088	-0.0035	-0.133
RLA	0.28	0.0900	0.011	3.91

Table 7.3: IAC and Global Moran's *I* values for the Ribble data.

Figure 7.14 presents the Local Moran's *I* values in the Ribble SAR, and figure 7.15 the histogram distributions for the FEMALE data in Ribble. The overall pattern of the data is similar to that presented in Glasgow and Reigate, whereby the FEMALE variable displays few spatial processes. The histogram, (figure 7.15) demonstrates that the distribution of the data is approximate to the normal curve. In comparison with the

FEMALE data presented above the spread is relatively large. As with the Reigate data, there are a number of EDs that have suppressed data. There is also a high positive tail for this distribution, which is not accounted for in the above description. Considering the distribution from figure 7.14 it is possible to see that there is a cluster of positive spatial autocorrelations in the north-western section of the SAR District. This area is a rural area and covers the majority of the Forest of Bowland, which is rural farming and forestry land. In terms of the proportion of females it is among the lowest, with the three areas all recording percentages below the 50% mark. There is also a higher level of spatial autocorrelation indicating spatial process identified in the urban centre of Clitheroe. This is an area of high retirement, and has a number of retirement homes within the urban centre. It is therefore likely that a greater number of older people will live there, and with females outliving males, there will be a higher proportion of female residents in these areas. Therefore, there are clear spatial processes apparent in this area of the Ribble SAR, which is reflected in the Local *I* values observed in the map figures. This can account for the high values of spatial association observed in the histogram.

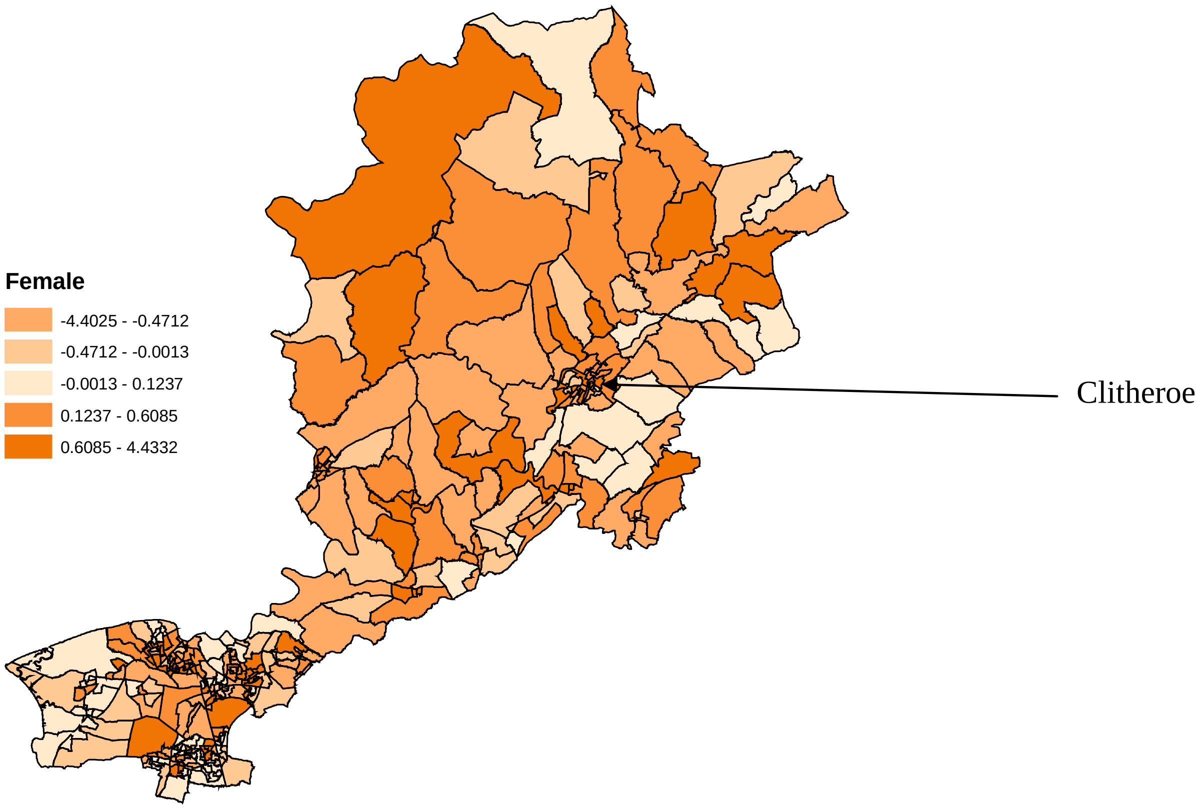
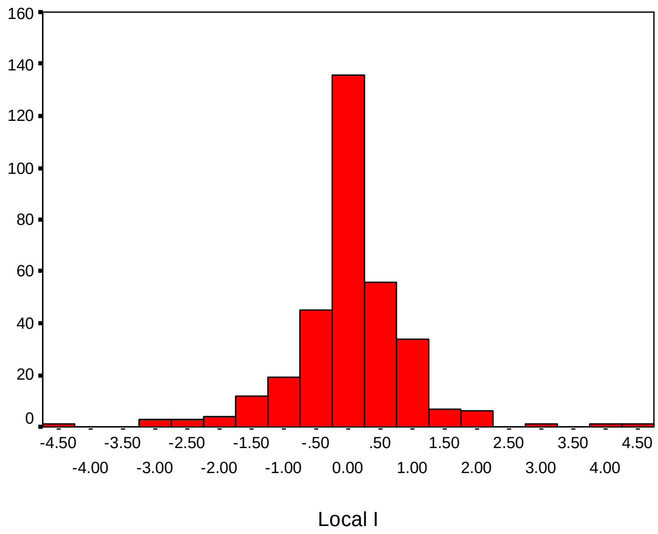


Figure 7.14: Local Moran's *I* for the FEMALE variable in Ribble, by ED with Ward boundaries imposed.



b)

Figure 7.15: Histogram of the FEMALE local *I* values.

Figure 7.16 shows the $\hat{u}_g$ estimates for RLA. Compared with the other Districts discussed the area effects ($\hat{u}_g$) in the Ribble SAR are relatively constant. The positive values of ED effects are largely concentrated in the rural areas. Figure 7.17 shows the Local Moran's *I* values for RLA within the Ribble SAR District. There are clear spatial processes in the Ribble District. The town of Clitheroe is observable as an area of high positive spatial autocorrelation demonstrating that there is a local effect in the RLA data. As Clitheroe is an urban area, where there is a greater concentration of people in a smaller space it is likely that greater homogeneity will be achieved, in comparison with the homogeneity observed in more rural areas. Thus, the existence of identifiable processes is more likely. However, this is not the case throughout the town, as there are values around zero in the central area of the town, demonstrating spatial independence perhaps related to a more commercial core area. The hinterland of the town also demonstrates spatial independence. The more rural areas of the Ribble District have higher level of positive spatial autocorrelation, demonstrating a more extensive process, which could be considered a regional effect. This process is clearly above the Ward level, as it groups a number of Wards together. The Southwestern part of the District exhibits the most negative spatial autocorrelation. These are EDs that form part of the town of Leyland (in the southern extreme) and the outskirts of the District. Leyland is an old industrial town, which experience industrial decline. There are few spatial processes observable in this area.

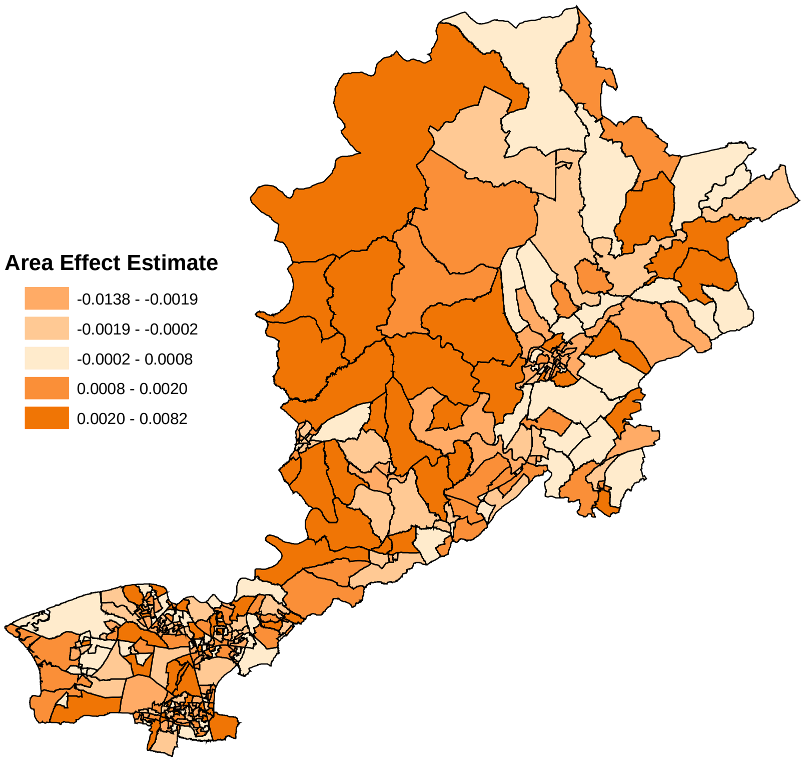


Figure 7.16: Ribble SAR area-level effects ($\hat{u}_g$) estimates for RLA which are lower than in the previous two RLA examples.

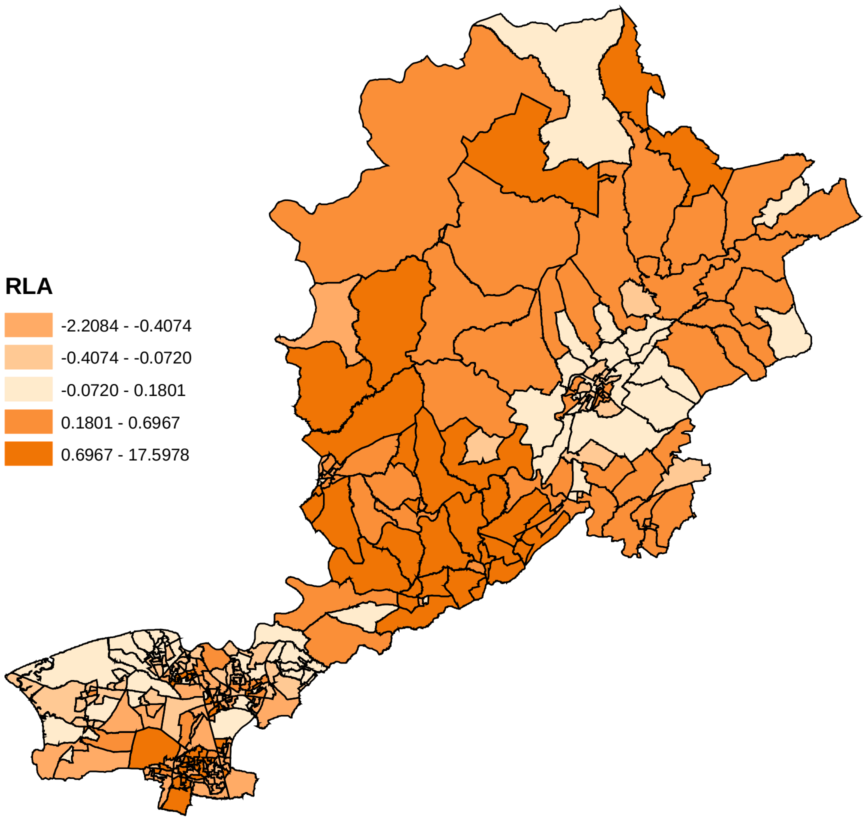


Figure 7.17: Local Moran's *I* for the RLA data in the Ribble SAR at the ED level with the Ward boundaries imposed.

There are a number of processes identified in the Ribble District. As with the Glasgow District, these processes occur at a number of different levels throughout the District. In the urban areas, such as Clitheroe and Leyland, there are low level, local, spatial processes. In the more rural areas, such as in the north east of the District the spatial processes are at a much higher, more regional level. The spatial processes are not as extensive as observed in Glasgow, which had the greatest IAC, but they are greater than Reigate, which had a lower IAC. The extent of the spatial processes appears, therefore, to be linked to the magnitude of the IAC.

7.2.4 Huntingdonshire SAR

The final area presented in this analysis is Huntingdonshire. This area is largely rural, and fairly affluent, although there are areas of lower affluence such as in the centre of Huntingdon itself. Therefore, it is an area that has the potential for a wide variety of processes that are potentially highly localised. The analysis again considers the FEMALE and RLA variables. The key data for the two variables is presented in table 7.4.

	IAC (ED)	**IAC (Ward)**	**Global *I***	**Z Score**
FEMALE	0.0107	0.000064	-0.00544	-0.61186
RLA	0.215	0.0407	-0.00555	-0.64099

Table 7.4: IAC and Global Moran's *I* values for the Huntingdonshire data.

Clearly there is less overall spatial association in the Huntingdonshire SAR in the FEMALE and RLA variables than for the other SAR areas discussed above, as the Global *I* values are very similar, as are the Z scores. It is notable that the Global *I* values and the Z scores are negative, suggesting that there is slight global negative spatial autocorrelation. This would signal a lack of spatial processes that are identifiable in the data presented at the ED level. The discussion below considers the potential local and regional processes present in Huntingdonshire using the FEMALE variable, where no processes are expected and then in the RLA variable where processes are likely.

The FEMALE Local Moran's *I* values, when geographically plotted, demonstrate that there is little evidence of spatial processes present in the distribution of the FEMALE population (figure 7.18 and 7.19). This is as expected, and reflects the findings with the previous areas. As with the other areas, the histogram reflects the approximation to the normal distribution with similar positive and negative tails, although the distribution is too peaked to actually be normal. The peak of the distribution occurs at zero, describing a distribution that predominantly has neither positive nor negative spatial autocorrelation, and therefore lacks evidence processes. However, there are some apparent processes in the FEMALE data that occur at a level below the Ward level boundaries. There is also a high degree of negative spatial autocorrelation at a similar level. The negative tails are influenced by the presence of a number of areal units with suppressed data, resulting in values that do not necessarily reflect the processes in the underlying data. However, this reflects the processes in the data available for analysis. Therefore, the effects noted here are present in all analysis using this data. Thus, it represents a relevant spatial process. However, an alternative to presenting the high negative values would be to assign the *I* value of the areal unit containing the suppressed data. There are also a small number of areal units that demonstrate high positive association. These appear in the northwestern edge of the District, and in the southern edge of Huntingdon.

Overall, the values of the local *I* statistics are not high for the RLA variable, in comparison with the values observed in the previous examples. However, they demonstrate some local and regional effects through the presence of spatial processes, even though the levels of association are not high. Figure 7.20 and 7.21 describe the distribution. It is worth noting, that the level of positive spatial autocorrelation is lower than in the FEMALE variable suggesting that there are fewer processes in the RLA variable than was present in the FEMALE data. The central area of the District, around the town of Huntingdon exhibits low negative spatial autocorrelation and therefore demonstrates disassociation and an overall lack of processes visible at the Ward level. In the northern part of the District there is also negative spatial autocorrelation, the magnitude of which increases in the northern areas. These EDs are adjacent to the City of Peterborough and therefore could reflect processes relating to the population of Peterborough. This also highlights another area of the MAUP, as the processes relating to Peterborough demonstrate

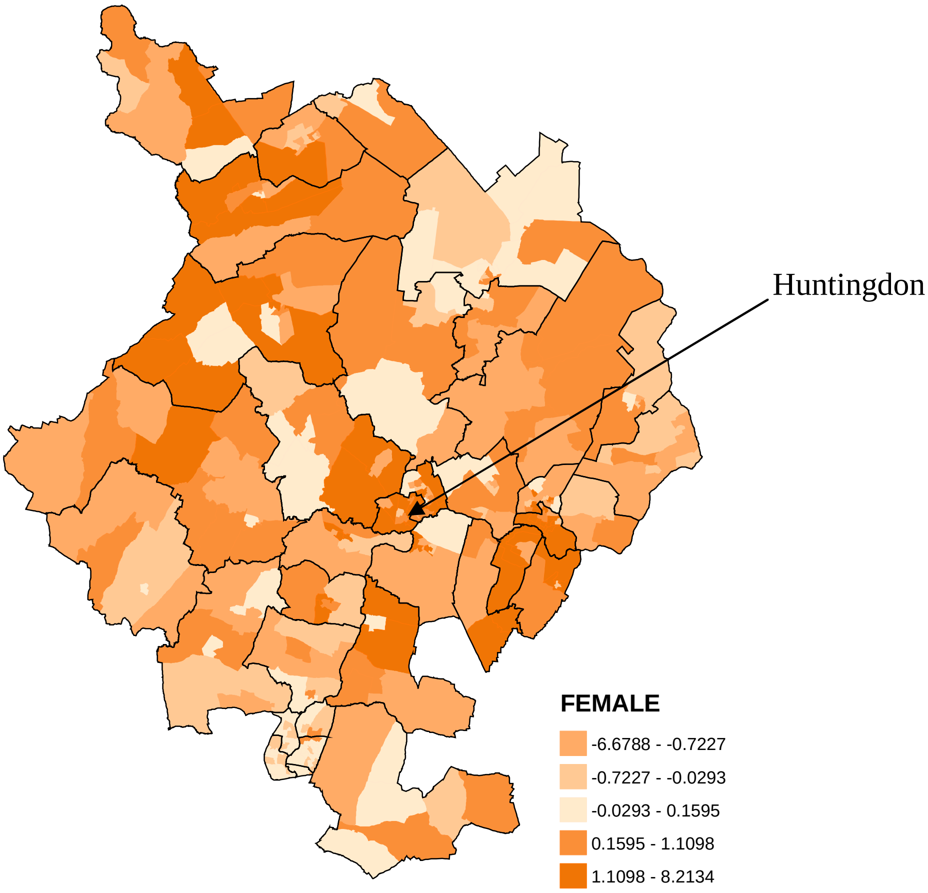


Figure 7.18: Local Moran's *I* values for the FEMALE variable in the Huntingdonshire SAR at the ED level with Ward boundaries imposed.

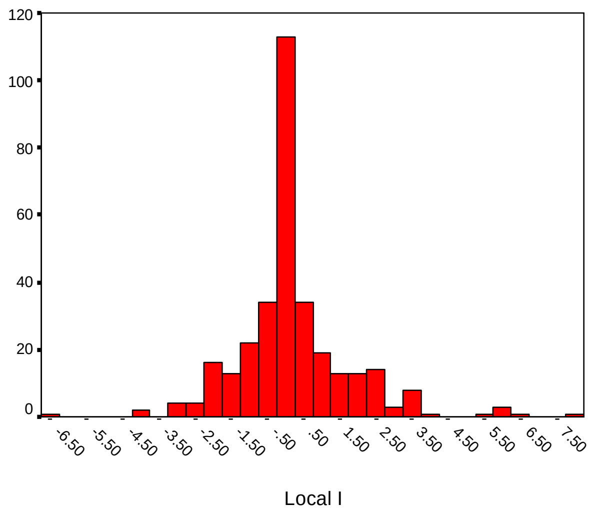


Figure 7.19: Histogram of the FEMALE Local Moran's *I* values for Huntingdonshire.

the existence of edge effects, whereby boundaries although presented as absolute in terms of either containing data or not containing data are not absolute in terms of the interactions that may occur across their boundaries. The pattern of increasing negative

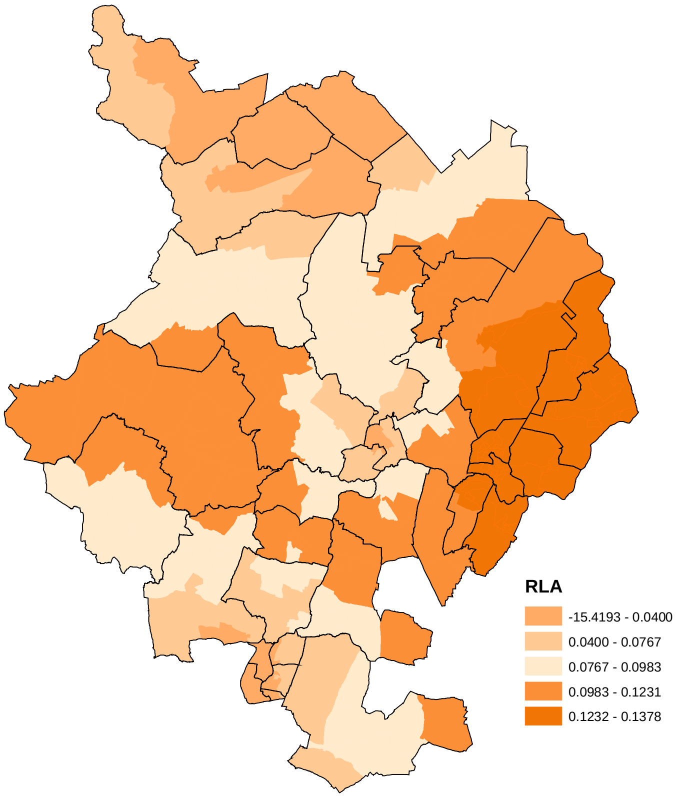


Figure 7.20: Local Moran's *I* values for the RLA variable in Huntingdonshire, by ED with the Ward boundaries imposed.

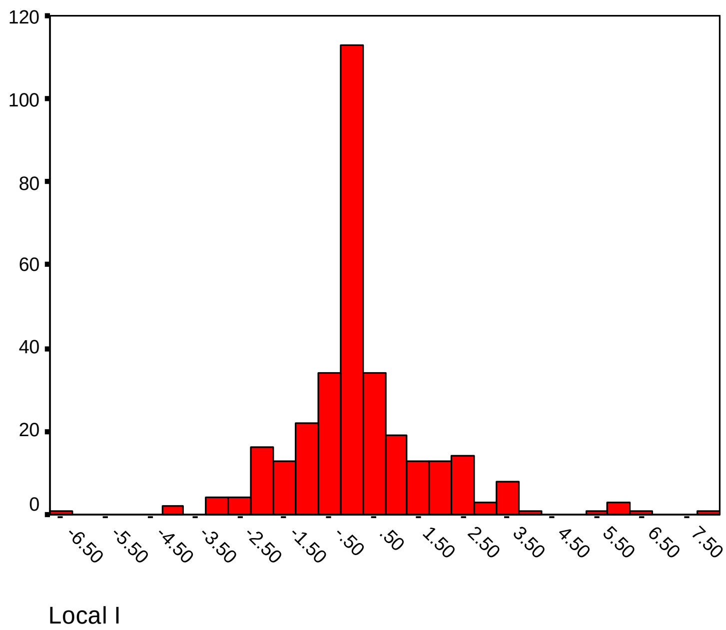


Figure 7.21: Histogram of the RLA Local Moran's *I* values for Huntingdonshire SAR.

spatial autocorrelation is repeated in the South of the District, with the EDs that are adjacent to the City of Cambridge. There is a large proportion of the District that exhibits zero spatial autocorrelation, depicting neither spatial association nor disassociation, and therefore there are few processes that can be identified between the EDs. These areas tend to reflect the most rural EDs in the District. Positive spatial autocorrelation is present in the remainder of the District. The strongest positive values are found on the Eastern side of the District, where the EDs are generally rural. However, there are some relatively large towns, such as St Ives, Bluntisham, Sommersham and Warboys in these EDs. All of these towns had a large proportion of housing built by local authorities in the past and it is, therefore, possible that there are some stronger spatial processes around these Districts. The other semi-rural areas in the Western part of the District also exhibit some positive spatial autocorrelation, although it is not as strong as exhibited on the Eastern side. The amount of grouping that is present in the Huntingdonshire SAR is surprising, as although the spatial autocorrelation is not very high, in positive terms, it is spatially concentrated, demonstrating the best evidence of spatial processes within a District. Furthermore, the evidence available here suggests that the spatial processes present in Huntingdonshire exceed the level observed in the previous Districts (Reigate and Ribble) both in terms of extent and clearly determined boundaries.

7.2.5 Discussion

The purpose of the above analysis was to investigate whether or not spatial processes could be identified demonstrating local and regional effects and whether or not they are related to the magnitude of the scale effect. The method was also designed to identify whether or not the processes identified at the ED level were translated into areal units at the Ward level, in order that the inconsistent nature of areal unit boundaries and spatial processes boundaries could be discussed. To do this, Districts with different levels of IAC in the RLA variable were selected, and compared to the relatively process free variable representing the proportion of females in the population. This analysis has highlighted a number of key findings, which are outlined below. They are:

- That Districts with high IACs in the RLA variable appear to have the greatest extent of population processes, seen in the differences between high IAC where there were a number of processes visible.
- That the processes in the population can occur at many different levels within a single District, suggesting that the one scale publication is an unrepresentative processes for many datasets.

- That the structures do not necessarily follow the Census boundaries. However, higher IACs tend to have data structures that are more similar to Census areal boundaries. This reflects the higher levels of within-area homogeneity that can be achieved.
- That there tend to be stronger process in urban areas than in rural areas, again demonstrated by the differences within the Ribble District between the towns and rural hinterland.

This evidence suggests that there are spatial structures between the areal units in census data. The different spatial processes that have been identified here demonstrate some of the differences that contribute to the scale effect, as they highlight spatial processes within the data that may alter relationship between variables depending on the degree to which the publication geography reflects them. Moreover, this evidence suggests that Green and Flowerdew (1996) highlighted an important and relevant concept in their discussion on local and regional effects.

7.3. Examining High IACs

In Chapter 4 a number of Districts were identified with IAC values that were statistical outliers. These Districts have been identified, and those variables that had outlier values have been selected for analysis using the spatial processes technique. The IAC outliers suggested that there was an unusually high level of with-area homogeneity in the Districts. This is to identify whether or not there are processes within these Districts, as would be expected if the results presented above are to be supported, and also to consider if high IAC data appears to have more processes, and whether or not these processes tend to coincide with the boundaries of publication geography. It is likely that they will coincide to a certain extent, given that high IACs describe a high level of within-Ward homogeneity. However, it is unlikely that any of the processes will match the higher-level geographies exactly. To emphasise this fact, the outlier variables will be supplemented using the FEMALE variable.

7.3.1. Spatial Processes in Plymouth

At the Ward level the District of Plymouth was highlighted as having outliers for 6 of the 8 variables that were investigated. Plymouth not only had the most outlier IACs, but also the highest IACs for 3 of the 6 variables. Below, these 3 variables, (UNEMP, OO and RLA) are presented after analysis using the techniques used to examine the spatial processes of the units from which the higher within-area homogeneity Wards are comprised. These are again supplemented by a fourth variable, FEMALE, to provide a contrast between the 3 variables with high within-ward homogeneity, and one that exhibits very low homogeneity. Due to the high nature of the within-ward homogeneity, it is expected that the 3 variables will exhibit high Moran's *I* values (local and global) within the Ward boundaries, and that there will be clear distinction between EDs which fall either side of these boundaries. Table 7.5 presents a summary of the statistical results for the 4 variables under consideration here. It is worth noting, that although the Ward level IACs for the variables (excepting FEMALE) were outliers, the IACs at the ED level for the three variables were not high, suggesting that the processes in the population are above the ED level.

	IAC (ED)	IAC (Ward)	Global Moran's *I*	Standardised *I*
FEMALE	-0.00003	0.00003	-0.000369	0.780659
UNEMP	0.008026	0.01274	0.038341	20.016882
OO	0.201779	0.17911	0.021385	11.588911
RLA	0.283865	0.27630	0.022133	11.960898

Table 7.5: Summary statistics for the 4 variables in the Plymouth SAR.

There is positive spatial association in the UNEMP, OO and RLA variables, with high values for the standardised *I* statistic. This spatial autocorrelation is not present in the FEMALE variable, where the Global *I* value is negative, demonstrating negative spatial autocorrelation, and the Standardised Moran's *I* is much lower than those observed in the other variables. Unusually, with the UNEMP variable the magnitude of the IAC increases between the ED and Ward level, demonstrating greater within-Ward homogeneity than within-ED homogeneity.

The lack of spatial autocorrelation described for the FEMALE variable above is observable (see figures 7.22 and 7.23), as is the expected lack of spatial process. This is reinforced by figure 7.23 which demonstrates that the FEMALE variable, with the lowest Local Moran's *I* values, also has the distribution with the least spread. The centre of the distribution is around the zero value, indicating neither positive nor negative spatial autocorrelation. This is as would be expected for the FEMALE variable.

Figure 7.24 presents the Local Moran's *I* for the UNEMP variable in a histogram. It exhibits high negative spatial autocorrelation, denoted by high values of the Local Moran's *I* in the south and north of the District. The northern Wards consist of a suburban area outside the main conurbation of Plymouth. Using the raw Census data, these Wards are a group with low incidence of unemployment, suggesting that they represent a more affluent area of Plymouth. This area represents a clear spatial process within the UNEMP variable. The Southern Wards of Plymouth with high Local *I* values are along the waterfront area. These areas have very high level of unemployment, and are a mixture of industrial docklands and terrace housing. This suggests that they represent an area of lower affluence, and demonstrate unemployment processes converse to those seen in the northern part of Plymouth. The central areas along with those to the west of the centre do not have high Local *I* values, and exhibit negative spatial autocorrelation. These Wards consist of a mixture of housing and industrial land along with a leisure complex. The mixture of land uses is likely to contribute to the increase of negative spatial autocorrelation in these Wards as a homogeneous population, at a level at which the data can be published, will be difficult to achieve. Thus, within-area homogeneity will be lower. There are clear divisions in the Local *I* values for the EDs and the locations of the Ward boundaries. Thus, the published Ward boundaries reflect the boundaries suggested by the spatial processes in this data. The UNEMP variable (figure 7.25) exhibits a greater degree of positive autocorrelation, and is skewed positively, with the peak of the distribution between -2.5 and 2.5. However, as the distribution is positively skewed, there are a greater number of EDs in the distribution with higher Local *I* values.

The OO variable has similar patterns that can be observed. For the OO variable, the north and south EDs and Wards demonstrate the greatest levels of spatial autocorrelation and therefore spatial processes, whilst the central area of the SAR District has negative spatial autocorrelation, therefore little obvious spatial processes between the EDs.

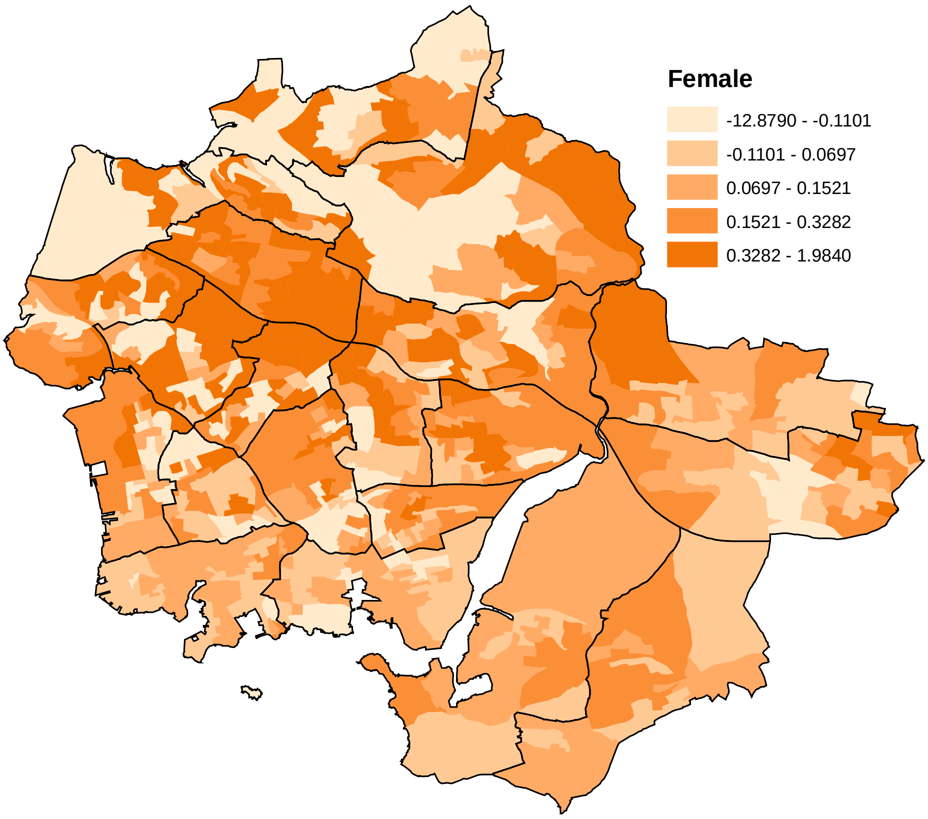


Figure 7.22: Local Moran's *I* for the Plymouth SAR District in the FEMALE variable.

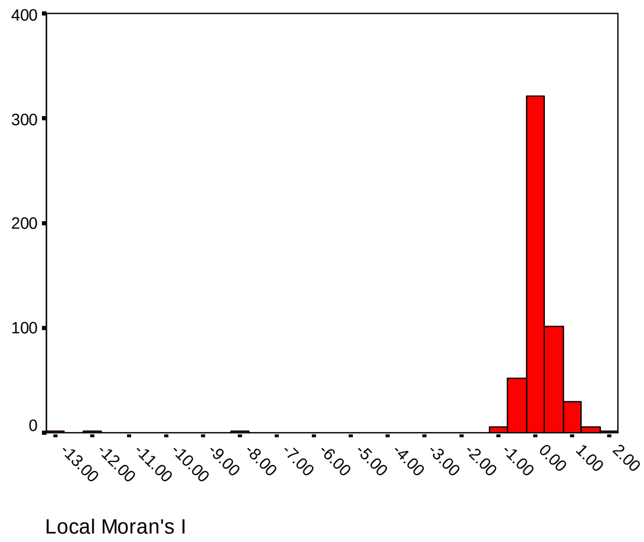


Figure 7.23: Histogram for the Local Moran's *I* at the ED level. Note the outliers in the distribution.

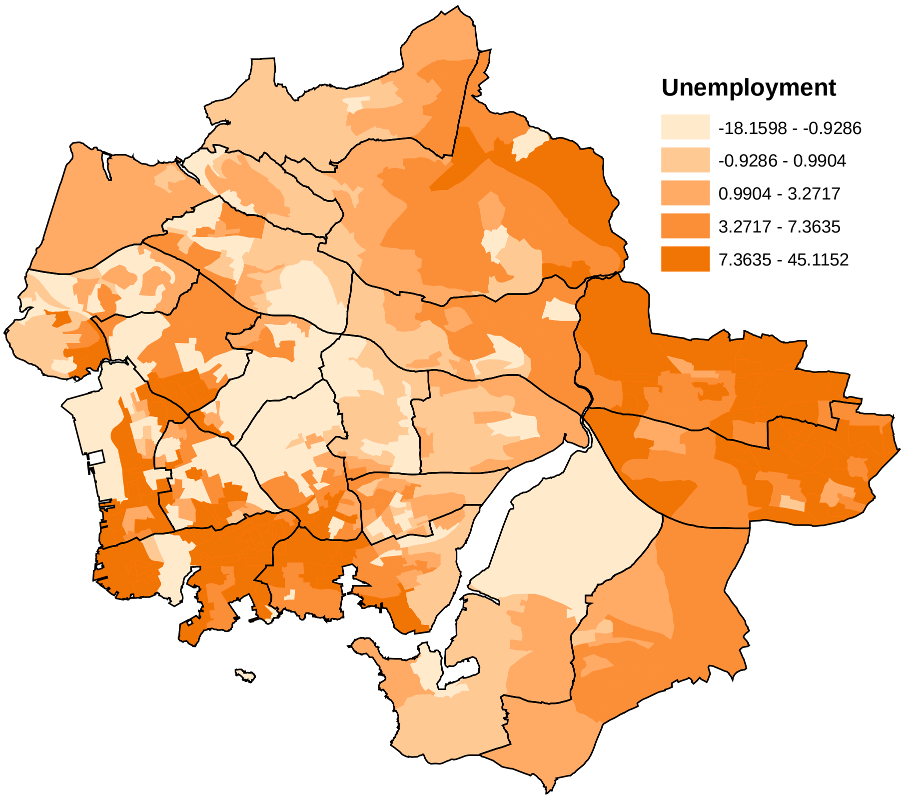


Figure 7.24: Local Moran's *I* of the UNEMP variable in Plymouth by ED with the Ward boundaries highlighted.

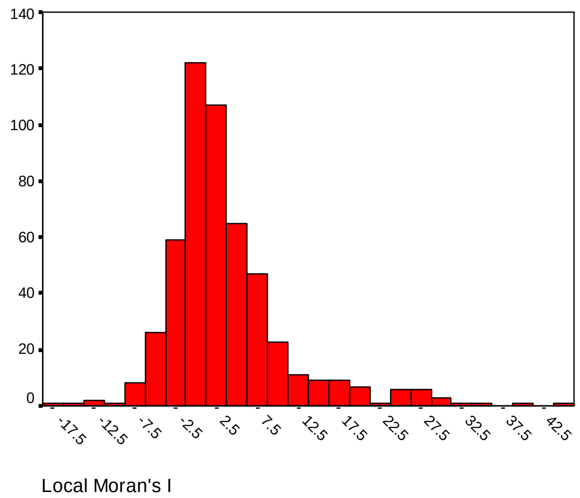


Figure 7.25: Histogram of the UNEMP Local Moran's *I* values in Plymouth.

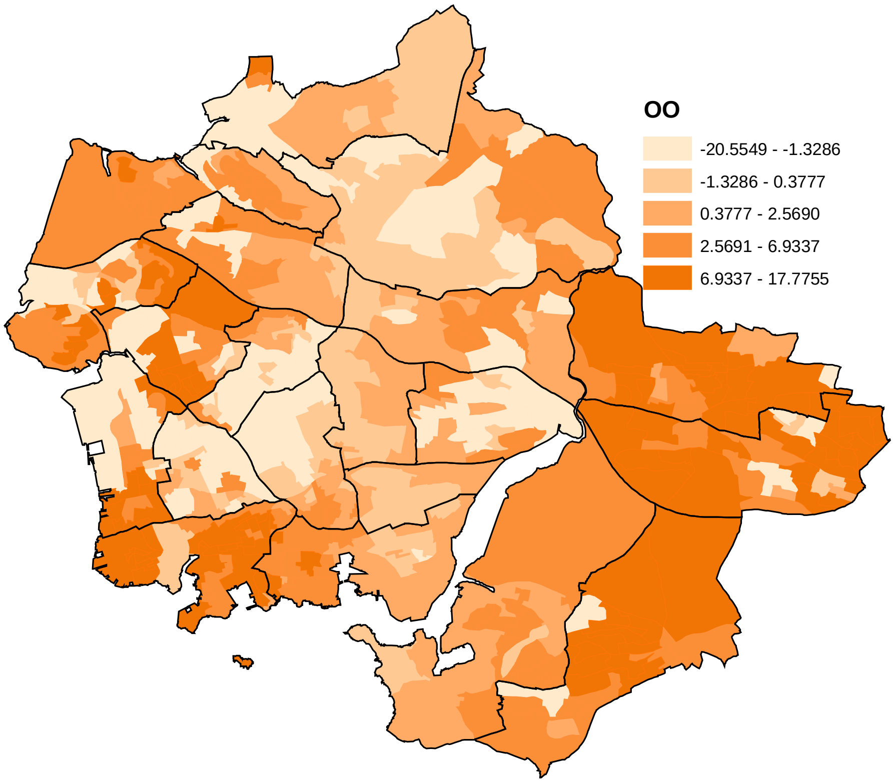


Figure 7.26: Local Moran's *I* values for the Owner Occupied variable in the Plymouth SAR by ED with the Ward boundaries imposed.

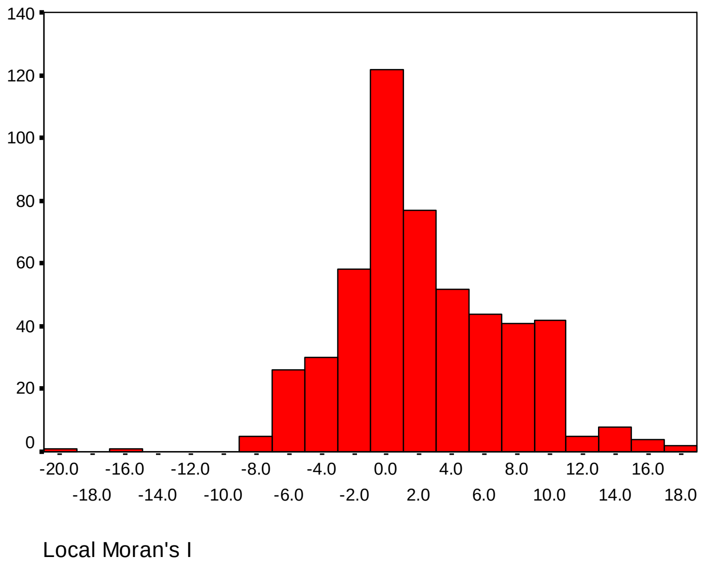


Figure 7.27: Histogram of the Local Moran's *I* values for the OO variable in Plymouth.

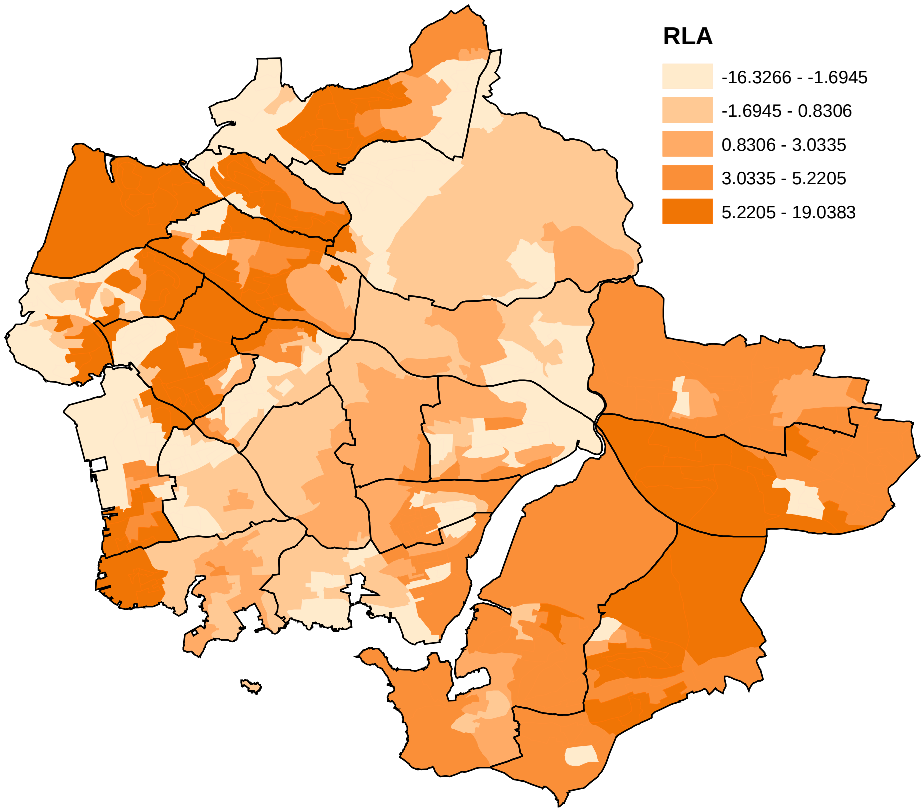


Figure 7.28: Local Moran's *I* values for the Rented Local Authority variable in the Plymouth SAR by ED with the Ward boundaries imposed.

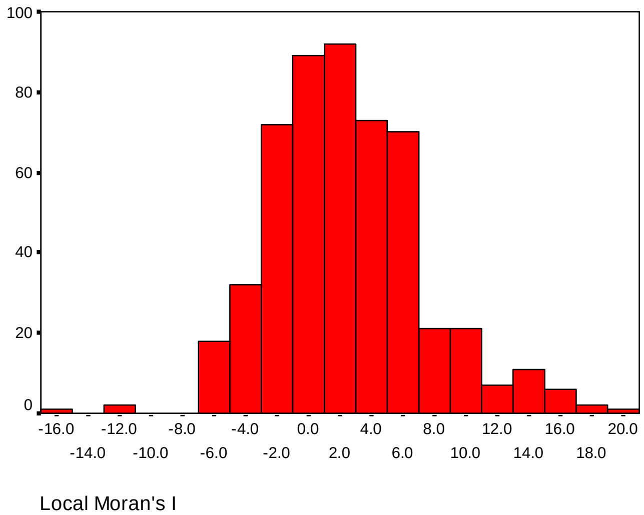


Figure 7.29: Histogram of the Local Moran's *I* values for the RLA variable in Plymouth.

The final figures, 7.26 and 7.27 present the Local Moran's *I* for the tenure variable OO, whilst 7.28 and 7.29 present the Local Moran's *I* for the RLA variable. Figure 7.26 demonstrates the spatial autocorrelation for OO. It is not as strong as that observed for UNEMP. However, there are clear spatial processes that match the Ward boundaries. These are in the South East and North West of the District. The South

Eastern Wards consist of the suburban areas known as Woodford, Plymton, Billacombe and Pomphlett. All of these are located away from the main centre of Plymouth, and are areas with high proportions of owner occupied properties. Again, this suggests that there is a relatively high level of affluence in these areas, supporting the conclusions drawn from the UNEMP analysis above. In the north of the District, the Wards consist of more industrial areas, and therefore with low proportions of owner occupancy, have high values of the Local *I* measure. This is also true for the coastal Wards in the South of the District where, again, much of the land use is commercial.

The OO distribution (figure 7.27) is positively skewed. It demonstrates a greater degree of spatial autocorrelation than was observed in the FEMALE data, which is as expected. The peak of the OO distribution is around the zero value indicating that the most common Local *I* value in the distribution is around zero. However, as with the UNEMP distribution, there are a number of EDs with higher *I* values resulting in a longer positive tail on the distribution.

The RLA (figure 7.28) pattern of spatial autocorrelation is similar to that of OO, although there are some minor differences. The Eastern and Western Wards have higher levels of association, as described by the Local Moran's *I*. High within-area homogeneity, identified using spatial autocorrelation, is again observed in the suburban areas to the East of Plymouth although the proportions of properties rented from local authorities are relatively low. This is the inverse of the pattern observed in the OO data, which is as would be expected. Thus, for the Eastern side of the District the high level of the homogeneity is based on the low incidence of the RLA variable. The converse is observed in the Western side of the District, where the incidence of the RLA variable is high. This evidence supports the theory, proposed in Chapter 4, that housing is a variable where it is easier to achieve homogeneity, partly because housing estates tend to be built to offer certain types of accommodation and attract a narrow population range, rather than a larger mixture of people. These, therefore, result in areas which are likely to either be owner occupied or rented from local authorities, and the scale of these estates frequently coincides with that of the census units such as EDs or Wards. Furthermore, they also provide convenient areas, which can easily be bounded, for areal units. The central belt of Plymouth has lower levels of Moran's *I*, including negative spatial autocorrelation demonstrating spatial disassociation. The EDs with lowest Moran's *I* values run along the route of the A388, the main road into the central area of Plymouth. Arterial routes such as this are likely to show lower levels of homogeneity, as there will be a large variety of land uses along them, including commercial and residential, and thus attract a wider range of the population. Within these distinctions there will be large differences, where commercial land use could be subdivided into shops, which may or may not have residential functions as well, to larger scale commercial use such as hotels, and trade businesses. This phenomenon was also observed within the Glasgow analysis, where the M8 motorway could be clearly identified as an area of zero spatial autocorrelation, and therefore an area with no spatial processes visible.

The histogram for RLA (figure 7.29), has a peak greater than zero, with the most common Local *I* value around 2. This clearly demonstrates that there is positive spatial autocorrelation in the distribution of the RLA variable, and that there are spatial processes within the RLA data. Moreover, these spatial processes are identified within the ED units, and can therefore be translated to Ward level processes.

7.3.2. Spatial Processes in Middlesborough

The Middlesborough District had two of the greatest outliers in the IAC distribution at the Ward level. These outliers occurred in the EMP and CAR0 variables. They are reviewed below, again with the addition of the FEMALE variable as a comparison. As expected, the FEMALE variable displays very negative or positive spatial autocorrelation (see table 7.6). This demonstrates that there is little systematic

	IAC (ED)	IAC (Ward)	Global Moran's *I*	Standardised *I*
FEMALE	0.000471	0.000281	0.002523	1.679955
EMP	0.051472	0.07798	0.022329	7.185019
CAR0	0.251614	0.463113	0.038446	11.666822

Table 7.6: Summary statistics for the 3 variables in the Middlesborough SAR.

process within this variable. The *I* values observed for the other two variables are both greater than for FEMALE, and both indicate positive spatial autocorrelation. Of the two variables, the CAR0 variable has the greater processes identified by the *I* values. The Global *I* measures are decomposed to identify specific processes within the population.

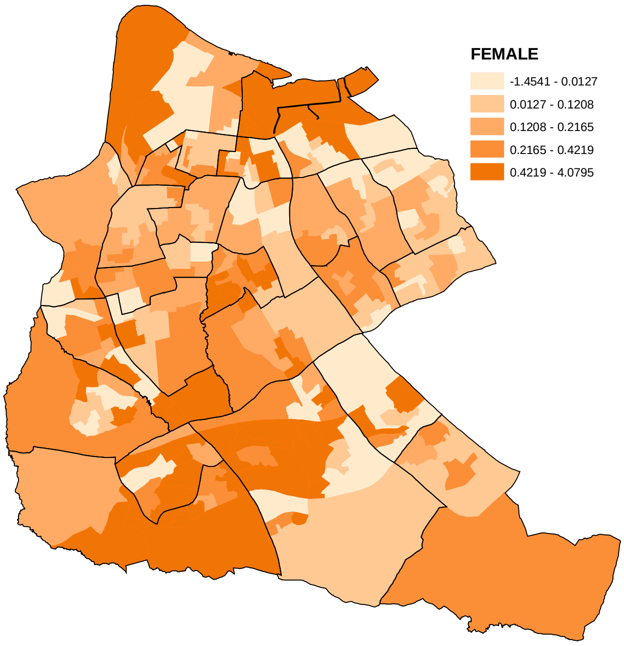


Figure 7.30: Local Moran's *I* for the FEMALE variable in Middlesborough, by ED with the Ward boundaries imposed.

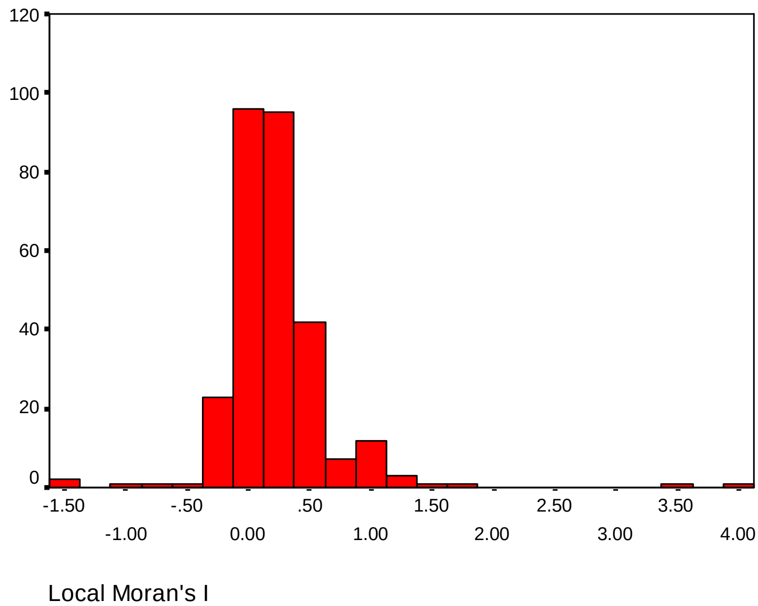


Figure 7.31: Histogram of the Local Moran's *I* values in the Middlesborough SAR.

Figure 7.30 depicts the distribution for the FEMALE variable, where there is little spatial autocorrelation visible between groups of EDs. This is an expected result, as there is low within-area homogeneity observable from the IAC measure. As with the other Districts where FEMALE has been tested for spatial processes, the majority of the *I* values in the FEMALE data are around the zero value (figure 7.31). This demonstrates neither positive spatial autocorrelation (evidence of process within the data) nor negative spatial autocorrelation (disassociation, and a lack of process identifiable by this analysis), as would be expected. Therefore, the distribution of FEMALE is similar to a random population. However, there are a number of EDs that have lower than expected levels of spatial autocorrelation for the FEMALE variable, demonstrating negative spatial autocorrelation. Although these EDs, in the north of the district, only have values of -1.5 they are still lower than the majority of the areas in Middlesborough. This area is an old industrial area, and also a Technology park, and is therefore likely to have fewer residents. This lack of population could then demonstrate a spatial process as people (male and female) would choose to live away from this area if possible.

Figure 7.32 presents the Local Moran's *I* measure on the distribution for the EMP variable. The range of *I* values is the greatest of the three variables considered for Middlesborough, and there are areas of strong positive or negative spatial association. In comparison with the analysis of variables in Plymouth, it is similar in magnitude to the tenure variables. The Northern and the Southern areas of the District both display high levels of positive spatial autocorrelation. The processes depicted by the stronger autocorrelation do not match the boundaries of the Wards at the northern edge of the District. However, on the north-eastern side they approximate to the Ward boundaries, demonstrating that the Census areal units, at least in part, reflect some of the processes within the employment (EMP) data. The EDs in the North of the District all represent areas with high incidence of the employment variable. The Southern part of the district, which also has strong positive spatial autocorrelation has low incidence of the employment variable. The EDs are, again, organised into Wards in groupings that loosely reflect the processes in the data. The higher levels of spatial autocorrelation in the north and the south of the district result in Wards that have relatively high within-area homogeneity. These Wards have low between area homogeneity, and therefore result in a high IAC, which measures the within-area homogeneity. The central EDs of the Middlesborough district have negative spatial autocorrelation. Here the EDs have a wide range proportions for the employment variable, and therefore would not be expected to provide evidence of strong spatial processes. This may be because the processes do not coincide with the level at which the data are available. It would be expected that the Local Moran's *I* would be negative, representing spatial disassociation between the EDs from which the Wards are constructed. It is possible that the boundaries of the EDs do not enable the processes of in the UNEMP variable to be observed, and different processes would be observed if there were different building blocks for the Wards.

Therefore, the Local *I* analysis of the EMP variable in Middlesborough indicates that there are spatial processes within the data. However, even in a relatively small District there are processes that occur at different scales for a single variable. Moreover, it is possible that high IACs may be achieved without the whole District being highly homogeneous, but with smaller pockets demonstrating high within-area homogeneity.

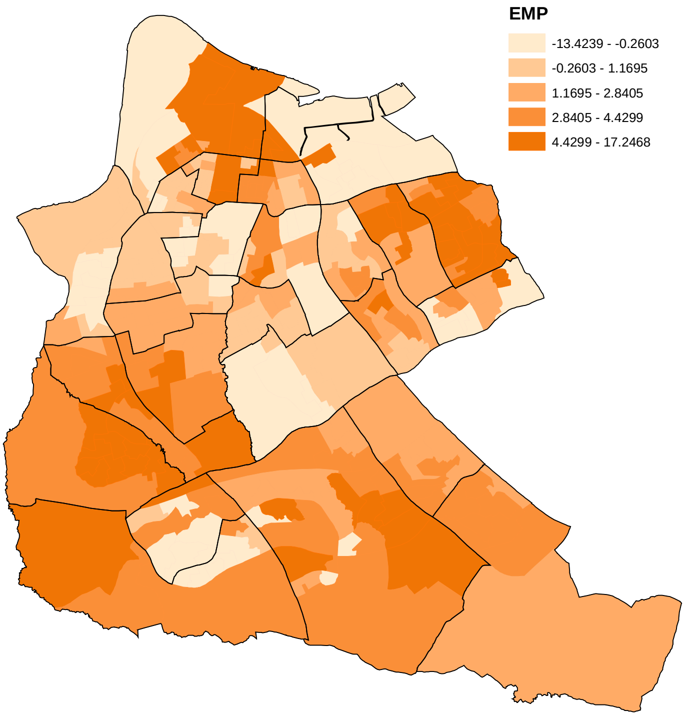


Figure 7.32: Local Moran's *I* for the EMP variable in Middlesborough by ED with the Ward boundaries highlighted.

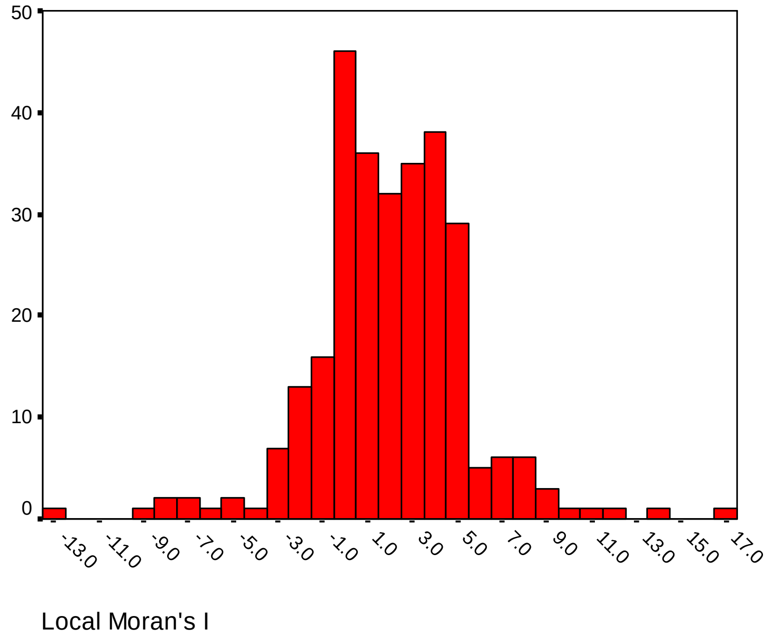


Figure 7.33: Histogram of the Local Moran's *I* values in the Middlesborough SAR.

Figure 7.33 presents EMP. Greater positive spatial autocorrelation is observable as the distribution is positively skewed, with the first distribution peak around the zero value. The majority of the data falls between zero and five, with a second peak around the 3.0 to 5.0 values. This allows the conclusion to be drawn that there are processes occurring within the EMP population. The overall range of the Local *I* values is greater for the EMP variable than for the FEMALE variable, demonstrating the greater level of association, and disassociation. For the construction of areal units matching the processes in the data, the disassociation would represent boundaries between Wards, whilst the association would be contained within these boundaries. Reference back to figure 7.32 demonstrates that this is the case for some of the Districts.

Figure 7.34 depicts the CAR0 variable. The processes that are visible in the data are similar to those identified in the EMP variable. However, the overall range of autocorrelation between the EDs is lower for the CAR0 Local *I* ranging from -14 to 13, compared with -13 to 17 for EMP. There are more spatial processes observable in the CAR0 variable than were shown in the FEMALE variable. This was expected, as the spatial autocorrelation is higher than in the FEMALE variable. The high levels of autocorrelation are in the northeast and south of the District. These relate to areas with high incidence in the northeast, and low incidence in the south of the CAR0 variable.

The high incidence Wards are around the areas of Pallister, Park End and Brambles Farm, which all had lower incidence of the EMP variable. This suggests that these are less affluent parts of the District. Moreover, it suggests that there is a potential link between the EMP and CAR0 variables. The southern Wards around Tollesby and Nunthorpe all exhibit low incidence of the CAR0 variable, and also high incidence of the EMP variable reinforcing this theory. The central area of the District has negative spatial autocorrelation. Around the central area there are Wards with high incidence of the CAR0 variable, neighbouring Wards with low incidence. Therefore, it is unsurprising that few processes can be identified for these Wards. The pattern of relatively few processes in the urban centres of the District is consistent with the other Districts analysed here, and was observed in the central area of Glasgow and Clitheroe discussed in section 7.2, and also that of Plymouth above.

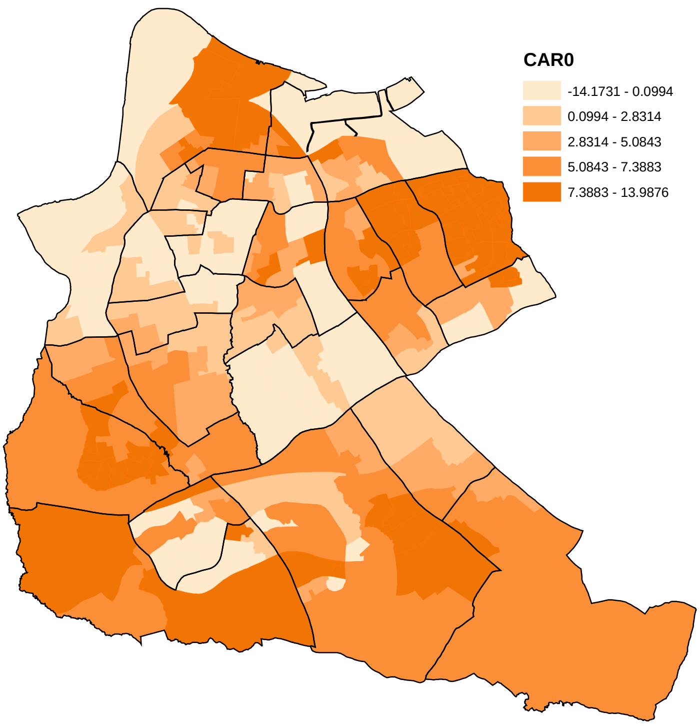


Figure 7.34: Local Moran's *I* values for the CAR0 variable in the Middlesborough SAR by ED with Ward boundaries imposed.

There is positive spatial autocorrelation in the CAR0 variable, shown in figure 7.34. The peak of the distribution is greater than zero, occurring at around six, suggesting strong spatial autocorrelation, and therefore indicating the presence of processes. As was demonstrated with figure 7.35 this high positive autocorrelation provides the EDs in the District with potential processes in the CAR0 data. Moreover, the majority of the data are accounted for in the zero to seven range of the Local *I*, as there are three minor peaks in the distribution at three, five and seven.

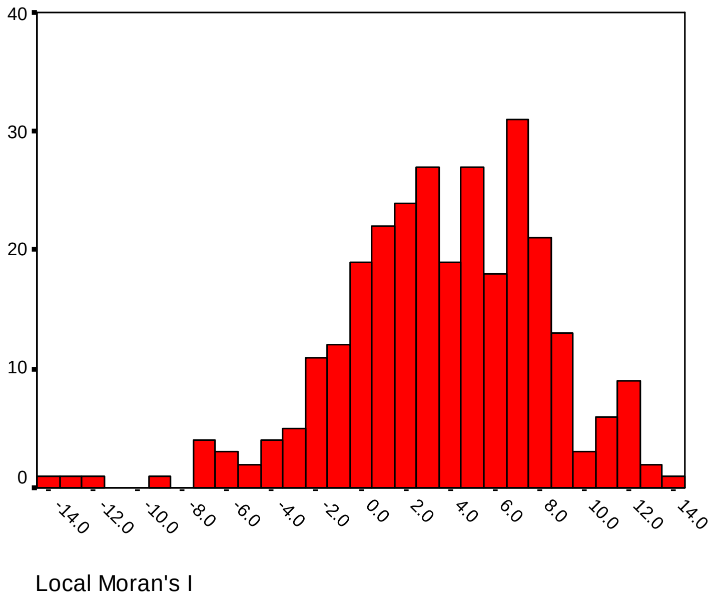


Figure 7.35: Histogram of the Local Moran's *I* values for CAR0 in the Middlesborough SAR.

Overall, there are areas that exhibit processes in the data that are reflected in the Ward boundaries. In the terms of Green and Flowerdew (1996), processes at this level can be considered as local effects. However, there are processes that extend beyond the Ward boundaries. These processes are a reflection of the regional effects, also discussed by Green and Flowerdew (1996).

7.3.2 Discussion

Above, the construction of Wards in the Districts of Plymouth and Middlesborough has been analysed. Plymouth and the RLA, OO and UNEMP variables were chosen as they exhibited extremely high IAC values at the Ward level. Thus, they provide an opportunity to evaluate the concepts proposed in the first part of this Chapter whereby higher magnitudes of IACs were hypothesised to be linked to the incidence of clear spatial processes that coincided with the boundaries of the publication geography. Consequently, clear patterns of homogeneity have been identified in the three high

IAC variables, with UNEMP displaying the highest level of spatial autocorrelation according to the Global Moran's *I* and Local Moran's *I* measures. This is in comparison to the IAC values, which measure within-ED and within-Ward homogeneity at the ED and Ward levels respectively. In the IAC measures, the RLA has the highest value, whilst OO and UNEMP have lower values. Therefore, it is possible to conclude that the UNEMP variable has the highest degree of spatial autocorrelation, and that the distribution of UNEMP is more concentrated. However, the extent of the concentration of the UNEMP variable does not match the scale of the Wards, resulting in lower IAC values. The tenure variables of RLA and OO have lower levels of spatial autocorrelation present at the ED level, and the processes in these variables matches that of the Ward boundaries more closely, resulting in the higher within-Ward homogeneity measures identified by the IACs. Therefore, high IACs indicate the presence of spatial processes at the Ward level, and reflected by Ward boundaries.

The results from the Middlesborough District were similar to those from Plymouth. The distribution of the FEMALE variable demonstrated a lack of process as expected. The other variables, EMP and CAR0, demonstrate more processes, identified by the positive spatial autocorrelation. However, these processes were not present throughout the whole of the SAR District. Moreover, they did not coincide at scales similar to Wards, identified by the approximate number of EDs required to form a Ward. Even when there were sufficient EDs grouped together, the location of the Ward boundaries did not consistently match the 'natural' boundaries of these processes.

Using the Districts and variables that were highlighted in Chapter 4 as outliers it has been demonstrated that spatial processes exist within areal unit data. These spatial processes are the realisation of the local and regional effects identified by Green and Flowerdew (1996). In Districts that have higher levels of within-area homogeneity (identified using the IAC) the spatial processes coincide better with the Ward boundaries more often than those with low within-area homogeneity (such as the FEMALE variable).

As demonstrated above, it is notable that the spatial processes do not always coincide, not only with the boundaries of the Wards, but also the scale at which the Wards are constructed. This has consequences for the analyst, as it can provide an indication of the level at which an analysis should be implemented. It can be argued, that the analysis should attempt to implement units at a scale, which reflects the processes in the data. However, as analyses need to be comparable, and the processes do not occur at similar levels within Districts, let alone at similar levels *between* Districts this may not be a practical approach.

Thus, in review the investigation of the outliers has further demonstrated the presence of local and regional effects in areal data. The main points are:

- That the outlier values identified in Chapter 4 have identifiable spatial processes.
- High IAC variables tend to have processes that coincide with the census boundaries, seen in the comparison between the outlier variables and proportion of females in a each district.
- Scales and processes are not consistent with the census boundaries even in these high IAC variables. However, they do tend to coincide more frequently than the processes observed in lower IAC districts.
- Processes in variables that are clearly linked, such as OO and RLA are highly similar.

7.4. Conclusions

It has been shown that, although an aggregation level is presented as a homogeneous set of zones, in reality the composition of these zones can be vastly different. Each variable can act in a manner that is unique, and thus each variable is susceptible to different processes that may occur at many different levels in any given area. Consequently, each variable is susceptible to a differing degree of the MAUP in a statistical analysis. The analysis presented here reaffirms the notion that it is not possible to define an ideal single Census geography that is suitable for the aggregation of all variables if the processes within the population are of prime concern in the analysis. Even if they are not of direct interest to the analysis, they clearly have an impact, as the processes that are operating between EDs and Wards.

Through necessity, the Census geography that is provided must be a compromise. However, it is possible using this methodology for users to critic Census geographies and their applicability to the variables that they are studying. Moreover, a means is provided for users of areal data to be aware of the extent to which processes operate in the data that they are using. Although it does not provide a quantification of these processes it does at least enable analysts to show that they exist.

There are three key trends identified in the discussion sections. These are reiterated below and state that:

1. Variables with high IAC values tend to have processes that coincide with the boundaries of the census areal units.
2. Variables with high IAC values tend to have a more visible processes between the EDs and Wards.
3. Processes can be identified in the spatial data. There are more processes present in data where the distribution moves away from the approximation to the normal distribution towards a positively skewed distribution.

The methodology also demonstrates a useful extension of the MLM technique, and allows it to be applied to spatial data processes that do not necessarily conform to the strict standard aggregation patterns. A next phase of this research is that the methodology will need to be tested for a larger number of areas and variables, and it will also need to be extended to define spatial processes between multiple variables.

Chapter 8

Conclusions and Discussions

8.1 Introduction

The previous four chapters have investigated the Modifiable Areal Unit Phenomenon using data from the British Census. Together, they have provided evidence of, considered factors that may contribute to, and investigated how differing levels of homogeneity contribute to, the scale effect. They have provided evidence that the changes in correlation coefficients between different boundary scales and delineation are statistically significant, and that the processes that lead to these differences can be investigated using a combination of multilevel modelling and spatial autocorrelation. In the introduction four questions were outlined that were to represent the main topics that this thesis would cover. They are presented below again, and considered:

1. Whether MAUP scale effect exists, and how important it is in UK Census data?
2. Whether or not the changes in correlation coefficients are statistically significant? If no significant changes are found then the concern over the scale effect may be overstated.
3. Is it possible to identify a suite of factors that contribute to the MAUP, and if so can they be used to understand the scale effect in more detail?
4. If it was possible to determine the extent to which spatial autocorrelation plays a role in the determination of the incidence of the MAUP? Can this be visualised as a set of processes within the data?

The following sections attempt to consider how well these issues have been addressed. Below, a review of the conclusions from each chapter is presented. These provide the specific findings of each section of analysis. From this, an overall conclusion is reached, which discusses the results and implications of these findings for the MAUP scale effect.

8.2 Magnitude of the scale effect

Chapter 4 presented evidence for the MAUP scale effect in the 1991 British population Census. There were a number of conclusions reached from this analysis, and they are presented below:

- In simple univariate MAUP analysis the magnitude of the MAUP scale effect is highly dependent not only on the variable that is under analysis, but also on geographical location.
- Of the eight variables considered from the British Census analysis, NONW, CAR0, OO and RLA exhibited the greatest incidence of the scale effect as measured by IAC.
- Overall, the Aggregation Effects between the individual and Ward levels are greater than those between the individual and ED levels. This represents the greater change in scale observed between these two aggregations.
- Similarly, Ward level IACs are smaller than ED level IACs indicating a fall in the levels of within-area homogeneity as the magnitude of aggregation rises, excepting for the OO variable. This could be due to the fact that OO measures a function of tenure, those people living in owner occupied housing, that that the level at which the population becomes more segregated in terms of their tenure is, in general, greater than that of a Ward.
- The size of the areal unit is highly important. Scotland, which has smaller basic spatial units than England and Wales, exhibited lesser scale effects and higher intra-area homogeneity than the equivalent units in England and Wales. When aggregated to a greater scale, for instance the Ward level, the measures of the scale effect reported similar effects in both the Scottish and English and Welsh data. This can be attributed to unit size as both Scotland and England and Wales have equivalent sized units at the higher Ward level aggregation.

From the evidence presented here, it is possible to answer the first of the four questions posed, and state that the MAUP scale effect does exist in 1991 UK Census data. The identification of differences in the magnitude of the MAUP via the AEs and IACs served two purposes. Firstly, to verify that the method proposed by Tranmer and Steel (2001) was applicable to large datasets. Secondly, it demonstrated that they can be used to measure the magnitude of the scale effect can be measured. Thus, this enabled the establishment of a review of scale effect in the UK Census data, and demonstrated that, it is not only prevalent, but also that the scale effect is variable over both space and variables. The differences in scale effect between urban areas and rural areas were also highlighted. However, as this chapter presented theoretical evidence of the MAUP scale effect, it was necessary to provide significant examples of the scale effect in actual statistical analysis. This is pursued in Chapter 5, which although it has a distinct set of objectives, is also a clear extension of the work in Chapter 4.

8.3 Correlation coefficients

One of the major questions, once evidence of the MAUP has been established, concerns the significance of the statistical uncertainty, and whether or not this statistical uncertainty is anything greater than an 'inconvenient' change in the level of the relationship. Therefore, it is useful to provide evidence that demonstrates the statistical significance for the changes in the relationship. This has been done in Chapter 5 through the use of significance testing for the differences in the correlation coefficients. Whilst not all changes in correlation coefficients were seen to be statistically significant, the majority clearly were. Overall, therefore, it is possible to conclude that the scale effect is of real importance to not only researchers but also to real world policy makers. This is not only because there is statistical uncertainty in correlation results, but crucially because this uncertainty is significant in a statistical context. The fact that the changes are statistically significant demonstrates that, the differences in the correlation coefficients are of a magnitude that should cause serious concern, and does demonstrate that the relationship can change to a degree where appreciable differences in outcomes can occur, again challenging the notion by Marble (2000) that the MAUP, although a problem, does not have serious consequences.

As with the other analyses, the key conclusions from the chapter are presented below:

- Differences observed in correlation coefficients in British Census data caused by the MAUP are statistically significant. Thus, it is possible to definitively state that the MAUP has serious statistical consequences.
- The range of correlation coefficients calculated for the different variables identified that the scale effect measures do provide a representation of the scale effect that is useful to gauge the impact of the scale effect.
- Overall, those variables that were related to the aggregation variable (for both the LLTI and CAR0 these were the UNEMP, EMP variables) and they

exhibited less variability in correlation coefficient than those that were not related.

- Some variables tended to indicate a greater incidence of significance in the change in correlation coefficients than others. For instance, the tenure variables of OO and RLA. However, the overall incidence that saw that the majority of the changes in correlation coefficient were significant was surprising.
- Both Bradford and Reigate exhibited changes that were statistically significant, although more significant changes were exhibited in the Bradford SAR than in Reigate, perhaps because of the more urban nature of the Bradford SAR. The Bradford area has been subjected to many more population influences than Reigate. These include the development and decline of old industry and coal mining. Reigate, on the other hand has not suffered from decline in the same way, and represents a more affluent, commuter community, which is more likely to be diverse.

This chapter completed the work set out in Chapter 4. Namely, it sought to determine if the theoretical scale effect that had been suggested were present in Census data. Beyond this, the implications of the second element of the MAUP were considered, the zonation effect, and evidence was also presented that there were significant statistical differences in the correlation coefficients of the analysis that was carried out between the different zonations at the same scale. Thus, it is possible to demonstrate the statistical importance of the MAUP, in a manner that has not previously been done.

8.4 Factors influencing the scale effect

Chapter 6 attempted to link the magnitude of the Aggregation Effects and the Intra-Area Correlations to external factors to increase the understanding of the scale effect. However, although the results vary considerable it was possible to determine some generalisable observations. However, this does reinforce the notion in the literature that the MAUP and the scale effects are largely unpredictable in their nature. Nevertheless, some conclusions were drawn. They were that:

- There was a positive relationship between the magnitude of the AEs and IACs and the weighted variance. This is not surprising, however, as both measures are directly calculated using the weighted variance results. The correlation coefficients were highly significant at 0.9.

- There was a positive relationship between the IAC and AEs and the proportion of the variable under investigation. As higher levels of homogeneity tend to lead to great incidence of the scale effect, as high homogeneity is more difficult to achieve at higher levels of aggregation, this also is not a surprising result. However, with correlation coefficients of only between 0.1 and 0.2 these relationships were not statistically significant
- Population density, used as a proxy for the level of urbanisation for an area was positively related to the magnitude of the scale effect. Thus, the more urban an area was, the greater the scale effect that would be exhibited in analysis of the data. This is due to the fact that urban areas tend to have more structured areas, especially in terms of residential locations, thus introducing a high degree of homogeneity into the population. Only the correlations for the NONW, EMP and RLA variables were significant.
- The differences in the average number of people in areal units serve to highlight the differences between the Scottish data and the data from England and Wales. Crucially, the Scottish data was far more homogeneous in the smaller units, demonstrating that smaller populations tend to produce more homogeneous zones. The correlation coefficient had a wide range of between 0.1 and 0.5, although none were significant.

The purpose of this chapter was to provide evidence for the third question, investigating whether or not it is possible to identify a suite of factors that contribute to the MAUP. Thus, the chapter serves to demonstrate that the MAUP is a highly complex problem. However, it is not simply related to a small number of factors as considered here, although relationships were identified between the magnitude of the scale effect as measured by the AEs and IACs and many of the factors considered. Only the weighted variance and the proportion of a variable were noted as having a relationship sufficiently strong to enable conclusions to be drawn. Other factors, such as population density, which was used as a proxy for urbanisation, were not sufficiently strong for any strong conclusions to be drawn. Nevertheless, this does aid understanding and prediction of the scale effect, it is possible to reinforce the notion that the scale effect, and indeed MAUP in general, is a highly pervasive complex phenomenon, as noted by Thomas and Anderson (1965) and Openshaw (1989) amongst others.

8.5 Spatial Processes

Having demonstrated the significance of the MAUP in statistical analysis and complexity of the scale effect, the last section of analysis sought to identify, conceptually, another set of influences behind the scale effect. Essentially, this work set out to demonstrate that there were other influences on the population, other than those measured in Chapter 6, which could contribute to the incidence of the MAUP. These influences were termed 'processes' and they would demonstrate that some contiguous basic level areal units were not only highly similar but shared characteristics. The presence of these processes, and their incidence or otherwise with publication boundaries would demonstrate one cause of the changing levels of homogeneity observed in aggregation, and also the non-random distribution of the population. Both of these are key causes of the MAUP. Thus, the hypothesis behind this was that the observed changes in the levels of within area homogeneity meant that it was likely that between-area homogeneity levels would also vary. Varying levels of homogeneity, in themselves may not alone be a serious problem. However, this could be compounded by differences between the boundaries used in the publication of the areal units, and the actual boundaries of the processes, and therefore the homogeneous areas. The conclusions reached in this section were:

- That processes exist generating the data that can be demarcated using patterns of spatial autocorrelations.
- Areas with higher levels of IAC tend to demonstrate processes that are relatively well contained by the boundaries used for the publication of the data
- Those areas with lower IACs demonstrated less consistency between the processes and boundaries used in data publication.
- There was a link between those areas with processes and matching boundaries that demonstrated as the processes and boundaries became less well matched, the magnitude of the scale effect was likely to increase. This was likely to occur as aggregation levels increased.
- Urban areas tended to have stronger processes identifiable than more rural areas.

The previous chapters have set out to determine specific elements of the MAUP, from existence to the implications it has for analysis, and explore factors that may be potentially linked to it. This final chapter considered a more conceptual topic by considering the question whether or not it was possible to assess the impact of spatial autocorrelation on the magnitude of the MAUP. Previous work (see for instance Goodchild 1986, Arbia 1989, and Openshaw 1986) has linked spatial autocorrelation to the MAUP. However, this work has not focused on the more local relationships that have been explored here. What this chapter demonstrated was that spatial autocorrelation varies across the areal units that are under analysis. Moreover, the consequences of this are that there are ‘natural’ combinations of units that could be exploited to form groups. What has not been explored in this chapter is the potential of this method to provide an algorithm that could be used to create aggregations of basic spatial units for analysis that reflect the spatial autocorrelation patterns. However, the demonstration that these patterns exist is important as it reinforces the notion of the local effects discussed by Flowerdew and Green (1996) in a visual context. At this point, it is possible to contend that the mis-match between the influences of spatial autocorrelation and the physical zone boundaries that are used in higher level analysis are partly responsible for the scale and zonation effects. It is incorrect to state that if the boundaries coincided there would not be scale or zonation effects. However, the data that were under analysis would be aggregated in a manner that better reflected the underlying trends.

8.6 Discussion

This thesis has presented a number of analyses to determine the magnitude, extent and causes of the scale effect. Although the focus of the work was on the scale effect, the zonation effect has also been demonstrated, and the significance of this component has been noted. Instead of considering the MAUP as a pervasive problem, it has been considered as an opportunity to investigate the data and obtain further information about the data under analysis. From the work here it is possible to build a picture of the scale effect in UK census data from 1991, and demonstrate that the nature of the MAUP is dependent on both the place and variables that are under analysis as well as the scale at which the analysis occurs and the definitions of the boundaries used. Moreover, the concept of homogeneity as a key determinant in the scale effect, identified and explored by Steel *et al* (1996a) and Tranmer and Steel (2001) has been reinforced. This is important as it will enable the analyst to, if not control for, at least recognise the consequences of using data in areal units. This can be done, not only through the recognition of the inherent problems as has traditionally been the case, but also through the acknowledgement that the areal units and the way in which they interact does provide further information about the data, as was demonstrated in Chapter 7.

However, this thesis was not designed to provide a full investigation to the MAUP. Due to the extent of the MAUP and specifically the scale effect, the zonation effect was not dealt with in detail. As such, this remains an issue which requires further statistical work to support the zone design work of Openshaw and Alvandies (1999) and Martin (2003a) amongst others. Relationships were identified that, although attempts were made to identify relationships between the incidence of the scale effect and measurable factors that could be related little progress was made toward the goal of predicting the incidence of the scale effect. This is an area of research that clearly needs more focus. It is highly likely that it may not be possible to predict the incidence of the MAUP scale or zonation effect as it is too complex to be fully broken into the components of a model. The final analysis chapter provided a combination of techniques to investigate the coincidence of zone boundaries with the boundaries that the data suggest. However, this technique was used and discussed in a theoretically and visual manner. A necessary extension of the technique would be an implementation for zone design, where it is possible to use the analysis to determine where the boundaries of aggregated zones should be placed. This would enable the zone structure to reflect the data processes, rather than be imposed with little relation to the various variables that may be under consideration. All zone systems are, by their nature, a compromise at best, but facilitating a technique that at least recognises the structures of the data, whilst not curing the MAUP scale or zonation effects may at least provide structures that reflect the processes within the data.

It is worth noting that the work carried out here focuses on British Census Data collected in 1991. At this point, it is over 20 years out of date, and as such provides a poor reflection of the UK in 2005. It was necessary to use this data to explore the methods discussed in the thesis because of the requirement for individual level data provided by the SAR release. As there is not yet a direct equivalent for the 2001

Census it was not possible to integrate the more up to date data. However, there are possibilities to overcome this problem. There is a planned release of individual level data, similar to that of the 1991 SARs (Dale and Teague, 2002). However, it was not available in time for inclusion in this work. As an alternative, the individual level data could be modelled, using the techniques discussed by Voas and Williamson (2000) or Williamson (2002) where by synthetic micro-data can be generated to provide a representative and realistic sample of the population. This would enable a more up to date analysis of the scale and zonation effects to be constructed. However, although the data are almost 15 years old they do, nevertheless, provide a useful base from which to assess the incidence of the scale and zonation effects in a large scale dataset.

Thus, it is possible to summarise the main findings of the thesis. Using the premise that MAUP should not be an acronym for the Modifiable Areal Unit Problem, but the Modifiable Areal Unit *Phenomenon* it was possible to investigate the scale and, to a limited extent, zonation effect not as something that required a solution, but as an opportunity to gain information. The first element of this was to shows the nature of the magnitude of the MAUP scale and zonation effects present in a real dataset, using real data structures, and that the impacts of the differences in the data were significant in a statistical sense. It was demonstrated that the MAUP is a result of the differences between the spatial processes in the data, and the zone boundaries within which the data were presented and published. These differences meant that the processes within the data were lost. The MAUP scale effect is also a consequence of changing levels of homogeneity present in data, not only across space at different locations but also at different levels of aggregation. It is clear that as aggregation gets higher then the level of homogeneity is, *ceteris paribus*, going to fall. This change is partly responsible for the scale effect. There is clearly far more analysis to be done with regard to both the scale effect and the zonation effect. However, a definitive demonstration that the MAUP is present in a large-scale dataset is crucial, as is the redefinition of the terms that enable research to take a new focus in order that it is possible that areal unit data are better understood.

Reference List

Alvanides S, Openshaw S and Rees P (2002) Designing your own geographies, in Rees P, Martin D and Williamson P (eds) *The census data system* (Chichester, Wiley) 47-65

Amrhein, C. (1995). Searching for the elusive aggregation effect: evidence from statistical simulations. *Environment and Planning A* **27**: 105-119.

Amrhein, C. and Flowerdew, R. (1989). The effect of data aggregation on a Poisson regression model of Canadian migration. *Accuracy of spatial databases*. M. F. Goodchild and S. Gopal, Taylor and Francis.

Anselin, L. (1995). Local Indicators of Spatial Association - LISA. *Geographical Analysis* **27**(2): 94 - 114.

Arbia, G., (1989), *Spatial Data Configuration in Statistical Analysis of Regional Economic and Related Problems*, Kluwer.

Blalock, H. M. (1964). *Causal Inferences in Nonexperimental Research*, University of North Carolina Press.

Boyle, P and Alvanides, S (2004). Assessing Deprivation in English Inner City Areas: Making the Case for EC Funding for Leeds City. In Clarke, G. and Stillwell, J. *Applied GIS and Spatial Analysis*. John Chichester, Wiley and Sons.

Chrisman, N. (1997) *Exploring Geographic Information Systems*, Chichester, Wiley.

Chrisman, N. (1999). What does 'GIS' mean? *Transactions in GIS* (**3**)2 pp.175-186.

Clark, W. A. V (1991) Geography in Court: expertise in adversarial settings. *Transactions of the Institute of British Geographers.* **16**(1) pp.5-20.

Clark W. A. V. and Avery K. L, (1976). The Effects of Data Aggregation in Statistical Analysis. *Geographical Analysis.* **8** 428 – 438.

Cliff, A. and Ord J. K. (1973). *Spatial Autocorrelation*. London, Pion.

Cliff, A. and Ord J. K. (1981). Spatial and temporal analysis: autocorrelation in space and time. *Quantitative Geography*. R. J. Bennet and N. Wrigley, Routledge & Kegan Paul.

Cockings, S. and Martin, D. (2005) Zone design for environment and health studies using pre-aggregated data Social Science and Medicine. **60**, pp.2729-2742

Courgeau, D., and Baccaini, B. (1998). Multilevel analysis in the social sciences. *Population*, **10**: 39-71.

CrimeStat (2003) Manual http://www.icpsr.umich.edu/NACJD/crimestat. html Accessed 14/03/03

Dale, A and Teague, A. (2002) Microdata from the census: Samples of Anonymised Records. *The Census Data System.* Rees, P., Martin, D. and Williamson, P. (Eds) Chichester, Wiley: 203-212.

Denham, C. (1993). Census Geography. *The 1991 Census User's Guide.* A. Dale and C. Marsh. London, HMSO.

Dueker, K. J., and Kjerne, D. (1989). *Multipurpose Cadastre: Terms and Definitions*. Falls Church, VA: ASPRS and ACSM.

Fisher, R. A. (1921). On the probable error of a coefficient of correlation deduced from a small sample. Metron, **1**, 3-32.

Flowerdew, R. (1998) Reacting to Ground Truth. *Environment and Planning A*. 30 pp.289-301.

Flowerdew, R and Green, M. (1994) New Evidence on the modifiable areal unit problem. *GIS and Spatial Modelling Workshop, Bristol*.

Flowerdew, R., Geddes, A. and Green, M. (2001). Behaviour of Regression Models under Random Aggregation. *Modelling Scale in Geographical Information Science*. N. J. Tate and M. Atkinson, Chichester, Wiley.

Fotheringham, A. S. and Wong, D. W. S. (1991). The modifiable areal unit problem in multivariate statistical analysis. *Environment and Planning A* **23**: 1025-1044.

Gehlke, C. E. and Biehl, K. (1934). Certain Effects of Grouping Upon the Size of the Correlation in Census Tract Material. *Journal of the American Statistical Association* 29 (Special Supplement): 169-170.

Getis, A and Ord, J. K (1992) The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis* 24(3): 189-206

Green, M. and R. Flowerdew (1996). New evidence on the modifiable areal unit problem. Spatial Analysis: In P. Longley and Batty. M, *Modeling in a GIS Environment*. GeoInformation: 41-54.

Goldstein, H. (1987). *Multilevel Models in Education and Social Research*, Oxford University Press.

Goldstein, H. (2003a). Multilevel Statistical Models. Kendall's Library of Statistics 3. 3rd Edition, Arnold.

Goldstein, H. (2003b). Multilevel Modelling of Educational Data. *Methodology and Epistemology of Multilevel Analysis*. D. Courgeau, Kluwer Academic Publishers.

Goodchild, M. F. (1986). *Spatial Autocorrelation*. CATMOG 47,Geo Books, Norwich.

Goodchild, M. F. (1992) Geographic Information Science. *International Journal of Geographic Information Systems*. 6(1):31-45

Goodchild, M. F. and Longley, P. A. (1999) The future of GIS and Spatial Analysis. Longley, P. A., Goodchild, M. F., Maguire, D., and Rhind, D. W. *Geographical Information Systems: Principles and Applications*. Wiley, London: 567-580

Gould, M. I., Jones, K., and Moon, G. (1997). Guest editorial: The scope of multilevel models. *Environment and Planning, A,* 29: 581-584.

Green, M. and Flowerdew R. (1996). New evidence on the modifiable areal unit problem. *Spatial Analysis: Modelling in a GIS Environment*. P. Longley and B. M, GeoInformation**:** pp.41-54.

Hagget, P. (1981) The edges of space. *European Progress in Spatial Analysis.* Bennet, R. J. (Ed) London Pion; 51-70.

Harris, J., Hayes, J., and Cole, K. (2002) Disseminating area statistics over the Web. *The Census Data System*. Rees, P., Martin, D. and Williamson, P. (eds) Chichester, Wiley. pp113-122.

Holt, D., Steel, D. G., and Tranmer, M. (1996a). Area Homogeneity and the Modifiable Areal Unit Problem. *Geographical Systems*. 3 181-200.

Holt, D. Steel, D G. Tranmer, M. Wrigley, N. (1996b). "Aggregation and Ecological Effects in Geographically Based Data." *Geographical Analysis* **28**(3): 244-261.

Jones, K. (1991). *Multi-level Models for Geographical Research*, Environmental Publications.

Kirby, A. M. and Taylor, P. J. (1976). A geographical analysis of voting patterns in the EEC Referendum. *Regional Studies* **10**: 183 - 191.

Lake, R. W., (1993) Planning and applied geography: positivism, ethics, and geographic information systems. *Progress in Human Geography* **17**: 404-413.

Law, C. M and Warnes, T. (1976) Changing geography of elderly in England and Wales. *Transactions of the institute of British Geographers.* **1**(4): 453 – 471.

Levine, N. (1996) Spatial statistics and GIS: Software tools to quantify spatial patterns. *Journal of the American Planning Association*. 1996, **62**(3): 381-392.

Matui, I. (1932) Statistical Study of the distribution of scattered villages in two regions of the Tonami Plain, Toyama prefecture. *Japanese Journal of Geology and Geography.* 2 pp.251- 266.

Marble, D. (2000). Some thoughts on the integration of spatial analysis and Geographic Information Systems. *Journal of Geographic Systems.* **2**(1) pp.31-35

Mark, D. M., (2004), Geographic Information Science: defining the field. In Foundations of Geographic Information Science. Eds Duckham, M., Goodchild, M. F., and Worboys, M. F. Taylor and Francis pp.3-18

Marsh, C. (1993). The Sample of Anonymised Records. The 1991 Census User's Guide. A. Dale and C. Marsh. London, HMSO: 295 – 311

Martin, D (1995), AZM Online Help File. www.soton.ac.uk

Martin, D. (2000) Automated zone design in GIS In: Atkinson, P. and Martin, D. (eds.) *GIS and Geocomputation Innovations in GIS 7* London: Taylor and Francis. 103-113

Martin, D., Nolan A. and Tranmer, M. (2001) The application of zone design methodology to the 2001 UK Census. *Environment and Planning A.* **33**, 1949-1962

Martin, D. (2001) "2001 Output areas: specification, demonstration and maintenance". Final report presented at ESRC/JISC Census Workshop presented at the School of Geography, University of Leeds, 8 February 2001 (Powerpoint presentation)

Martin, D (2003a). Developing the automated zoning procedure to reconcile incompatible zoning systems. *International Journal of Geographic Information Science.* 17(2): 181-196.

Martin, D. (2003b) "Output Areas for 2001" *The Census Data System.* (EDs) Rees, P. Martin, D. and Williamson, P: 37-46.

Morrill, R. L. (1973). Ideal and reality in reapportionment. *Annals of the Association of American Geographers.* **63**(4): 463-477.

NCGIA (1989) The Research Plan for the National Centre for Geographical and Information Analysis. *International Journal of Geographic Information Systems*. **3**(2): 117-136.

Openshaw, S. (1976). A geographical solution to scale and aggregation problems in region-building, partitioning and spatial modelling. *Transactions of the Institute of British Geographers* **2**: 459-472.

Openshaw, S. (1977a). A geographical solution to the scale and aggregation problem in region-building, partitioning and spatial modeling. *Transactions of the institute of British Geographers*, New Series, 2: 459-472.

Openshaw, S. (1977b). "Optimal zoning systems for spatial interaction models." *Environment and Planning A* **9**: 169-184.

Openshaw, S. (1977c). "Algorithm 3: A procedure to generate pseudo-random aggregations of N zones into M zones, where M is less than N." Environment and Planning A **9**: 1423-1428.

Openshaw, S. (1978). "An empirical study of some zone-design criteria." *Environment and Planning A* **10**: 781-794.

Openshaw, S. (1984), *The Modifiable Areal Unit Problem*. CATMOG 38. GeoBooks, Norwich.

Openshaw, S (1991). A view on the GIS Crisis in Geography, or, using GIS to put Humpty-Dumpty back together again. *Environment and Planning A*, **23:**.621-628

Openshaw, S (1992). Further thoughts on Geography and GIS: a reply. *Environment and Planning A*, **24:** 463-466

Openshaw, S. (1996) ‘Developing GIS-relevant zone-based spatial analysis methods’, in Longley, P. and Batty, M. (eds) Spatial Analysis: Modelling in a GIS Environment (GeoInformation International, Cambridge): 55-73.

Openshaw, S. and P. J. Taylor (1979). A million or so correlation coefficients, three experiments on the modifiable areal unit problem. In N. Wrigley, *Statistical Applications in the Spatial Sciences*. London, Pion**:** 127-144.

Openshaw, S. and P. J. Taylor (1981). The modifiable areal unit problem. *Quantitative Geography*. R. J. Bennet and N. Wrigley, Routledge & Kegan Paul.

Openshaw, S. and Rao, L. (1995) Algorithms for reengineering 1991 Census geography. *Environment and Planning A*, 27: 425-46

Openshaw, S. and S. Alvanides (1996). Designing Zoning Systems for representation of socio-economic data. *Spatial analytical perspectives on GIS: GISDATA 5*. M. M. Fischer, H. J. Scholten and D. J. Unwin. London, Taylor & Francis.

Openshaw, S. and Alvanides, S. (1999). Applying geocomputation to the analysis of spatial distributions. *Geographical Information Systems: principles, techniques, management and applications*. P. A. Longley, M. F. Goodchild, D. J. Maguire and D. W. Rhind. New York, John Chichester, Wiley**:** 267-282.

Pickles, J. E. (1995). Representations in a n Electronic Age: Geography, GIS and Democracy. In *Ground Truth - the social implications of Geographic Information Systems*, Pickles, J. E. (ed) The Guilford Press. pp.1-30

Raper, J. (2000) *Multidimensional Geographic Information Science.* London, Taylor and Francis.

Rasbash, J., Browne, W., Goldstein., H., Yang, M., et al. (2000). *A user's guide to MLwiN* (Second Edition). London, Institute of Education.

Robinson, A. H., (1956) "The Necessities of Weight Values in Correlation Analysis of Areal Data. *Annals of the Association of American Geographers*, **46**: 233 – 236)

Spiekermann, K., and Wegener M. (2000) Freedom from the Tyranny of Zones: Towards New GIS-based Spatial Models. In Fotheringham, A. S and Wegener, M. *Spatial Models and GIS: New Potentials and New Models*, Taylor and Francis: 45-62.

Steel, D, G. and Holt, D. (1994), *Analysing and adjusting for aggregation effects: the ecological fallacy*. University of Southampton, Centre for survey data analyses. Technical Report No.94-4.

Steel, D. G., and Holt, D (1996a). Analysing and Adjusting Aggregation Effects: The Ecological Fallacy Revisited. *International Statistical Review.* 64(1) 39-60.

Steel, D. G. and Holt, D. (1996b). "Rules for random aggregation." *Environment and Planning A* **28:** 957 - 978.

Steel, D. G. Holt, D. and Tranmer, M. (1996c). "Making Unit-Level Inferences From Aggregated Data." *Survey Methodology* **22**(1): 3 - 15.

Taylor, P. J. and J. B. Goddard (1974). Geography and statistics: an introduction. *The Statistician* **13**: 149 - 155.

Taylor, P. J. and Overton, M (1991). Further Thoughts on Geography and GIS. *Environment and Planning A.* 23: 1087-1094.

Taylor, P. J., and Johnston, R. J., (1995),GIS and Geography. In Pickles, J (ed) *Ground Truth – the social implications of Geographic Information Systems*. The Guilford Press: 51-67.

Thomas, E. N., and Anderson D. L., (1965), Additional comments on weighting values in correlation analysis of areal data. *Annals of the Association of American Geographers* **55:** 492 – 505

Tobler, W.R., 1970 A computer movie simulating urban growth in the Detroit region: *Economic Geography*, 46: 234-240.

Tooze, M. J. (1976). Regional elasticity's of substitution of the United Kingdom in 1968. *Urban Studies* **13**: 35 - 44.

Tranmer, M. (1999). Using Census Data to Investigate the Multilevel Structure of Local Populations. Department of Social Statistics. Southampton, University of Southamption**:** 300.

Tranmer, M. and D. G. Steel (2001). Using Local Census Data to Investigate Scale Effects. *Modelling Scale in Geographical Information Science*. N. J. Tate and P. M. Atkinson, John Chichester, Wiley, Chichester**:** 105-122.

Tranmer, M, Steel, D. G. and Fieldhouse, E (2003). Exploring small area population structure with Census data. *Methodology and Epistemology of Multilevel Analysis. Method Series 2.* D Courgeau (Ed). Kluwer Academic Publishers: 121-156.

Upton, G. and Fingleton, B. (1985) *Spatial Data Analysis by Example: Volume I Point Pattern and Quantitative Data*, Chichester, Wiley.

Voas D. and Williamson P. (2000) An evaluation of the combinatorial optimisation approach to the creation of synthetic microdata, *International Journal of Population Geography*, 6, 349-366.

Williamson P. (2002) 'Synthetic microdata', Rees, P. Martin, D. and Williamson, P. (Eds) *The Census Data System*, Wiley, Chichester, 231-241.

Wrigley, N. (1995). Revisiting the Modifiable Areal Unit Problem and the Ecological Fallacy. *Diffusing Geography*. Cliff, A. D., Gould, P. R., Hoare, A. G. and Thrift, N. J. (Eds). Oxford, Blackwell; 49-71.

Yule, G. U. and Kendall, M. G. (1950). An Introduction to the Theory of Statistics, Charles Griffin and Company Limited.