UNIVERSITY OF SOUTHAMPTON

FACULTY OF LAW, ARTS & SOCIAL SCIENCES

School of Social Sciences

Three Essays on Sexual Behaviour and Sexually Transmitted Disease in the UK

by

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ABSTRACT

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This thesis aims to explore the measurement of and the correlation between risky sexual behaviour and chlamydia and gonorrhoea infection in the UK in three chapters. The first of these explores methods of calculating rates of Chlamydia and gonorrhoea infection at UK genitourinary medicine (GUM) clinics. Data from KC60 returns from clinics in the Northwest, Southwest and East Midlands of England are used to provide a numerator for the rates and three methods are tested to derive the denominator: Thiessen polygons, 15 mile boundaries, and 30 minute drive times. The study finds that the rates calculated are relatively insensitive to the method chosen and thus the simplest approach, the Thiessen polygons, is recommended. The analysis also highlights substantial regional differences in GUM service accessibility.

The second chapter uses latent class analysis to derive a measure of risky sexual behaviour with respect to chlamydia and gonorrhoea infection. Data from the National Survey of Sexual Attitudes and Lifestyles II, a nationally representative survey of sexual behaviour in Britain, has been analysed in order to identify patterns of behaviours associated with increased disease risk A 3-class solution is obtained, with individuals classified on the basis of the number of partners they have had in the last 12 months.

The third chapter examines the relationship between the rates of chlamydia and gonorrhoea infection and the measure of risky sexual behaviour. Small area estimates of risky behaviour are obtained for all wards in England using synthetic regression methods. These are then aggregated in line with the Thiessen polygons in order to explore the correlation with the rates of chlamydia and gonorrhoea infection. There is a positive correlation for both infections, but far stronger for gonorrhoea than chlamydia (r=0.70 and r=0.41 respectively), suggesting that although risky behaviour may explain some of the observed variation, further research is need to explore other possible explanations.

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DECLARATION OF AUTHORSHIP

I, Beth Stuart, declare that the thesis entitled **Three Essays on Sexual Behaviour and Sexually Transmitted Disease in the UK** and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- none of this work has been published before submission.

Signed: ……..
Date:…….

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1. INTRODUCTION

1.1 BACKGROUND AND CHAPTER OUTLINE

Chlamydia is the most common sexually transmitted disease (STD) in the western world (World Health Organisation, 2007) and the most commonly diagnosed in the United Kingdom (UK), where the number of diagnoses has been rising steadily since the mid-1990s (Health Protection Agency, 2006). Chlamydia is caused by the bacterium *chlamydia trachomatis* and is highly contagious. However, a large proportion of infected individuals will have no symptoms. Although it is difficult to obtain exact figures, it is estimated that chlamydia infection is asymptomatic in 75% of women and 50% of men (Centers for Disease Control, 2006; National Chlamydia Screening Programme, 2009).

Although chlamydia infection can be successfully treated with a course of antibiotics, its asymptomatic nature means that many individuals may not realise that they require testing or treatment until they have already begun to develop some of the more serious long-term consequences. For males these include inflammation of the epididymis or prostate, urethritis and, in rare cases, Reiter's syndrome, an arthritic condition. There is also some evidence of a link between male infertility and chlamydia infection (Cunningham and Beagley, 2008; National Chlamydia Screening Programme, 2009). Females also suffer from inflammation, usually of the cervix or urethra, and in some cases Reiter's syndrome. They also are vulnerable to pelvic inflammatory disease (PID) which is associated with pelvic pain, infertility and an increased risk of ectopic pregnancy (National Chlamydia Screening Programme, 2009). PID develops in between 10% and 40% of women with untreated chlamydia infection (Hillis and Wasserheit, 1996).

Neisseria gonorrhoeae is the second most common bacterial sexually transmitted disease (after chlamydia) in the UK (Health Protection Agency, 2007a). Between 1995 and 2002, the number of diagnoses made increased by 155% (Health Protection Agency, 2007b). Although most cases of gonorrhoea can be treated

with a simple course of antibiotics, the *N. gonorrhoeae* bacteria have shown the ability to develop resistance to the drugs used for first line treatment and the Gonococcal Resistance to Antimicrobials Surveillance Programme (GRASP) now monitors the emergence of resistant strains of the disease (Health Protection Agency, 2007c). In men, gonnorhoea is often symptomatic. Approximately 85% of men will develop symptoms within 14 days. However, between 50% and 80% of women remain asymptomatic (Lynch, 2000). As with chlamydia infection, untreated gonorrhoea infection can lead to PID and its associated complications.

Chlamydia and gonorrhoea infection pose a substantial public health burden. It is estimated that chlamydia infection costs the National Health Service up to £100 million each year both in treating the infection and in addressing the long-term consequences (Department of Health, 2008). The "Choosing Health" White Paper made sexual health one of the key target areas with the aim of stopping the rise in the diagnoses of sexually transmitted disease within two years. It included £17.5 million specifically to tackle chlamydia. Funds were to be made available through Primary Care Trusts (PCTs), which are responsible for commissioning and implementing sexual health services locally (HM Government, 2004). Therefore it is essential to understand whether the prevalence of chlamydia and gonorrhoea varies regionally to ensure that appropriate plans can be put in place to encourage testing and treatment and that funding is distributed efficiently.

However, the availability of estimates of local rates of these STDs is limited. The Health Protection Agency produces some estimates but only at the Strategic Health Authority level. Strategic Health Authorities are intended to oversee the health services in their region on behalf of the Secretary of State for Health. They provide a link between the Department of Health and the local services provided at the Primary Care Trust level. In 2002, there were 28 Strategic Health Authorities in England. In 2006, this number was reduced to ten (National Health Service, 2008). In contrast, in 2002 there were152 Primary Care Trusts. Thus the aggregation of the data to Strategic Health Authority level means the loss of

information about the situation at the local level. Therefore, Chapter 2 explores methods to produce reliable estimates for smaller geographical areas.

Producing rates of chlamydia and gonorrhoea requires data on the number of cases for the numerator and the population exposed to risk for the denominator. Data on the number of cases were taken from the KC60 returns submitted to the Health Protection Agency by clinics in the Northwest and Southwest of England. Using the capabilities of a Geographical Information System (GIS), the study tests three methods of deriving the population exposed to risk: drawing Thiessen polygons, drawing a boundary around each clinic and calculating drive-times to the clinics.

The study finds that the method chosen had little impact on the rates for either chlamydia or gonorrhoea and therefore the simplest method, and the one that made the fewest assumptions, is recommended – the Thiessen polygon method. However, the study does identify substantial regional differences in rates that require further explanation.

A reasonable hypothesis may be that these differences arise due to regional differences in the prevalence of risky sexual behaviour. In this thesis "risky sexual behaviour" refers to those behaviours which increase the odds of an individual contracting either chlamydia or gonorrhoea. Chlamydia and gonorrhoea cannot survive outside the human body for more than a few minutes and thus transmission is almost exclusively through sexual contact. As a result, recent sexual behaviour is, at the individual level, likely to be a good predictor of disease risk. Of course not all individuals engaging in risky behaviours will contract an infection. However, these individuals represent the group from which those testing positive are most likely to be drawn.

In the "Choosing Health" White Paper, the Government indicated that they believed there to be a link between the rise in sexually transmitted diseases and the increase in "risk-taking sexual behaviour…across the population." (HM

Government, 2004, p.4) Further, in a study following the pilot of the National Chlamydia Screening Programme in Portsmouth, researchers found that "a high risk subgroup of the general population, despite being relatively small in size but with a high number of sexual partnerships per case, is critical in the infection dynamics of chlamydia." (Evenden et al., 2006, p.11).

A number of risky behaviours have been identified by previous observational studies but observational studies can only take us so far. Whilst they allow us to quantify the risks associated with particular behaviours, they do not tell us how those behaviours are interrelated. In Chapter 3, we apply the technique of latent class analysis to data from the National Survey of Sexual Attitudes and Lifestyles II (NATSAL II) in order to identify whether there are particular groups of "risky" individuals and, if so, what the characteristics of these groups are. Latent class analysis is a technique that helps to identify groups of individuals who share similar interests, values, characteristics or behaviours (Magidson and Vermunt, 2004).

The study finds that the key feature of risky behaviour is whether an individual had had more than one sexual partner in the last year and this simple measure performs well in predicting whether an individual in the NATSAL II sample tests positive for chlamydia. Chapter 3 then goes on to explore the prevalence of risky behaviour by age, sex, marital status and ethnic group.

The study described in Chapter 3 gives a simple way of identifying individuals who are at risk of chlamydia or gonorrhoea infection. However, as Geoffrey Rose observed, "I find it increasingly helpful to distinguish two kinds of aetiological question. The first seeks the causes of cases and the second seeks the causes of incidence." (Rose, 1985, p.33). Although risky behaviour as defined in Chapter 3 is a good predictor at the individual level, it may or may not be able to explain the variations at the regional level observed in Chapter 2. For example, the prevalence of risky behaviour may not vary much between regions, suggesting that some other explanation is more likely to account for the regional variation in

rates. Rose argues that in order to find the determinants of population prevalence and incidence rates, we must study not the characteristics of individuals but the characteristics of populations, though the two may obviously be related.

Therefore Chapter 4 in this thesis explores the extent to which regional differences in rates of infection are due to differences in the prevalence of risky behaviour in the population. In order to do this, regional estimates are made of the prevalence of risky behaviour in each of the small areas for which we have calculated rates of chlamydia and gonorrhoea infections. The calculations use data from NATSAL II and the 2001 UK census to derive small area estimates of risky behaviour in a synthetic regression model. The estimates are first made at ward level and then aggregated to correspond with the clinic catchment areas used in Chapter 2.

The ward level estimates of risky behaviour showed that the prevalence of risky behaviour is higher in urban areas and that this prevalence can be predicted by using the proportion of single individuals as a proxy measure**.** The small area estimates of risky behaviour showed a positive correlation with both chlamydia and gonorrhoea infection. This correlation was stronger for gonorrhoea than for chlamydia ($r=0.70$ and $r=0.41$ respectively) but nonetheless suggests for both diseases that some of the regional variation can be explained by variation in the prevalence of risky behaviour. However, further research is required in order to determine whether there are other equally good, or even better, possible explanations.

Finally, Chapter 5 reviews the findings of all the preceding chapters and considers their implications for UK health policies. A number of areas for further research have suggested themselves as a result of the work undertaken as part of this thesis and these are also set out in the final chapter.

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2. MEASURING RATES OF CHLAMYDIA AND GONORRHOEA INFECTION AT GENITOURINARY MEDICINE CLINICS IN ENGLAND

ABSTRACT

This study aims to calculate the rates of chlamydia and gonorrhoea infection at genitourinary medicine (GUM) clinics in England. Data on the number of cases are available from KC60 returns from GUM clinics in the Northwest, Southwest and East Midlands regions of the country, but the population exposed to risk is required in order to calculate rates of infection. This study tests three different methods of deriving the exposed to risk: Thiessen polygons, 15 mile boundaries, and 30 minute drive times.

It was found that the method of deriving the population exposed to risk did not significantly affect the estimated chlamydia or the gonorrhoea rates. Thus the best choice of method was deemed to be the simplest approach, the Thiessen polygons. The 15 mile and 30 minute drive time models did, however, highlight substantial differences in the accessibility of GUM services between the regions.

2.1 INTRODUCTION

Chlamydia trachomatis is the most prevalent sexually transmitted disease (STD) in the Western world (World Health Organisation, 2007) and the most commonly diagnosed sexually transmitted disease (STD) at genitourinary medicine (GUM) clinics in the UK (Health Protection Authority, 2006a). In about 75% of infected women and 50% of infected men, it is asymptomatic but the long-term effects of infection can be serious, including chronic pain, ectopic pregnancy and infertility, as well as being the most frequent cause of pelvic inflammatory disease (Centers for Disease Control, 2006). It is estimated that Chlamydia trachomatis costs the National Health Service (NHS) up to £100 million each year both in treating the infection and in addressing the long-term consequences and, according to the Health Protection Authority (HPA), chlamydia diagnoses have been rising steadily since 1995 (Health Protection Authority, 2006b).

Neisseria gonorrhoeae, often called gonorrhoea, is the second most common bacterial sexually transmitted disease (after chlamydia) in the UK (Health Protection Authority, 2007a). Although most cases of gonorrhoea can be treated with a simple course of antibiotics, the *N. gonorrhoeae* bacteria have shown the ability to develop resistance to the drugs used for first line treatment and the Gonococcal Resistance to Antimicrobials Surveillance Programme (GRASP) initiative now monitors the emergence of resistant strains of the disease (Health Protection Authority, 2007b).

As a result of the rising burden of sexually transmitted diseases in the UK, on 27 February 2007, the National Institute for Health and Clinical Excellence (NICE) issued guidance for UK health professionals aimed at reducing sexually transmitted disease incidence. They cited the 300% rise in chlamydia and 200% rise in gonorrhoea over the last 12 years before advising that health professionals identify individuals whose sexual history puts them at increased risk of disease and undertake one-to-one structured discussions aimed at behaviour change (National Institute for Health and Clinical Excellence, 2007).

However, these statistics on the alarming rise in chlamydia and gonorrhoea are based on a count of the number of individuals presenting with these diseases at UK GUM clinics. This count is widely used because the data to calculate it are easily available. GUM clinics submit returns to the HPA which provide data on the number of diagnoses they have made.

Recent technological developments have changed our ability to diagnose and report the presence of disease. New initiatives, such as the National Chlamydia Screening Programme and the "Condom Essential Wear" campaign, are encouraging more people to get tested. The rise in disease diagnoses may reflect these changes. Without knowing the size of the population from which these individuals come, it can be difficult to compare meaningfully between groups or over time.

The ideal measure of chlamydia and gonorrhoea infection would be a rate – the number of infected individuals divided by the total population at risk of infection. However, identifying the population at risk is not straightforward. The current approach taken by the Health Protection Authority in their calculations is to aggregate the returns made by the GUM clinics in each Strategic Health Authority (SHA) and then to divide by the total population in that SHA. However, this measure includes a number of individuals who are not at risk of either infection, such as children. It also includes individuals who would not have attended the clinic because it is too far away from their home. Moreover, much of the detail of the differences between regions has been lost because the data for the clinics have been aggregated.

This study will explore alternative methods of deriving the population exposed to risk of infection and will use this population to calculate chlamydia and gonorrhoea case rates for each clinic. There are a number of techniques using a Geographic Information System (GIS) which can help us to allocate populations to clinics and improve upon the rates that are currently provided by the HPA.

With accurately calculated rates, we can begin to compare across locations in the UK. In an era of limited resources, it is important to know which areas to target in order to ensure that measures to reduce disease incidence are implemented where they are most needed. This may mean sending extra resources to places with high rates or alternatively, it may mean asking questions about why some areas have much lower rates than their neighbours. Do these areas have genuinely lower rates and if so, why? Or do they represent areas where GUM services are being under-utilised and where additional efforts are needed to encourage individuals to attend for testing? It is only once we have reliable measures of sexually transmitted infection that we can begin to think about tackling these questions.

The objectives of this study are:

- To derive the population for whom each clinic is the nearest GUM service using Thiessen polygons
- To derive the population for whom each clinic is "accessible" – i.e. within 15 miles
- To derive the population who live within 30 minutes driving time of each clinic
- To compare these populations to explore whether GUM clinics suffer from accessibility problems which warrant the additional complexity of the drive time model
- To calculate case rates of chlamydia and gonorrhoea for each clinic in the Northwest, Southwest and East Midlands of England using as a denominator each of the populations described above
- To explore whether there are any spatial clusters of chlamydia or gonorrhoea rates

2.2 DATA

The data have been taken from KC60 returns made by GUM clinics in the Northwest, Southwest and East Midlands Strategic Health Authority Regions of England. The KC60 return was conceived primarily as a way to measure the workload of GUM clinics but actually provides the main source of data on sexually transmitted diseases (Catchpole et al., 1999). It records all new episodes of a sexually transmitted disease and all GUM clinics have a statutory responsibility to provide information via the KC60 form on all clinic attendees each quarter. The limited data reported include:

- condition(s) diagnosed;
- sex;
- number of male cases which were homosexually acquired; and
- age group.

(EuroSurveillance, 1998)

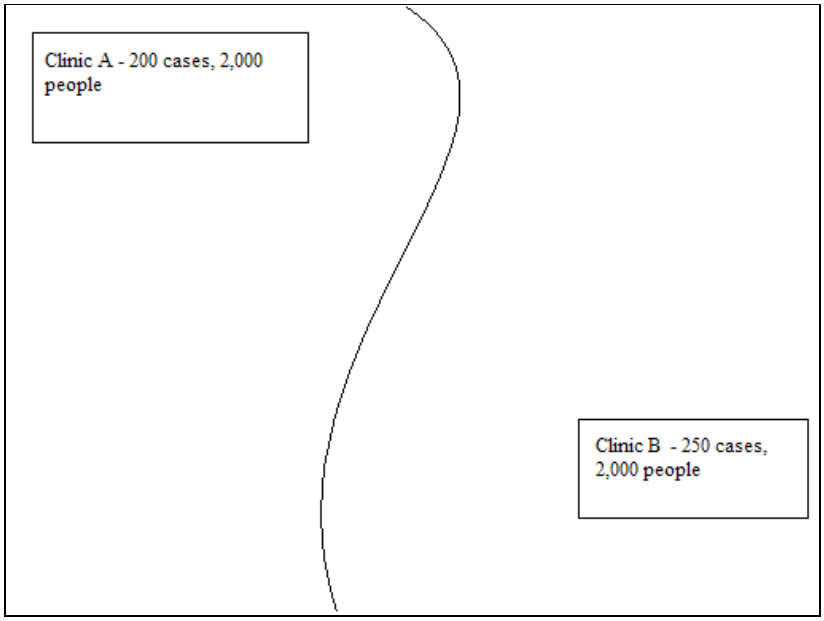
We will use the data reported in 2001, as they were provided for the majority of clinics in the Northwest, East Midlands and Southwest regions and, as this chapter's main aim is to look at the feasibility of different approaches to deriving rates, the actual timeframe of the data is not particularly relevant.

The study will concentrate on the Northwest, Southwest and East Midlands regions because the decision to publish the information disaggregated by clinic is made at the local HPA level and we were able to obtain data only for these areas.

The clinic data were cross-checked against the list of clinics in the HPA audit of GUM clinic waiting times (Health Protection Authority, 2007c) in order to ensure that no clinics were excluded from the study because of failure to provide permission for their KC60 data to be reported at the clinic level. If any clinics are missed, the effect would be to underestimate the rates in the surrounding clinics. To see this, imagine a region with 4,000 people and two clinics, A and B. These

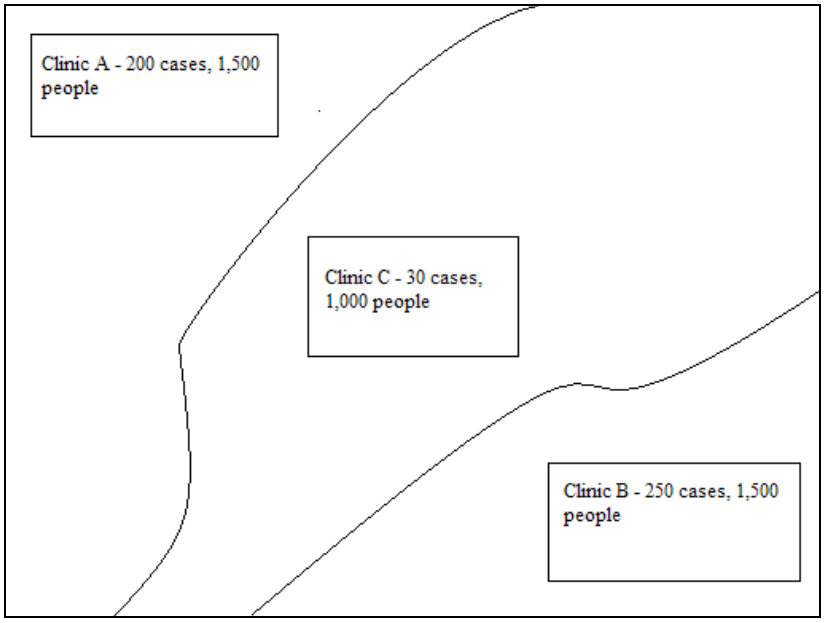
clinics have reported 200 and 250 cases respectively on their KC60 returns and there are 2,000 people in the catchment area of each clinic (see Figure 2.1)

Figure 2.1 Example catchment area with two clinics



Now imagine that there is actually a third clinic, C, which was excluded from the original analysis. Some of the people from both clinic A and clinic B actually should be in the catchment area of clinic C, as in Figure 2.2. The result is that the catchment areas for clinics A and B get smaller, meaning that they have a smaller population than they did before we included clinic C but the same number of cases reported. This would mean a smaller denominator when calculating the rate and hence a higher rate. We have done our best to ensure that we have included all GUM clinics in the Northwest, Southwest and East Midlands in order to avoid this sort of underestimate.

Figure 2.2. Example catchment area for three clinics.



We have been able to identify four clinics as part of this cross-checking process, Westmorland General Hospital, Furness General Hospital, John Coupland Hospital and Louth County Hospital which all chose not to allow their numbers of diagnoses to be released in 2001. We have still computed the exposed to risk for these clinics and thus ensured that the denominators for the clinics around them are not distorted in the way illustrated in the example above. However, without knowing how many people have been diagnosed with either chlamydia or gonorrhoea, it has not been possible to compute rates for these clinics.

The GUM clinic is not the only setting in which individuals can seek diagnoses and treatment for sexually transmitted diseases. Family planning clinics and General Practitioners' (GP) surgeries also offer these services. For approximately 40% of individuals who eventually attend a GUM clinic, their GP will be their first point of contact (Cassel et al., 2003).

Because the KC60 data are clinic-specific, the outcome measure will be the rate of disease diagnosed at clinics rather than the rate of the disease in the general population. To address this problem, we would have preferred to use a data

source which included diagnoses in all healthcare settings but no such data source currently exists. Some other sources that we considered were:

- The National Chlamydia Screening Programme (NCSP). The NCSP was launched in England in 2003 and, by March 2008, it covered all 152 primary care trusts, with a total of 11,377 registered testing sites (National Chlamydia Screening Programme, 2009). It offers screening to 16-25 year olds in settings outside of the GUM clinics, such as local pharmacies. However, whilst this age group represent the largest number of cases diagnosed each year (Health Protection Authority, 2006c), people aged over 25 years are still regularly diagnosed with chlamydia and should be included in both the count of individuals infected and the total population at risk of infection.

  Although the NSCP is likely to represent a significant source of data on chlamydia diagnoses in the future, at the time that this work was carried out it did not cover the whole country and data were not available even for those areas which were covered. The data collected are detailed, including an individual's postcode of residence, but it is unclear whether these data will be made available to researchers given concerns regarding confidentiality. Data on tests made from April-December 2008 are now being made publicly available at PCT level but not for smaller geographical areas.

- The General Practice Research Database (GPRD). The GPRD includes anonymised records for 3.4 million active patients (GPRD.com, 2007). It allows researchers to analyse sexually transmitted disease rates as diagnosed within general practice. But policies vary by locality and many GPs' surgeries will recommend that an individual goes to a GUM clinic for testing, confirmation of a result and/or treatment (Lazaro, 2006). As a result, the actual diagnosis may be made and recorded outside of the general practice setting. It is estimated that only 25% of women and 5.1%

of men receive treatment from their GP (Hughes et al., 2006). Moreover the data provided by the GPRD provide limited information on the location of practices. Since our calculations will involve a geographical element, it is not possible to use these data in our study.

- Microbiology laboratory reports. All laboratories in England and Wales are invited to report on sexually transmitted diseases which they diagnose and the results are published quarterly in Communicable Disease Report (CDR) Weekly, now published as the Health Protection Report. These reports provide data on all tests carried out. This means that they cover all healthcare settings; however, there can be double counting, such as when an individual is initially tested at a GP's surgery but then referred to GUM clinic and retested to confirm the result. Moreover, since reporting is voluntary, a number of laboratories do not report.

It is believed that GUM clinic data capture the largest number of cases, since most cases are thought to present at a GUM clinic at some stage (Cassel et al., 2003), and KC60 is certainly the most widely used in the ongoing discussion about trends in STD incidence in the UK. For the purposes of this study we have therefore chosen to use these data in spite of their limitations.

2.3 METHODS

2.3.1 DERIVING THE POPULATION EXPOSED TO RISK – THE THEORY

In calculating rates, it is vital that we do not violate the principle of correspondence – i.e. we must ensure that events included in the numerator correspond with the exposed to risk in the denominator (Hinde, 1998). Our numerator includes all chlamydia or gonorrhoea cases diagnosed at a particular GUM clinic. Therefore our denominator should only include those people who could be diagnosed and, if they were to be diagnosed, would be included in this numerator for that clinic. This is not simply the total population in a given area. Some people, for example very young children, have a virtually non-existent risk of contracting these diseases. Both chlamydia and gonorrhoea are almost exclusively sexually transmitted so the population at risk should exclude those who are not sexually active. Moreover, the denominator for each clinic should only include those individuals who, were they to suspect an STD, would attend that clinic.

Taking the first consideration, we find that some simplifying assumptions are required. There is no dataset available which provides a count of the total number of sexually active individuals in each region. The National Survey of Sexual Attitudes and Lifestyles II (NATSAL II), a nationally representative survey of sexual behaviour in Britain, was interested primarily in the behavioural correlates of HIV transmission (Erens et al., 2001). It defined the sexually active population by an age interval. Those under 16 and over 44 years old were considered to be at minimal risk of STD transmission and were therefore excluded from the study. The National Chlamydia Screening Programme also sets the lower age band at 16 years. In both cases this is likely to be because 16 years is the age of consent, below which sexual activity is not legally permitted.

It is well known that sexual activity does begin earlier. A study by Stone and Ingham found that amongst young people in Southampton who had only ever attended one site for sexual health services, the median age at they had first

accessed sexual health services was 15 years (Stone and Ingham, 1999). Before the age of 15, about 18% of boys and 15% of girls report having had sexual intercourse (Tripp and Viner, 2005). But those under 16 years represented 1.6% of all chlamydia cases in 2002 and those over 45 years accounted for 1.7%. For gonorrhoea the percentages were 1.8% and 5.6% respectively (Health Protection Authority, 2006a). Choosing the age range 16-44 years means that we will account for the majority of the population at risk of chlamydia and gonorrhoea, and by maintaining consistency with the NATSAL data we will be able in Chapter 4 to compare the rates derived here with data on the prevalence of certain sexual behaviours estimated from NATSAL II.

The numerator data are taken from GUM clinics. To derive an appropriate denominator we still need to determine which individuals would attend which clinics. One approach would be to assume that people attend the clinic in their Primary Care Trust (PCT) or to use some other similarly convenient administrative boundary. However, a number of PCTs contain more than one clinic. In these areas, data would have to be aggregated. We would lose some of the detail that might tell us about differences between clinics that share an administrative area. For example, as shown in Figure 2.3, Newquay and District Hospital and Royal Cornwall Hospital at Treliske were both part of the Central Cornwall PCT. However, it turned out that the lowest rates of chlamydia in the Southwest region were at the Newquay clinic whilst some of the highest were at the Royal Cornwall clinic. Why two clinics located so close to one another should have such different rates is an interesting question which we would have missed had we simply aggregated their data because they were in the same PCT.

Similarly, in PCTs without a GUM clinic, we would have to assume that people do not access any GUM services. However, this assumption is likely to be false. A PCT is an arbitrary administrative border and there is no reason why people would not cross it to access nearby services. For example, Teignbridge PCT has no GUM clinic (Figure 2.3). However, Torbay Hospital lies very close to its border. It

might be reasonable to suppose that if people from Teignbridge suspect they have an STD, they travel to Torbay.

Figure 2.3 Southwest clinics and Primary Care Trusts

A more realistic assumption might be that people attend the clinic located nearest to them. When a sexually transmitted disease is suspected an individual can attend a GUM clinic directly, or may be referred by a GP. Attending a clinic has a cost in terms of time and expense so it might be reasonable to assume that each patient chooses to attend their nearest clinic. But “nearest” can mean a lot of different things. It can refer to distance or to the time taken to travel there. This

chapter will explore a variety of different ways of measuring a patient's nearest clinic.

The simplest way or measuring, or identifying, a patient's nearest clinic is called a Thiessen (or Voronoi) polygon. A Thiessen polygon demarcates an area around each clinic. Within this area lie all the locations for which the Euclidean distance (i.e the distance "as the crow flies") to this clinic is less than the Euclidean distance to any other clinic (Boots, 1986). Thiessen polygons can be drawn by hand by connecting each clinic to all the surrounding clinics. The lines connecting the clinics are then perpendicularly bisected. The smallest area enclosed by joining the perpendicular bisectors is the Thiessen polygon. If any place is equidistant from two clinics, it will lie on the boundary of the polygon. If it is equidistant from three or more points, it will form one of the vertices of the polygon. In practice, these polygons are more usually constructed using a computer program.

A problem with the Thiessen polygons is that although they assign everyone to their nearest clinic, there will be people who simply live too far away even from their nearest clinic for it to be practical for them to attend. In this case, it is likely that they will seek treatment in an alternative setting, such as a GP surgery or family-planning clinic. So these people should not be included in the denominator for their nearest GUM clinic because they are not at risk of attending any GUM clinic.

There is no established definition of "remoteness" from health services. We have chosen to classify those who live more than 15 miles from a GUM clinic as being remote from this service. This is based on the NHS policy of reimbursing travel costs to those who live more than this distance from the clinic (National Health Service, 2007).

Both the Thiessen polygon and the boundary approaches are distance-based – "nearness" is defined based on the straight-line or "crow-fly" distance between the clinic and the individual's address. Crow-fly distances have a distinct advantage of

being simple to measure. However, they may not correspond very well to the routes that people take in the real world. The nearest clinic might be only two kilometres away but if you have to cross a river and there is no bridge you may have to travel much further to reach the clinic than a crow-fly distance would predict.

It is possible instead to base our model on the amount of time which it takes to travel from a given point to the nearest clinic. Individuals who live in locations where the travel time to the nearest clinic is considered too long should be excluded from the denominator. As with those for whom the journey is too far, it is likely that they would seek treatment in an alternative location.

Much like "remoteness", there is no established duration that is considered "too long" to expect individuals to travel. A number of studies of the accessibility of NHS services have used a drive time of more than 30 minutes (see for example Propper et al., 2000; North Bristol NHS Trust, 2004; Wood and Gatrell, 2002) and this study will follow that convention, though we will also examine the population distribution of drive times in 5 minute intervals.

2.3.2 DERIVING THE POPULATION EXPOSED TO RISK – METHODS

The starting point for all the calculations was to geo-reference each clinic based on its postcode. The clinic location would provide the starting point from which all other calculations of distance would be made. Northing and Easting grid references were obtained for each clinic based on the postcode. This was done using the 2000 All Fields Postcode Directory, made available by UKBORDERS.

Each clinic was then mapped in ArcGIS onto an administrative map of England, showing the country divided into Lower Super Output Areas (LSOAs) from the 2001 Census, which was also provided by UKBORDERS. LSOAs are a geography created for the 2001 Census. They have a minimum population of 1,000 people, a mean population of 1,500 and are generally made up of four to six

census Output Areas, the smallest census geography unit (Office for National Statistics, 2006). We chose to work with LSOAs rather than Output Areas for two reasons. Firstly as there are fewer LSOAs than Output Areas, the computing power required is reduced and secondly, due to disclosure requirements, data are readily available for LSOAs from the Neighbourhood Statistics Service (provided by the Office for National Statistics) but not for Output Areas. Therefore we used the data from the Neighbourhood Statistics Service to obtain the 2001 Census estimates of the population aged 16-44 years for each LSOA.

Both the Thiessen polygons and the 15 mile boundaries around each clinic were drawn using ArcGIS. These figures were "clipped" to the LSOA map. "Clipping" these figures ensures that the polygons and boundaries correctly trace the coastline of the UK and that they maintain the same projected coordinate system as the other data layers. The total population aged 16-44 for each polygon was obtained by selecting within ArcGIS the LSOAs which had their population centres within that polygon. The population figures for the selected LSOAs were then summed to give a total population for each polygon. When the population was to be restricted to the 15 mile boundary, LSOAs were only selected if their population centre fell within that distance.

There are several different approaches to creating a drive time model. The simplest is to use some of the readily available internet trip planning software such as www.multimap.com or Google Maps. They have excellent data on the road network and provide good travel time estimates for single trips. However, these are less useful when the travel time must be computed from a large number of starting points as each one has to be manually inputted.

A vector-based model extends the theory used by this approach to a more general model. The model estimates the time that it will take to travel a particular road segment between nodes, or intersections of roads (Lovett et al., 2002). Figure 2.4 below illustrates how the vector model operates. Imagine that the blue square is the postcode centroid in a particular region, the boundaries of which are

represented by the blue lines. The model then calculates the time taken to travel from the blue point to the road (the first red point), the time between each of the road intersections (the other red points, following the brown line) and the time between the road and the clinic (the green point). Added together, these times give the total travel time.

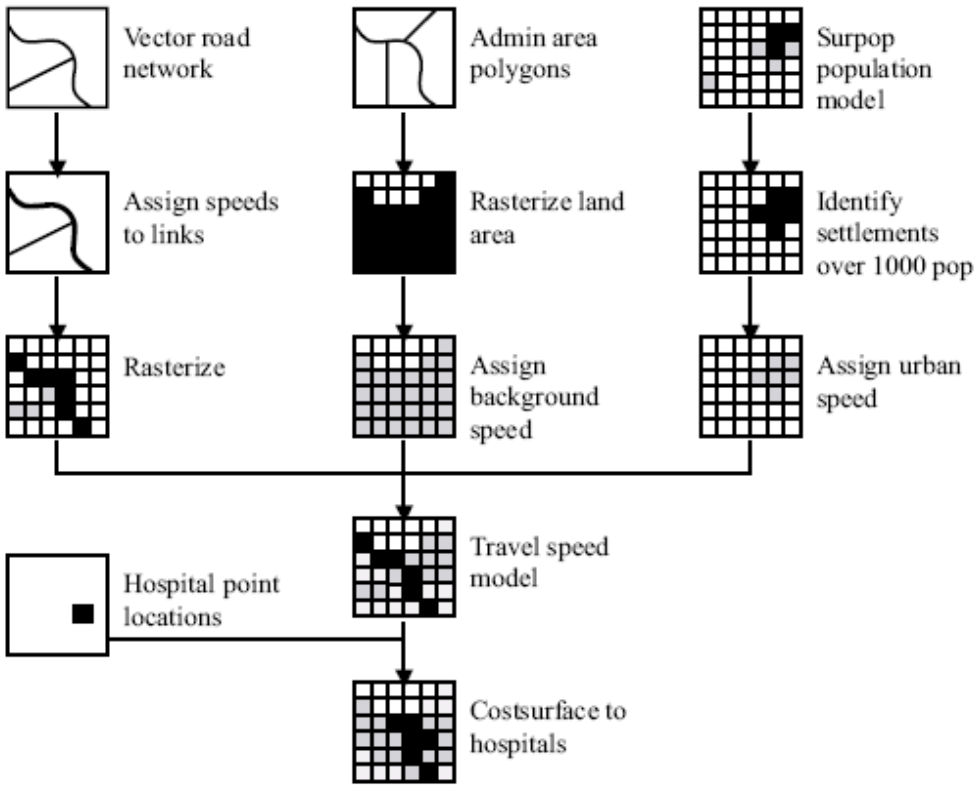
Figure 2.4 Path-finding example in the vector model

However, this is just one possible path. Another route, following the orange lines rather than the brown lines, could involve turning left onto Fulton Street, whilst still another involves a left onto Dey Street. The vector model evaluates all possible paths between all the start points and end points which you specify and finds the shortest travel times. For example, in the Northwest, the model would work out all the possible paths between approximately 4,500 LSOA centroids and the 25 GUM clinics and select the shortest. The results would be returned in a 4,500 x 25 matrix of travel times.

Such an approach is computationally intensive. Moreover, because the calculations are done from centroids, there can be distortions. For example, the blue point was the centroid for this particular area and from this point it might be quickest to travel to clinic A. But for someone living on Wall Street (at the purple point in Figure 2.4, for example), clinic B is probably closer. This will not be reflected in the calculations since all calculations will be done from the centroid. For these reasons, the vector model is usually more suited to calculations where we have a fixed set of start points, such as patient addresses, rather than being interested in travel times over a region more generally.

So we have opted instead for a surface model. The surface model is a raster-based approach which involves converting data to a grid format and then creating a more generalised surface of drive times to each clinic by representing these as a continuous cost-surface (Martin et al., 2002). An illustration of the raster-based approach to calculating travel times to hospitals was given by Martin et al. in their 2002 article and is reproduced in Figure 2.5.

Figure 2.5 Stages of cost surface calculation



This study will follow a very similar approach to that set out above. First, we obtained a representation of the UK road network from the Ordnance Survey Meridian 2 Collection (1:50,000 scale). This includes four classifications of road types: motorway, A-road, B-road and minor road. Each road type was then assigned a background speed. This required us to make some assumptions about how quickly traffic moves along each road type. A car's speed, and hence the time taken to complete a journey, varies by time of day, by region and even by driver.

The speeds we assigned to the roads in our model, shown in Table 2.1 below, were based on the average road speeds reported by the Department of Transport (2004) and upon empirical work to verify travel times to health services done by

Haynes et al. (2006). In areas where there are no roads, it was assumed that individuals could cross the land to the nearest road at a background walking speed.

Speeds on roads in urban LSOAs were assumed to be half of those in rural LSOAs to take into account the time-cost of traffic congestion in urban areas. The designation of an LSOA as urban or rural was based on classifications made by the Rural and Urban Area Classification Project, a joint project sponsored by the Countryside Agency, the Department for the Environment, Food and Rural Affairs, the Office for National Statistics, the Office of the Deputy Prime Minister and the Welsh Assembly Government (Office for National Statistics, 2005). This is the one respect in which this study methodology differs from that set out in Figure 2.5. In their study Martin et al. used the Surpop database to identify urban areas, which were defined as those with a population greater than 1000. Their calculations were undertaken prior to the publication of the LSOA designations used in this study and it has been confirmed with Professor Martin that had the LSOA designations been available, they would have been considered as an alternative.

Table 2.1 Travel speeds on UK roads – assumptions used for drive time calculations

Road type	Rural Speed (miles per hour)	Urban Speed (miles per hour)
Motorway	65	33
A-road	45	23
B-road	30	15
Minor road	20	10
Walking	4	4

It is important to note that our calculation of travel time will actually be a measure of estimated drive times. It will not include other activities which effect the overall travel time, such as the time spent trying to park at the clinic. Nor does it represent the time taken to get to a clinic by individuals who do not have access to a car and who therefore rely on public transport. Therefore these calculations will

only represent an approximation of the true time taken for an individual to get to the clinic.

Both the road network and the land area maps were then rasterised to turn the UK map into a grid of 100 metre squares in ArcGIS. The travel time to cross each square is calculated based on the background speeds assigned to each road type, creating a travel-time raster. The Cost Distance function in the Spatial Analyst toolpack then uses this raster to calculate a value for each square which represents the least cost in terms of travel time between that square and nearest endpoint (clinics). The travel times were used to trim the area around the clinics so that persons living more than 30 minutes away are not included in the exposed to risk.

The road network will include 100 metre squares in which, for example, a motorway bridges a minor road. The model does not realise that the motorway cannot be joined at this point and will calculate the travel time assuming that the individual joins the motorway. The tendency of the model to ignore how the features of the road network actually interact is a small weakness in regional calculations such as ours where interest is in travel times over the whole of the Northwest and Southwest areas. However if this method were to be applied to local area calculations, such as transit through a major city, the problem could be substantial.

The population has been allocated to clinics on the assumption that people travel to the clinic closest to their address, where “closest” is defined in terms either of distance or drive time depending on the model, on the date of the 2001 census. In practice, this is unlikely to be true for all attendees. The most common reason for this is that clinics tend to have limited opening hours, restricted to the times when many people are at work. A clinic in the town where an individual works may be more convenient than one near his or her home. In large urban areas where many people work but fewer people live, we may thus under-estimate the population at

risk and hence over-estimate the rate. Similarly, in suburban areas, we may over-estimate the population at risk and under-estimate the rate.

2.3.3 SPATIAL CLUSTERING

Once we have derived appropriately calculated rates of chlamydia infection, we might be interested to know whether these rates conform to any patterns. Do high rates cluster together? Does the rate at one clinic seem to depend on the rates at other, surrounding clinics? Spatial autocorrelation is a measure of the extent to which data exhibit this sort of clustering. When high values are generally located near to other high values or low values near to other low values, the data are said to show positive spatial autocorrelation. When it is distributed so that high values are generally next to low values, the data show negative spatial autocorrelation (Fotheringham et al., 2002).

In addition to providing us with information about the patterns of chlamydia and gonorrhoea distribution, identifying any spatial autocorrelation is vital because most statistics, particularly in regression analyses, are based on the assumption that observations are independent of one another. The presence of spatial autocorrelation violates this assumption and so spatial dependence must be specifically controlled for in statistical calculations (Lembo, 2007).

Spatial autocorrelation can be measured in a number of ways but the classic measure is Moran's *I*. It compares the value at one location with the value at all the other locations. When *I* approaches one, there is evidence of strong positive spatial autocorrelation, whilst an *I* approaching negative one shows evidence of strong negative spatial autocorrelation. Further details on the calculation of Moran's *I* can be found in the statistical appendix. We can also obtain a Z-test statistic which tests the null hypothesis that the observed values are the result of a random process (no spatial autocorrelation) against the alternative hypothesis that there is spatial correlation. These calculations have been done using GeoDa, a program created specifically for the analysis of spatial data (Anselin, 2003).

2.4 RESULTS

2.4.1 NORTHWEST ENGLAND

2.4.1.1 Number of cases

The numbers of cases reported at each clinic is presented in Table 2.2 below. What is immediately apparent is that far fewer cases of gonorrhoea are diagnosed across all clinics than of chlamydia. This reflects the position of chlamydia as the most commonly diagnosed infection at GUM clinics in the UK. The highest numbers of cases of both infections in the Northwest were diagnosed in Liverpool and Manchester, which is unsurprising as these are the two largest cities in the region.

Table 2.2 All new cases diagnosed at Northwest clinics in 2001

Clinic	Chlamydia cases	Gonorrhoea cases
Ormskirk Hospital	92	10
Workington Community Hospital	99	9
Halton General Hospital	109	21
Royal Albert Edward Infirmary, Wigan	116	27
Burnley General Hospital	125	41
St Helens and Knowsley Hospital	130	51
Hope Hospital	138	55
Cumberland Infirmary	144	18
Chorley and South Ribble District General Hospital	144	14
Warrington and District General Hospital	164	27
Trafford General Hospital	191	28
Macclesfield District General Hospital	201	31
Leighton Hospital	208	57
Fairfield General Hospital	235	54
Ashton Community Care Centre	235	57
Southport District General Hospital	279	36
Royal Oldham Hospital	312	95

Clinic	Chlamydia cases	Gonorrhoea cases
Tameside and Glossop Centre for Sexual Health	328	86
Royal Blackburn Hospital	364	75
Royal Preston Hospital	393	115
Stepping Hill Hospital	408	25
Countess of Chester Hospital	415	57
North Manchester Hospital	420	144
Victoria Hospital, Blackpool	425	200
Arrow Park Hospital	471	88
Baillie Street Health Centre, Rochdale	528	79
Royal Bolton Hospital	581	150
Withington Hospital	706	201
Manchester Royal Infirmary	758	443
Royal Liverpool Hospital	1130	443

2.4.1.2 Thiessen polygons

Using the Thiessen polygon approach we can begin to see how the case rates change once we control for the population exposed to risk. The rates for each clinic, using the Thiessen polygon as the catchment area, are presented in Table 2.3 below. The 95% confidence intervals are based on the Poisson distribution and have been calculated in STATA. Figures 2.7 and 2.8 show quartile maps of the chlamydia rates and gonorrhoea rates respectively in each Thiessen polygon. These quartiles are for the combined distribution for all three regions in the study, allowing for easy comparison. Note that although the boundaries for the Strategic Health Authority are shown on figures for all regions, the models used in this study have allowed people to cross administrative borders in order to attend their nearest clinic.

The chlamydia rates in the Northwest range from 1.12 per 1,000 at the Royal Albert Edward Infirmary in Wigan up to 8.56 per 1,000 at the Baillie Street Health Centre in Rochdale. Although Liverpool had by far the greatest number chlamydia

cases diagnosed, it only had the sixth highest rate. And similarly, though Southport was towards the middle of the table in terms of number of cases diagnosed, it has the fourth highest rate.

The gonorrhoea rates range from 0.18 per 1000 population aged 16 – 44 years in Workington Community Hospital up to 3.64 per 1000 population aged 16 – 44 years at Manchester Royal Infirmary. The rate in Manchester is much higher than any other clinic. The second highest rate, 2.09 per 1000 population aged 16 – 44 years, is in a nearby suburb of Manchester, Withington.

As shown in Figure 2.6 below, there is a fairly strong positive correlation between chlamydia and gonorrhoea rates with a correlation coefficient of 0.68. This indicates that clinics with high chlamydia rates tend to also have high rates of gonorrhoea and suggests that there may be a similar underlying source of elevated rates.

Figure 2.6 Northwest clinics - Graph of 2001 chlamydia and gonorrhoea rates calculated using the Thiessen method

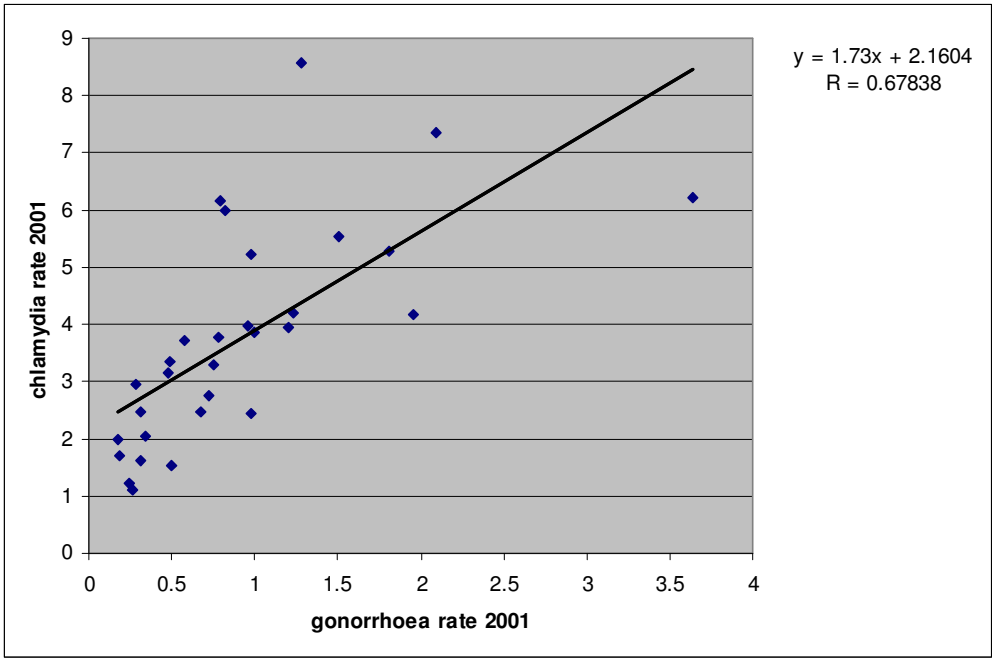


Table 2.3 Chlamydia and gonorrhoea rate in 2001 for population aged 16-44 years for Northwest clinics - Thiessen polygon catchment areas

Clinic	Chlamydia rate per 1,000 population aged 16-44 years	Gonorrhoea rate per 1,000 population aged 16-44 years
Royal Albert Edward Infirmary, Wigan	1.12	0.26
St Helens and Knowsley Hospital	1.22	0.48
Burnley General Hospital	1.53	1.00
Halton General Hospital	1.62	0.31
Ormskirk Hospital	1.71	0.19
Workington Community Hospital	1.98	0.18
Warrington and District General Hospital	2.05	0.34
Hope Hospital	2.45	0.97
Leighton Hospital	2.46	0.67
Cumberland Infirmary	2.47	0.31
Tameside & Glossop Sexual Health Centre	2.75	0.72
Chorley and South Ribble District General Hospital	2.96	0.29
Stepping Hill Hospital	3.16	0.24
Fairfield General Hospital	3.28	0.75
Trafford General Hospital	3.36	0.49
Macclesfield District General Hospital	3.73	0.58
Royal Blackburn Hospital	3.79	0.78
Royal Bolton Hospital	3.86	1.00
Royal Oldham Hospital	3.96	1.21
Ashton Community Care Centre	3.97	0.96
Victoria Hospital, Blackpool	4.16	1.96
Royal Preston Hospital	4.20	1.23
Arrow Park Hospital	5.22	0.98
North Manchester Hospital	5.28	1.81
Royal Liverpool Hospital	5.54	1.51
Countess of Chester Hospital	5.99	0.82
Southport District General Hospital	6.17	0.80
Manchester Royal Infirmary	6.23	3.64
Withington Hospital	7.35	2.09

Clinic	Chlamydia rate per 1,000 population aged 16-44 years	Gonorrhoea rate per 1,000 population aged 16-44 years
Baillie Street Health Centre, Rochdale	8.56	1.28

Figure 2.7 Northwest clinics - Quartile map of 2001 chlamydia rates using the Thiessen polygon method

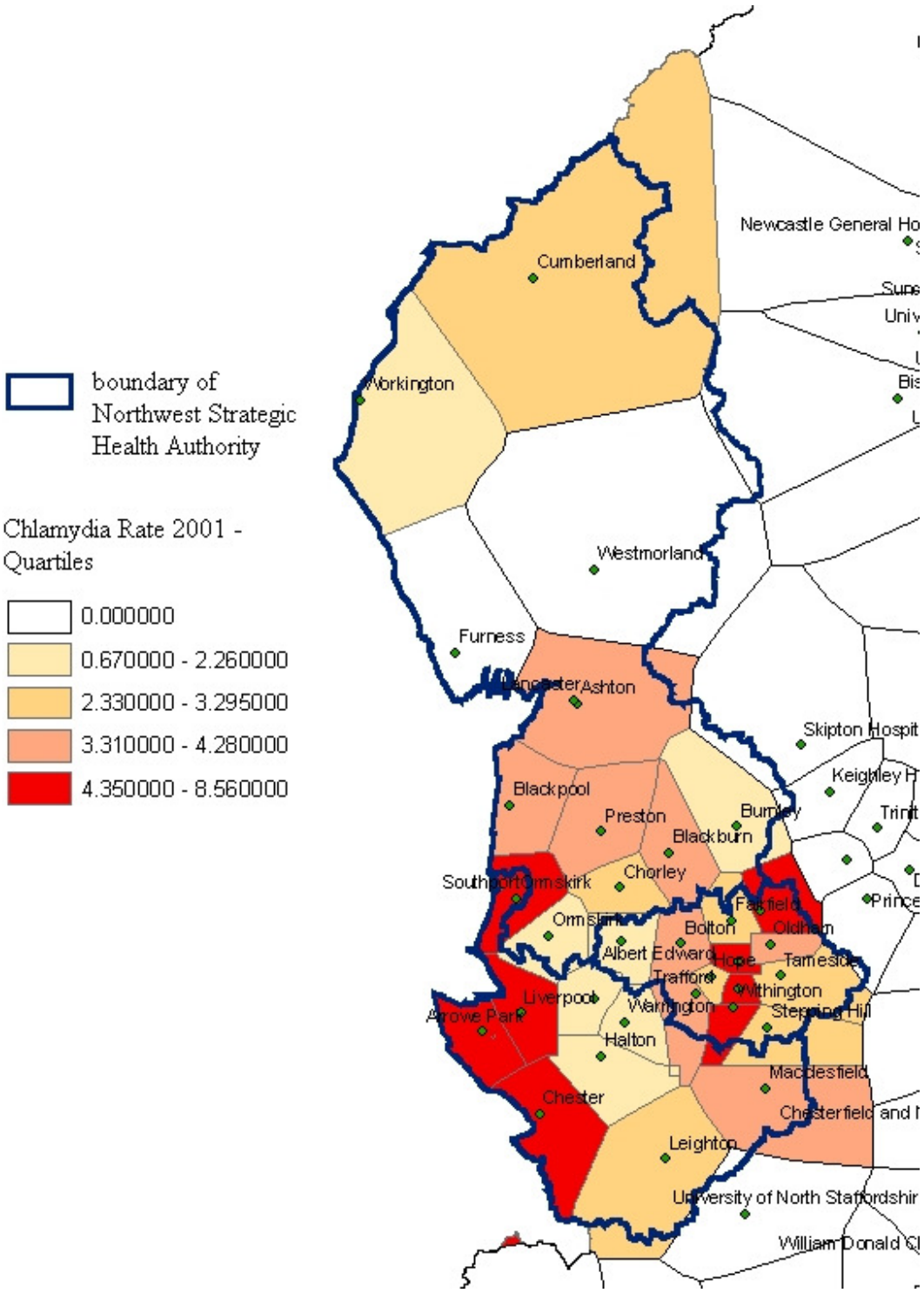
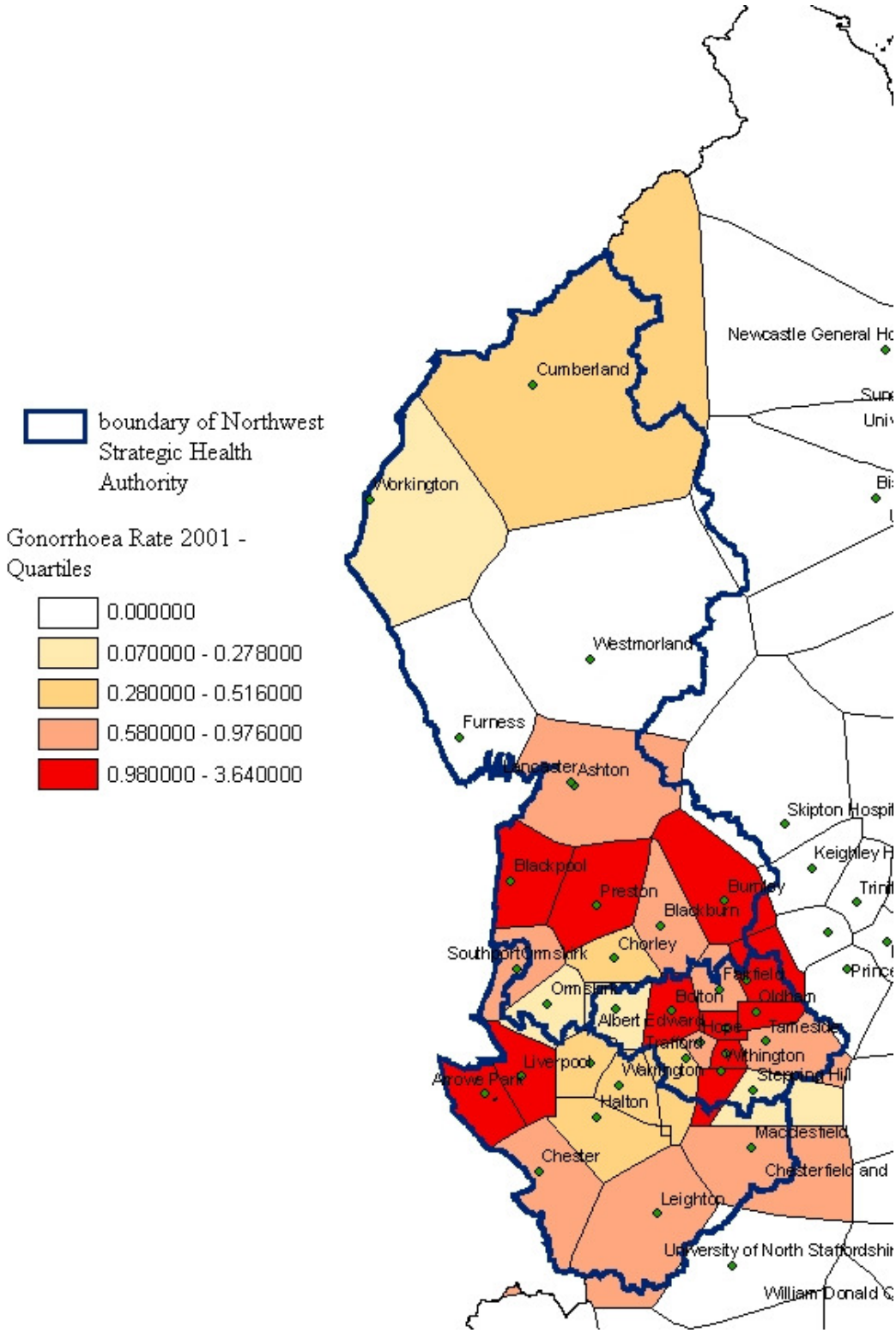


Figure 2.8 Northwest clinics - Quartile map of 2001 gonorrhoea rates using the Thiessen polygon method

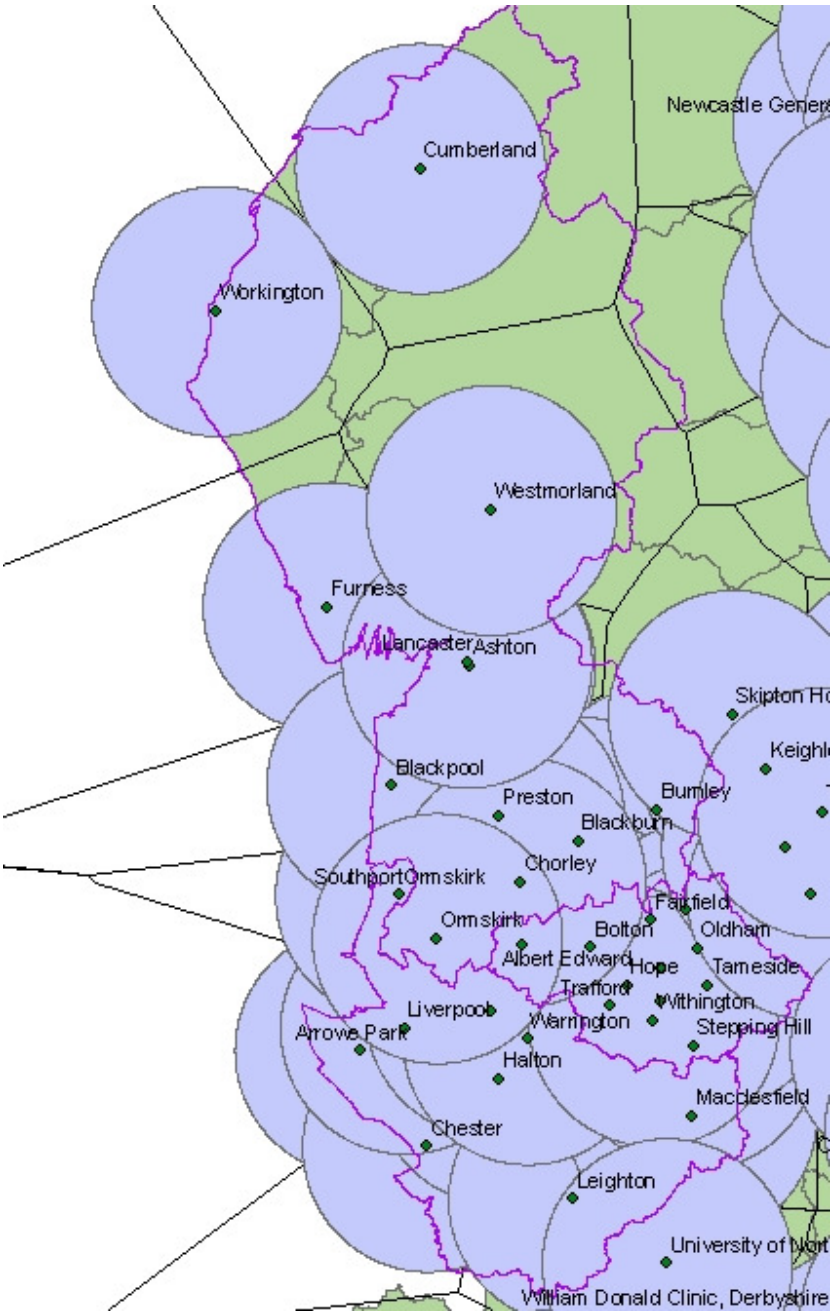


2.4.1.3 15 mile boundaries

Figure 2.9 shows that very little of the Northwest is not covered by one of the 15 mile boundaries (in purple). The areas that are excluded, in the northern-most region of Cumbria, are relatively unpopulated and account for only 1% of the Northwest population aged 16-44 years.

These individuals were originally allocated to one of four clinics: Westmorland and Furness General Hospitals (which are not included above as they have chosen not to report their figures as discussed in Section 2), Cumberland Infirmary and Workington General Hospital. The rates for Cumberland Infirmary and Workington General Hospital can be adjusted to exclude those who live outside the 15 mile boundary but it can be seen that even for these two clinics, the change is small. Chlamydia rates rise from 2.47 to 3.18 for Cumberland and from 1.98 to 2.14 for Workington. Gonorrhoea rates rise from 0.31 to 0.40 for Cumberland and 0.18 to 0.19 for Workington. Remoteness with respect to distance from a clinic does not seem to be an issue in this region.

Figure 2.9 Northwest clinics with 15 mile boundaries



2.4.1.4 Drive time model

Remoteness with respect to the driving time is also not much of an issue in the Northwest. Table 2.4 below shows the percentage of the population that lives within a given drive time of a GUM clinic. Only 2% of the population lives more than 30 minutes from a clinic and only 6% more than 20 minutes.

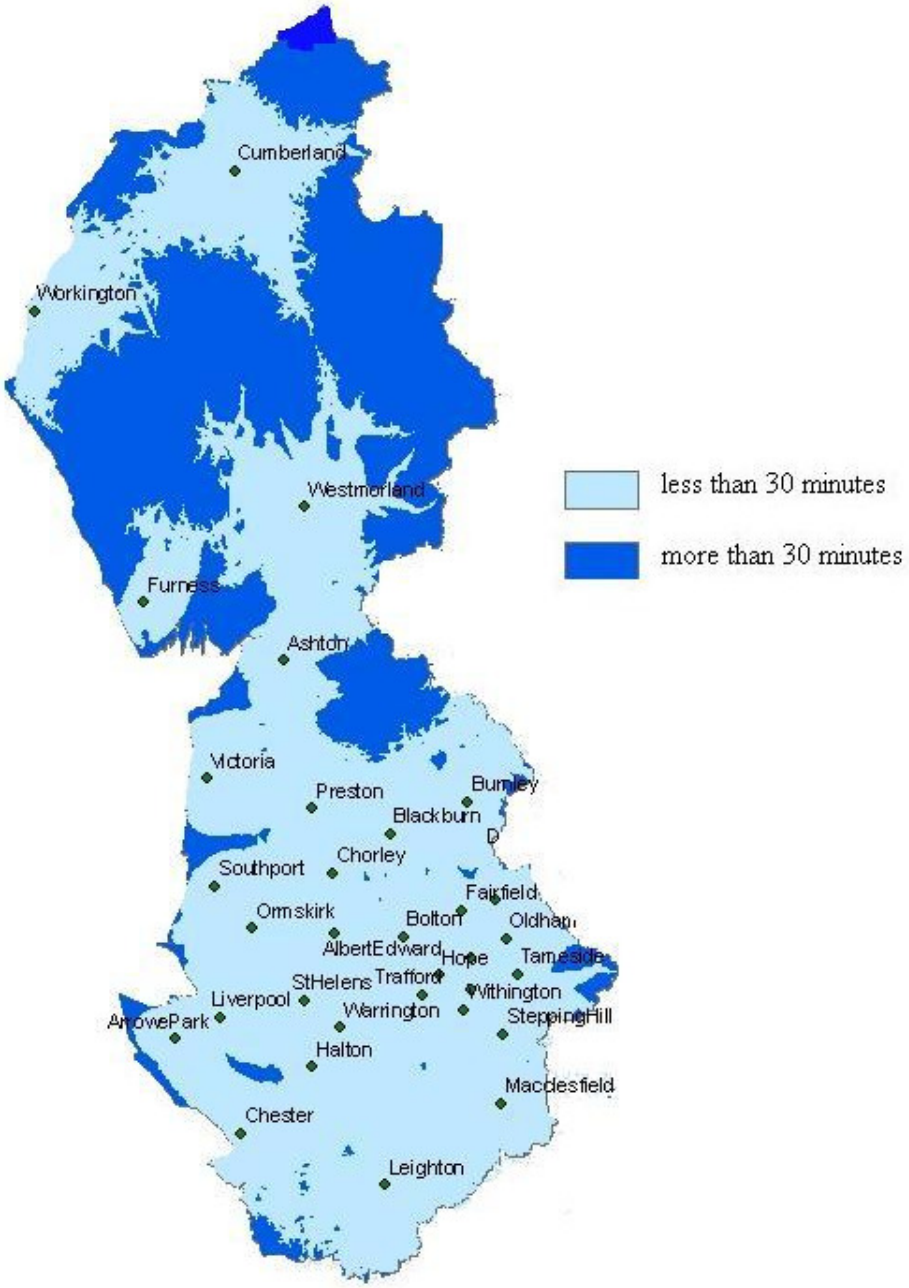
Table 2.4 Travel time to the nearest clinic in Northwest

Time to nearest clinic	% of population aged 16-44 years living within this travel time to nearest clinic	Cumulative % of population aged 16-44 years living within this time to nearest clinic
0 – 4.99 minutes	20%	20%
5 – 9.99 minutes	39%	59%
10 – 14.99 minutes	25%	85%
15 – 19.99 minutes	9%	94%
20 – 24.99 minutes	3%	97%
25 – 29.99 minutes	1%	98%
30 – 34.99 minutes	1%	99%
35 – 39.99 minutes	0%	99%
40 – 59,99 minutes	1%	100%
60 minutes plus	0%	100%

Although some areas (shown in dark blue on Figure 2.10 below) are clearly less accessible they are mainly in the less populated, more rural areas which do not have easy access to the motorways and A-roads. The same clinics are affected by this remoteness as when measured with the crow-fly distance approach, though the travel time model does manage to give further refinement. For example, although the individuals in the vicinity of the Burnley clinic were all within 15 miles, a number were found by the travel-time model to live more than 30 minutes away.

For the Northwest, it seems that we add very little by moving away from the Thiessen approach. Most people are able to easily access their nearest clinic and so the added complexity of the distance and travel time models are not needed.

Figure 2.10. Northwest clinics with 30 minute drive time catchment areas



2.4.2 EAST MIDLANDS

2.4.2.1 Number of cases

In the East Midlands, the highest number of cases were diagnosed in Leicester and Nottingham (Table 2.5). It was unclear from the East Midlands data whether the clinics in Gainsborough and Louth had not diagnosed any cases or whether their information was simply omitted from the report provided from the Health Protection Authority. However, since both the chlamydia and the gonorrhoea cases were zero, it seems more likely to be the latter.

Table 2.5 All new cases diagnosed at East Midlands clinics in 2001

Clinic	Chlamydia cases	Gonorrhoea cases
John Coupland Hospital, Gainsborough	0	0
Louth County Hospital	0	0
Skegness and District Hospital	43	21
Pilgrim Hospital	105	14
Grantham and Kestven Hospital	143	10
Retford Hospital	157	26
Loughbourough General Hospital	177	9
King's Mill Hospital	270	83
Lincoln County Hospital	363	54
Chesterfield and North Derbyshire Royal Hospital	415	33
Warren Hill Centre, Kettering General Hospital	478	61
Northampton General Hospital	511	108
William Donald Clinic, Derbyshire Royal Infirmary	666	231
Leicester Royal Infirmary	1146	257
Nottingham City Hospital	1324	475

2.4.2.2 Thiessen polygons

In the East Midlands, the chlamydia rates range from 2.00 per 1,000 population aged 16 – 44 years in Loughborough to 5.09 per 1,000 population aged 16 – 44 years in Lincoln (Table 2.6). As shown in Figure 2.12, this is a far narrower range of values than seen in the Northwest, though this may reflect the relatively small number of clinics in the East Midlands. Again, controlling for the population exposed to risk has made a difference here, as it did in the Northwest. Loughborough was middle of the table in terms of cases diagnosed but has the lowest rate in the region using the Thiessen method.

Loughborough also has the lowest rate of gonorrhoea infection at 0.11 per 1000 population aged 16 – 44 years whilst the highest rate (1.65 per 1000 population aged 16 – 44 years) is in Nottingham. The correlation between chlamydia and gonorrhoea rates is less strong than in the Northwest, probably in part reflecting the smaller number of clinics in the East Midlands. However, the relationship still shows a positive correlation with a correlation coefficient of 0.48 (Figure 2.11).

Figure 2.11 East Midlands clinics - Graph of 2001 chlamydia and gonorrhoea rates calculated using the Thiessen method

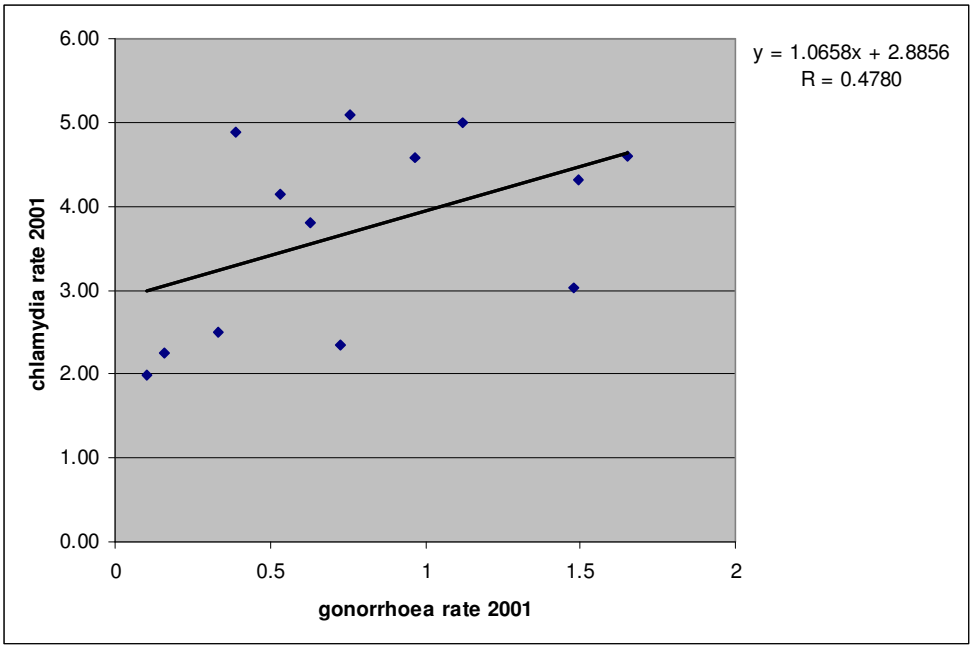


Table 2.6 Chlamydia and gonorrhoea rate in 2001 for population aged 16-44 years for East Midlands clinics - Thiessen polygon catchment areas

Clinic	Chlamydia rate per 1,000 population aged 16-44 years	Gonorrhoea rate per 1,000 population aged 16-44 years
John Coupland Hospital, Gainsborough	0.00	0.00
Louth County Hospital	0.00	0.00
Loughborough General Hospital	2.00	0.11
Grantham and Kestven Hospital	2.24	0.16
King's Mill Hospital	2.35	0.72
Pilgrim Hospital	2.50	0.33
Skegness and District Hospital	3.03	1.48
Retford Hospital	3.80	0.63
Warren Hill Centre, Kettering General Hospital	4.15	0.53
William Donald Clinic, Derbyshire Royal Infirmary	4.31	1.49
Northampton General Hospital	4.57	0.97
Nottingham City Hospital	4.60	1.65
Chesterfield and North Derbyshire Royal Hospital	4.88	0.38
Leicester Royal Infirmary	5.01	1.12
Lincoln County Hospital	5.09	0.76

Figure 2.12 East Midlands clinics - Quartile map of 2001 chlamydia rates using the Thiessen polygon method

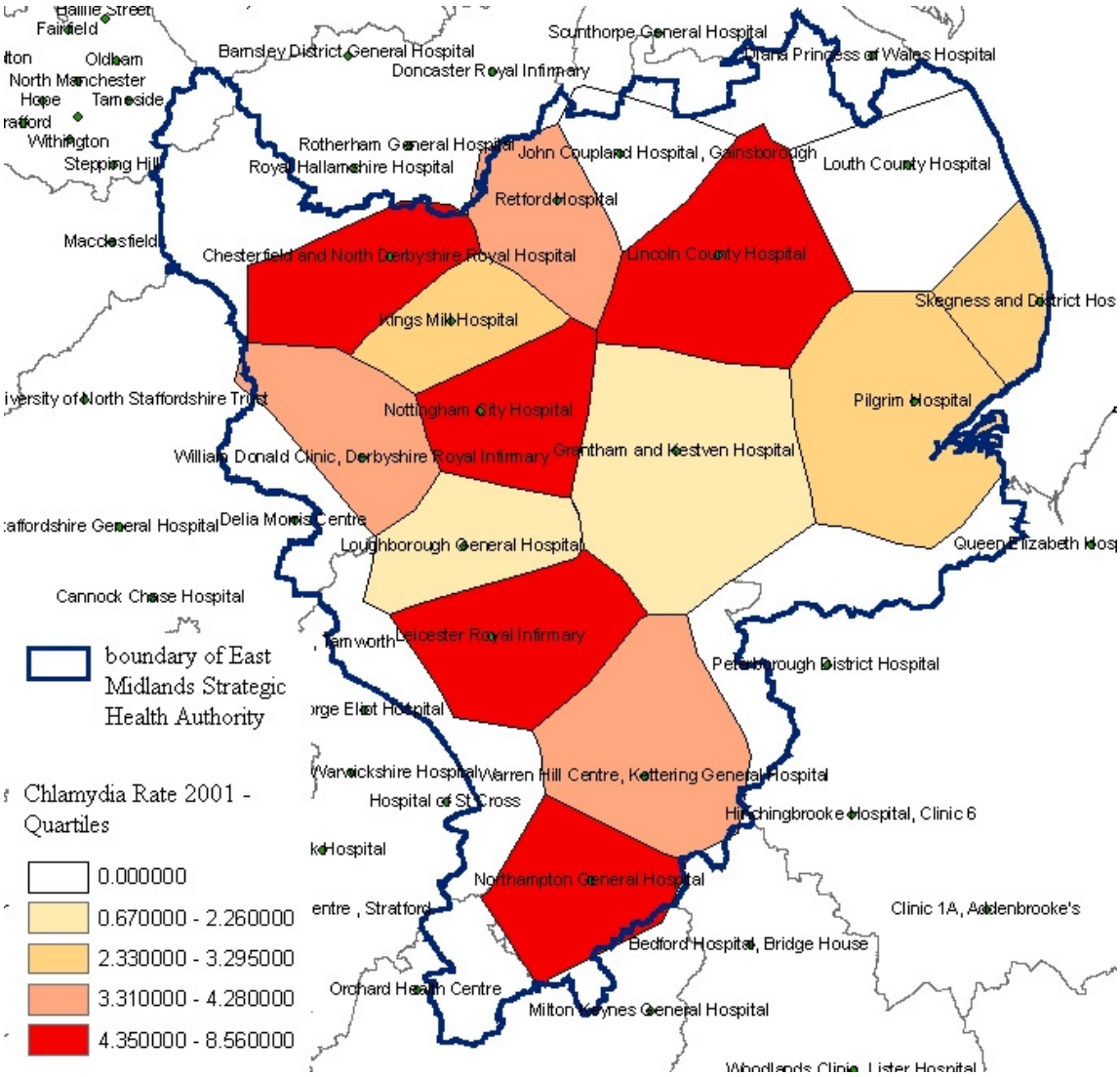
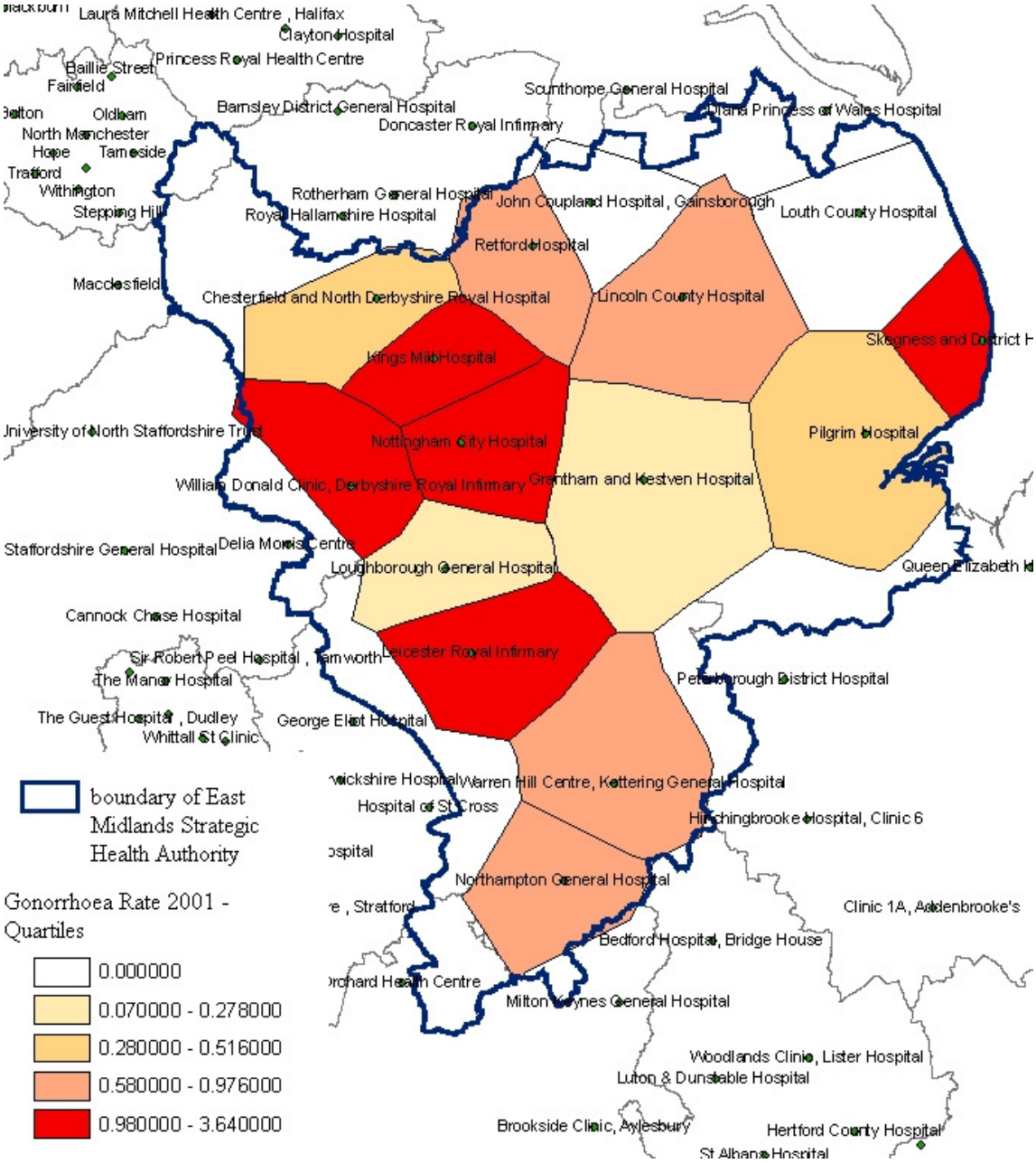


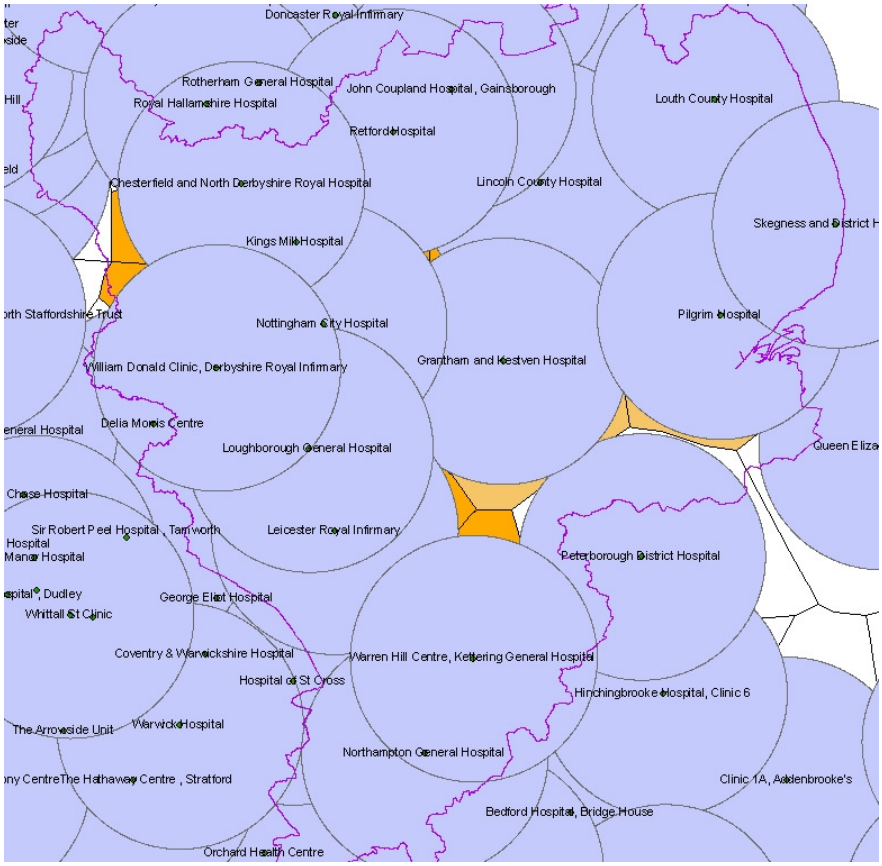
Figure 2.13 East Midlands clinics - Quartile map of 2001 gonorrhoea rates using the Thiessen polygon method



2.4.2.3 15 mile boundaries

Figure 2.14 below shows that the East Midlands, like the Northwest, contains very few areas from which the distance to the nearest clinic is more than 15 miles. There are some gaps, most notably in the area to the west of Leicester Royal Infirmary and south of Grantham and Kesteven Hospital. However, the population aged 16 – 44 years living in a gap is only 14,371, representing just 1.02% of the population of the East Midlands aged 16 – 44 years. With such a small proportion of the population affected, we have not recalculated the rates of chlamydia or gonorrhoea. It seems that on this distance-based measure, clinics in the East Midlands do not suffer from problems of accessibility.

Figure 2.14 East Midlands – 15 Mile Boundaries



2.4.2.4 Drive time model

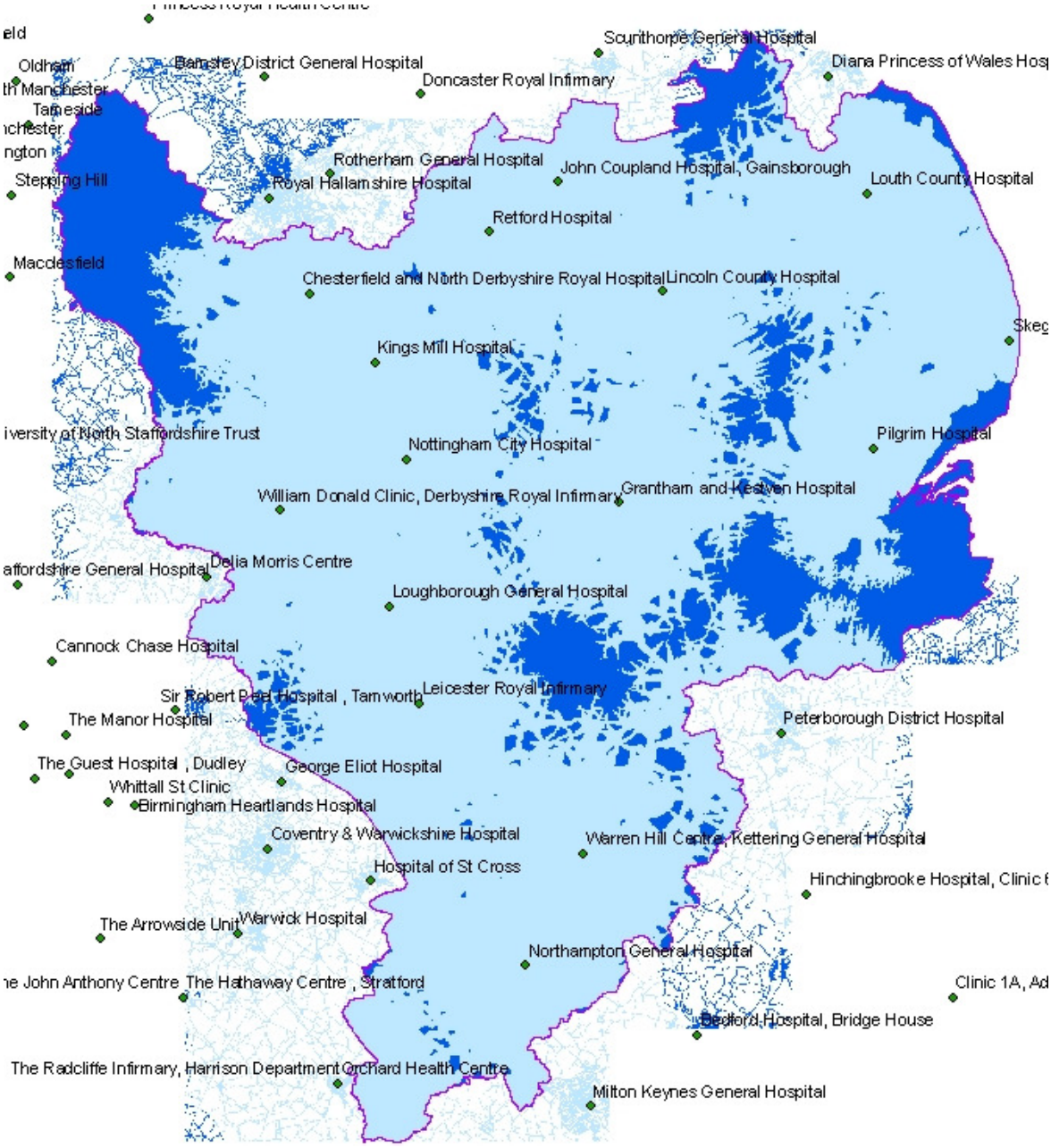
Accessibility in the East Midlands is generally very good, with only 4% of the population living more than 30 minutes from a clinic. Many of these live in the more rural areas such as the southern part of the Peak District or in the gaps already identified by the 15 mile boundary model. These areas are shown in dark blue in Figure 2.15.

Although access is very good if we use a measure of 30 minutes, Table 2.7 shows that accessibility may be somewhat sensitive to our choice of threshold. If, for example, we were to consider as remote those individuals who live more than 20 minutes away, a full 18% of the population would be affected.

Table 2.7 Travel time to the nearest clinic in East Midlands

Time to nearest clinic	% of population aged 16-44 years living within this travel time to nearest clinic	Cumulative % of population aged 16-44 years living within this time to nearest clinic
0 – 4.99 minutes	19%	19%
5 – 9.99 minutes	27%	46%
10 – 14.99 minutes	18%	64%
15 – 19.99 minutes	18%	82%
20 – 24.99 minutes	9%	91%
25 – 29.99 minutes	4%	96%
30 – 34.99 minutes	2%	97%
35 – 39.99 minutes	1%	98%
40 – 59,99 minutes	2%	100%
60 minutes plus	0%	100%

Figure 2.15 East Midlands clinics with 30 minute drive time catchment areas



2.4.3 SOUTHWEST

2.4.3.1 Number of cases

Table 2.8 illustrates that in the Southwest, the highest numbers of cases are diagnosed in Bristol and Bournemouth. As in the Northwest and the East Midlands, the largest number of cases are to be found in the largest cities, which is likely to be a direct reflection of the larger population, and as in the other regions, there are far more chlamydia than gonorrhoea diagnoses.

Table 2.8 All new cases diagnosed at Southwest clinics in 2001

Clinic	Chlamydia cases	Gonorrhoea cases
Newquay and District Hospital	35	7
West Cornwall Hospital, Penzance	47	5
Chippenham Community Hospital	50	5
Weston General Hospital	59	7
Yeovil District Hospital	99	11
Royal Devon and Exeter Hospital	109	23
Torbay Hospital	136	23
North Devon District General Hospital	192	15
Salisbury District Hospital	194	14
Cheltenham General Hospital	197	34
Weymouth and District Hospital	214	9
Royal Cornwall Hospital, Treliske	225	22
Taunton and Somerset Hospital	239	28
Royal United Hospital, Bath	279	46
The Great Western Hospital, Swindon	406	64
Gloucester Royal Hospital	520	152
Derriford Hospital Level 5, Plymouth	531	78
Royal Bournemouth Hospital	700	167
Bristol Royal Infirmary	881	409

2.4.3.2 Thiessen polygons

In the Southwest, the chlamydia rates range from 0.67 per 1,000 population aged 16 – 44 years at Newquay and District Hospital up to 5.12 per 1,000 aged 16 – 44 years at Weymouth and District Hospital (Table 2.9). As in the Northwest and the East Midlands, the position of many clinics in the table changed substantially when we controlled for the population exposed to risk. Weymouth, for example, was in the middle of the table in terms of cases diagnosed but has the highest chlamydia rate.

The gonorrhoea rates start from 0.07 per 1000 population aged 16 – 44 years and rise to 1.38 per 1000 population aged 16 – 44 years in Bristol. And as in the East Midlands, the correlation between the two rates is positive but not as strong as in the Northwest, with a correlation coefficient of 0.49.

Figure 2.16 Southwest clinics - Graph of 2001 chlamydia and gonorrhoea rates calculated using the Thiessen method

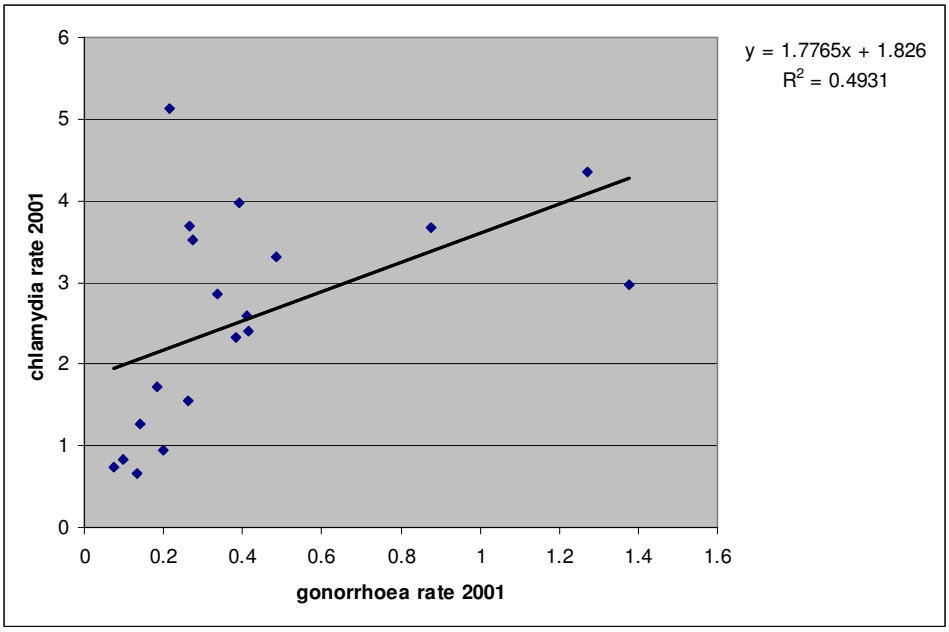


Table 2.9 Chlamydia and gonorrhoea rate in 2001 for population aged 16-44 years for Southwest clinics - Thiessen polygon catchment areas

Clinic	Chlamydia rate per 1,000 population aged 16-44 years	Gonorrhoea rate per 1,000 population aged 16-44 years
Newquay and District Hospital	0.67	0.13
Chippenham Community Hospital	0.73	0.07
Weston General Hospital	0.84	0.10
Royal Devon and Exeter Hospital	0.95	0.20
Yeovil District Hospital	1.27	0.14
Torbay Hospital	1.56	0.26
West Cornwall Hospital, Penzance	1.72	0.18
Royal United Hospital, Bath	2.33	0.38
Cheltenham General Hospital	2.40	0.41
The Great Western Hospital, Swindon	2.60	0.41
Taunton and Somerset Hospital	2.86	0.34
Bristol Royal Infirmary	2.97	1.38
Derriford Hospital Level 5, Plymouth	3.31	0.49
North Devon District General Hospital	3.52	0.28
Royal Bournemouth Hospital	3.67	0.88
Salisbury District Hospital	3.69	0.27
Royal Cornwall Hospital, Treliske	3.98	0.39
Gloucester Royal Hospital	4.35	1.27
Weymouth and District Hospital	5.12	0.22

Figure 2.17. Southwest clinics – Quartile map of 2001 chlamydia rates using the Thiessen polygon method

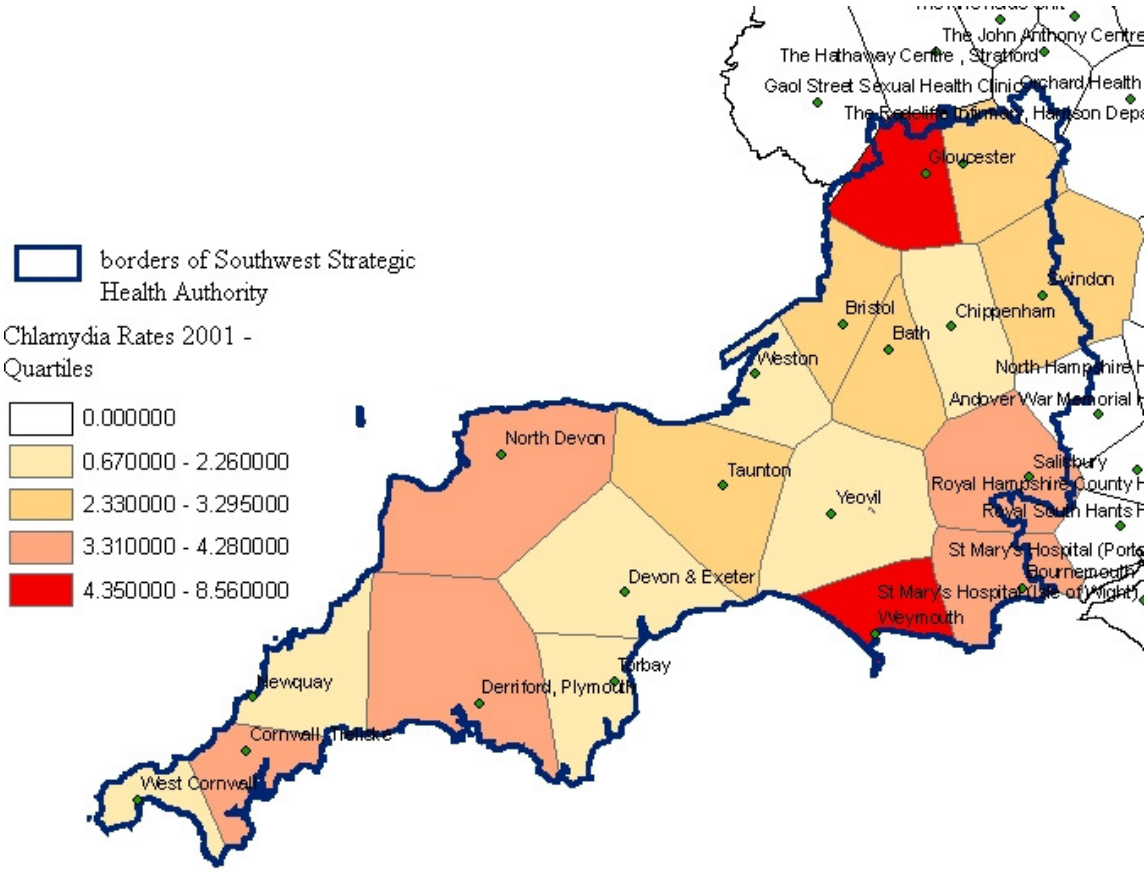
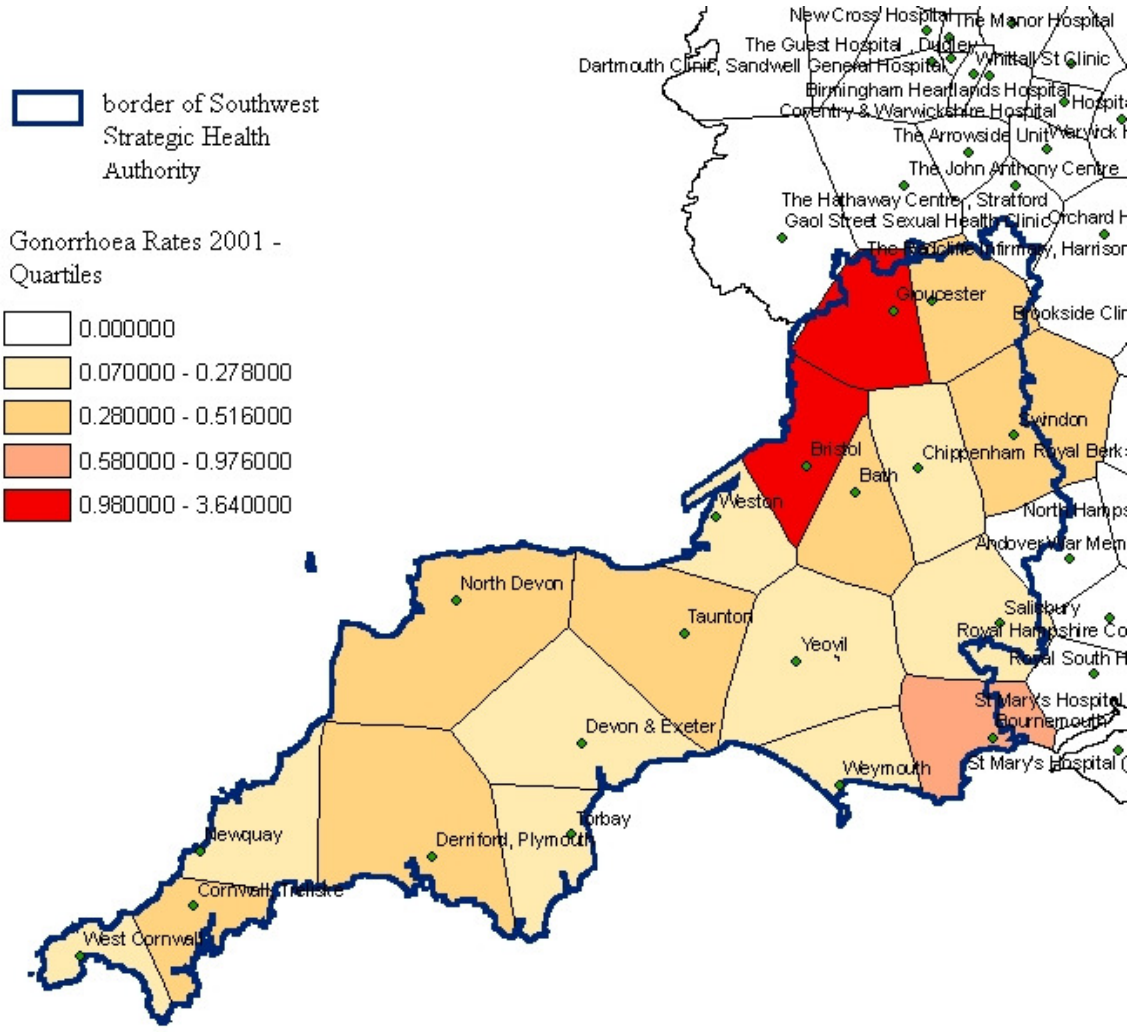


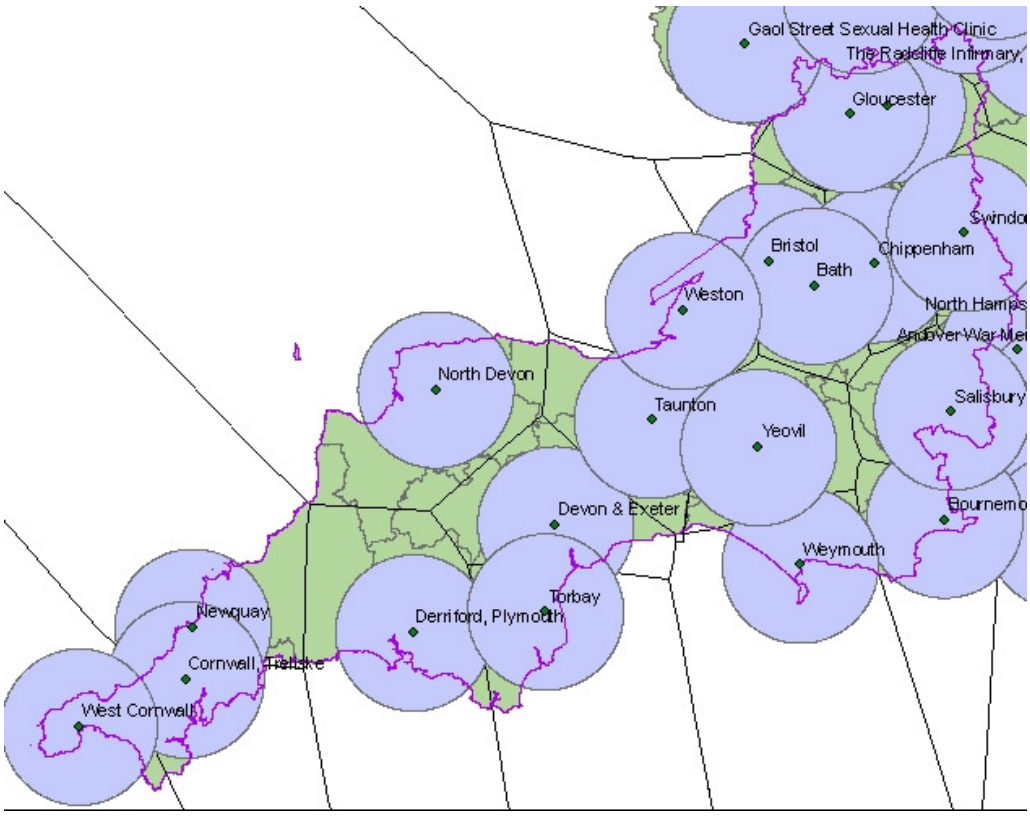
Figure 2.18 Southwest clinics – Quartile map of 2001 gonorrhoea rates using the Thiessen polygon method



2.4.3.3 15 mile boundaries

In contrast to the other two regions, the map (Figure 2.19) of the Southwest shows far more polygons containing areas that were classed as more than 15 miles from a clinic. Virtually every clinic includes at least a small area that was deemed to be remote on this measure. However, these areas were relatively sparsely populated and overall only about 6% of the population aged 16-44 years was affected.

Figure 2.19 Southwest clinics with 15 mile boundaries



Because virtually every clinic has been affected, we recalculated the rates for the Southwest excluding those individuals for whom the clinic was considered to be remote. This reduces the population exposed to risk (i.e. the denominator) and correspondingly increases the rates. But these changes are spread across the clinics such that the changes to the rates are relatively small. The new rates shown in Table 2.10 differ little from those derived using the Thiessen polygon method and the differences fall within the sampling error of the original estimates, as illustrated by the overlapping 95% confidence intervals in Figures 2.20 and 2.21 below.

Table 2.10 Chlamydia and gonorrhoea rate in 2001 for population aged 16-44 years for Southwest clinics - 15 mile boundaries

Clinic	Chlamydia rate per 1,000 population aged 16-44 years	Gonorrhoea rate per 1,000 population aged 16-44 years
Chippenham Community Hospital	0.74	0.07
Weston General Hospital	0.90	0.11
Newquay and District Hospital	0.99	0.20
Royal Devon and Exeter Hospital	1.04	0.22
Yeovil District Hospital	1.52	0.17
Torbay Hospital	1.60	0.27
West Cornwall Hospital, Penzance	1.76	0.19
Cheltenham General Hospital	2.47	0.43
Royal United Hospital, Bath	2.57	0.42
The Great Western Hospital, Swindon	3.09	0.44
Bristol Royal Infirmary	2.99	1.39
Taunton and Somerset Hospital	3.23	0.38
Derriford Hospital Level 5, Plymouth	3.69	0.54
Royal Bournemouth Hospital	3.77	0.90
Royal Cornwall Hospital, Treliske	4.07	0.40
Salisbury District Hospital	4.10	0.30
North Devon District General Hospital	4.65	0.36
Gloucester Royal Hospital	4.77	1.39
Weymouth and District Hospital	5.22	0.22

Figure 2.20 Comparison of chlamydia rates in the Southwest derived using the Thiessen and 15 mile methods (bars denote 95 percent confidence intervals)

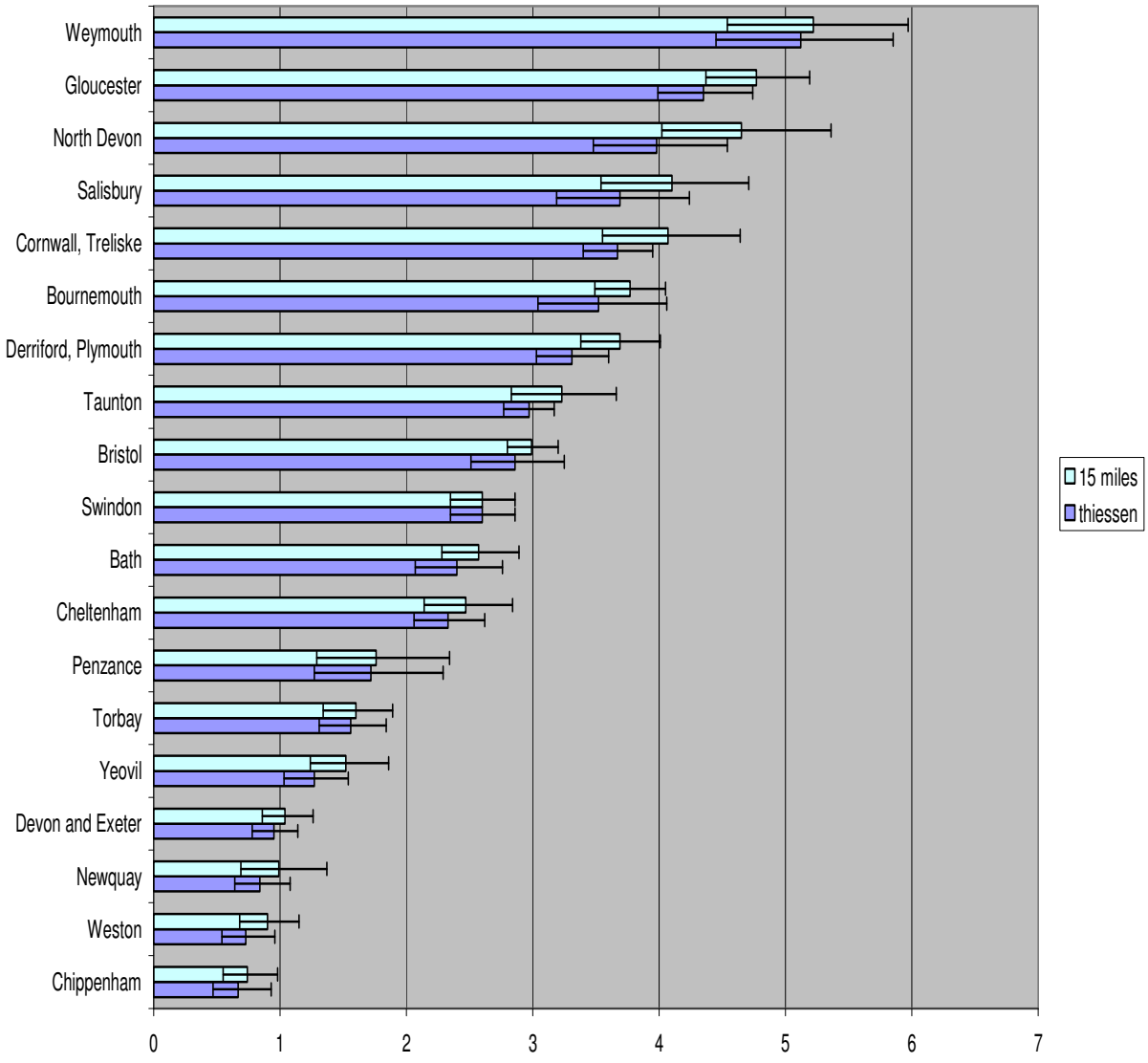
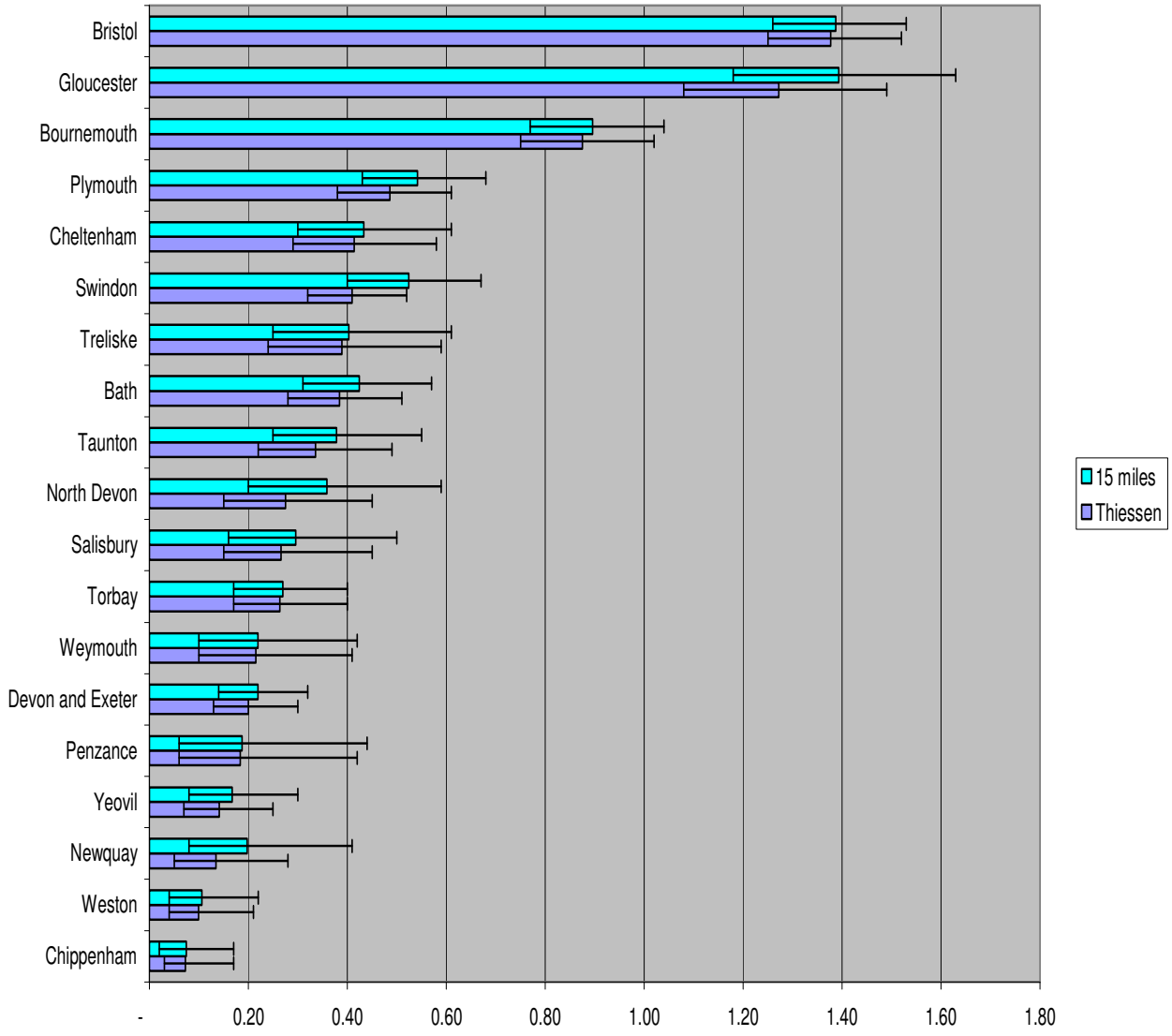


Figure 2.21 Comparison of gonorrhoea rates in the Southwest derived using the Thiessen and 15 mile methods (bars denote 95 percent confidence intervals)



2.4.3.4 Drive time model

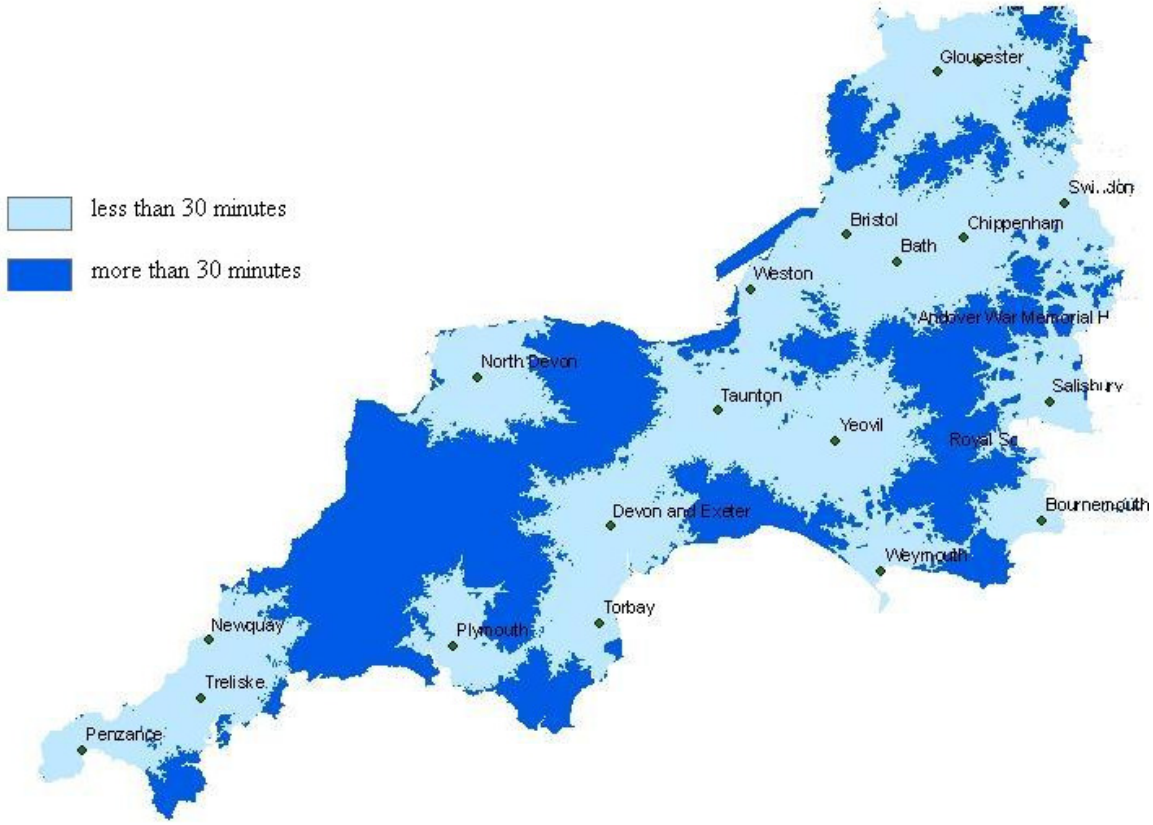
The situation with respect to driving time in the Southwest is very different from that observed in the Northwest and more extreme than was observed in the East Midlands. The travel time analysis shows a number of areas where clinic access is problematic. As shown in Table 2.11 below, 10% of the population live more

than 30 minutes away from a clinic and almost one in three live more than 20 minutes away. Figure 2.22 shows that virtually every clinic's catchment area contains an area which is considered remote, denoted by a dark blue patch, from which the trip will take more than 30 minutes.

Table 2.11 Travel time to the nearest clinic in Southwest

Time to nearest clinic	% of population aged 16-44 years living within this travel time to nearest clinic	Cumulative % of population aged 16-44 years living within this time to nearest clinic
0 – 4.99 minutes	16%	16%
5 – 9.99 minutes	23%	39%
10 – 14.99 minutes	17%	56%
15 – 19.99 minutes	14%	70%
20 – 24.99 minutes	11%	81%
25 – 29.99 minutes	9%	90%
30 – 34.99 minutes	4%	94%
35 – 39.99 minutes	3%	97%
40 – 59,99 minutes	3%	100%
60 minutes plus	0%	100%

Figure 2.22. Southwest clinics with 30 minute drive time catchment areas



However, the impact on the rates is once again very limited (Table 2.12). For most clinics, they increase compared to both the rates calculated using the Thiessen and the crow-fly distance methods. This reflects the further reduction in the denominator as we exclude those individuals who live more than 30 minutes away. But the increases are modest and again, as shown in Figures 2.23 and 2.24 below, the 95% confidence intervals overlap.

Table 2.12 Chlamydia and gonorrhoea rate in 2001 for population aged 16-44 years for Southwest clinics - 30 minute drive time

Clinic	Chlamydia rate per 1,000 population aged 16-44 years	Gonorrhoea rate per 1,000 population aged 16-44 years
Chippenham Community Hospital	0.82	0.08
Weston General Hospital	0.89	0.11
Newquay and District Hospital	0.90	0.18
Royal Devon and Exeter Hospital	1.08	0.23
Yeovil District Hospital	1.66	0.18
Torbay Hospital	1.71	0.29
West Cornwall Hospital, Penzance	1.76	0.19
Cheltenham General Hospital	2.56	0.44
Royal United Hospital, Bath	2.69	0.44
Bristol Royal Infirmary	3.00	1.39
The Great Western Hospital, Swindon	2.60	0.49
Taunton and Somerset Hospital	3.33	0.39
Royal Bournemouth Hospital	4.01	0.96
Derriford Hospital Level 5, Plymouth	4.09	0.60
Royal Cornwall Hospital, Treliske	4.30	0.42
Salisbury District Hospital	4.44	0.32
North Devon District General Hospital	4.77	0.37
Gloucester Royal Hospital	4.95	1.45
Weymouth and District Hospital	5.67	0.24

Figure 2.23 Comparison of chlamydia rates in the Southwest on all three methods

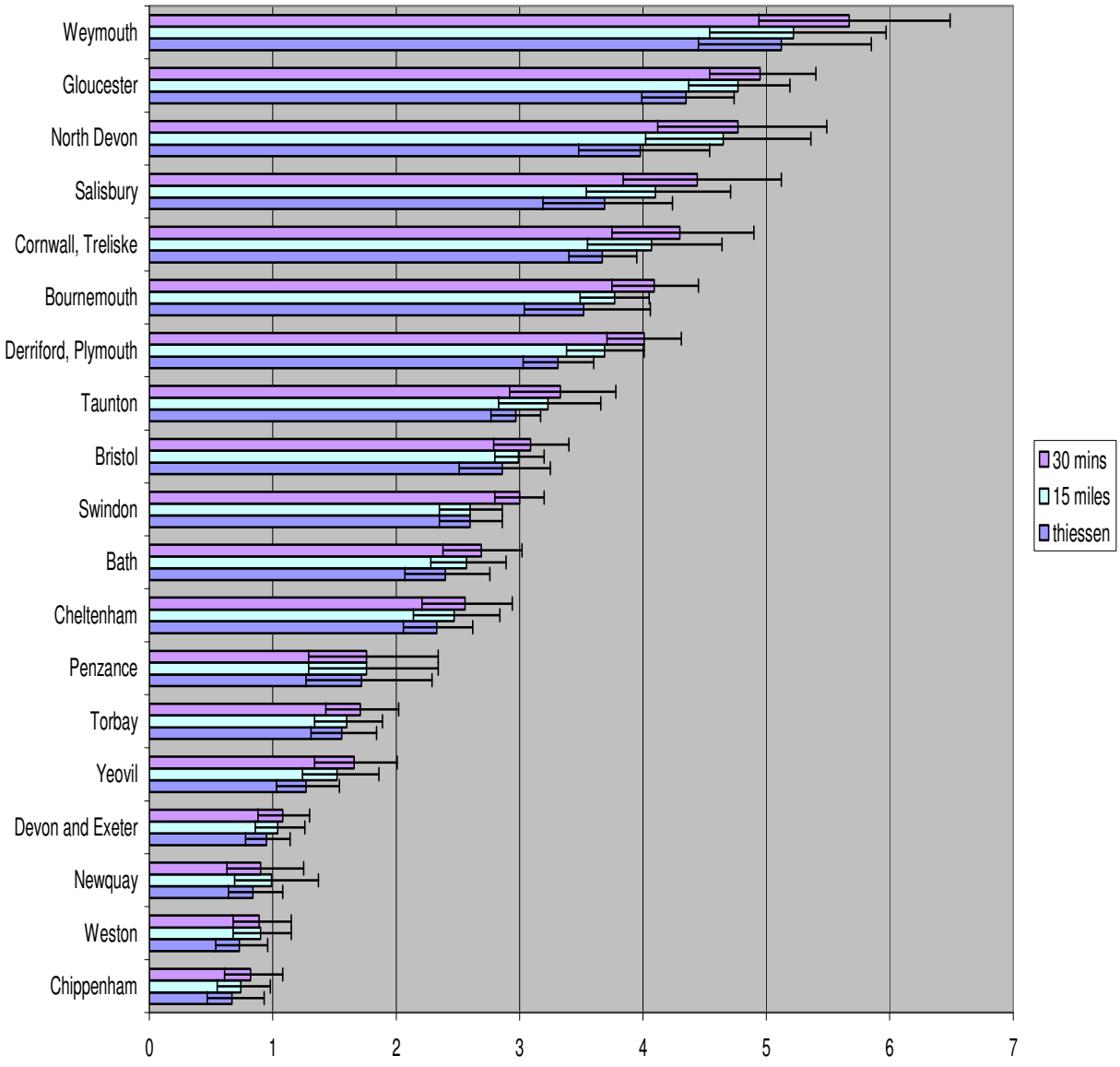
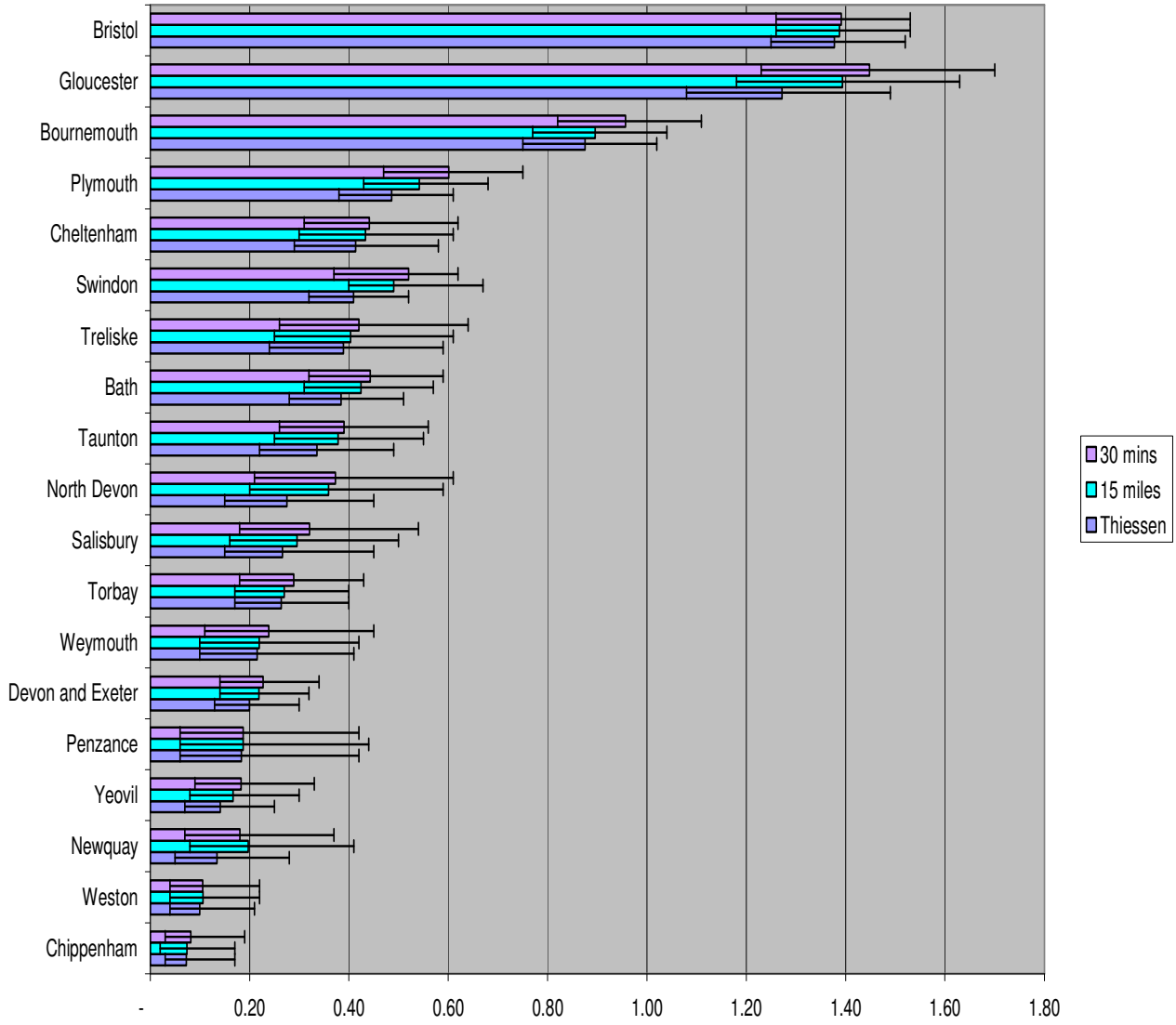


Figure 2.24 Comparison of gonorrhoea rates in the Southwest on all three methods



However, if we calculate the rates using a drive time of less than 20 minutes, rather than 30 minutes, the change to the rates is substantial, as shown in Figures 2.25 and 2.26. This is because 30% of the population in the Southwest must travel for more than 20 minutes to access their nearest GUM clinic. Excluding these individuals from the calculations means very large reductions to the exposed to risk. Some clinics are more affected than others. The population exposed to risk in Swindon reduces by only 8% in comparison with the population used in the Thiessen polygon approach. In contrast the population exposed to risk in

Newquay reduces by 69%. Although 30 minutes has been used in a number of previous studies, clearly areas of the Southwest are very sensitive to the threshold chosen. There is little empirical evidence about the amount of time individuals are willing or able to spend travelling in order to access sexual health services. Further research in this area is needed in order to assess whether there is a significant problem with accessibility in the Southwest.

Table 2.13 shows the rates using the 20 minute drive time model. Comparing this to Table 2.11, which shows the results of the 30 minute model, shows that there is little change in the order in which the clinics occur. Those with the lowest rates in the 30 minute model are also those with the lowest rates in the 20 minute model. Although the rates may be higher using a 20 minute threshold, and although some clinics may be more affected than others, overall the areas that we have identified as areas with high rates remain areas of high rates regardless of the method chosen.

Figure 2.25 Comparison of chlamydia rates in the Southwest, including 20 minute drive time threshold

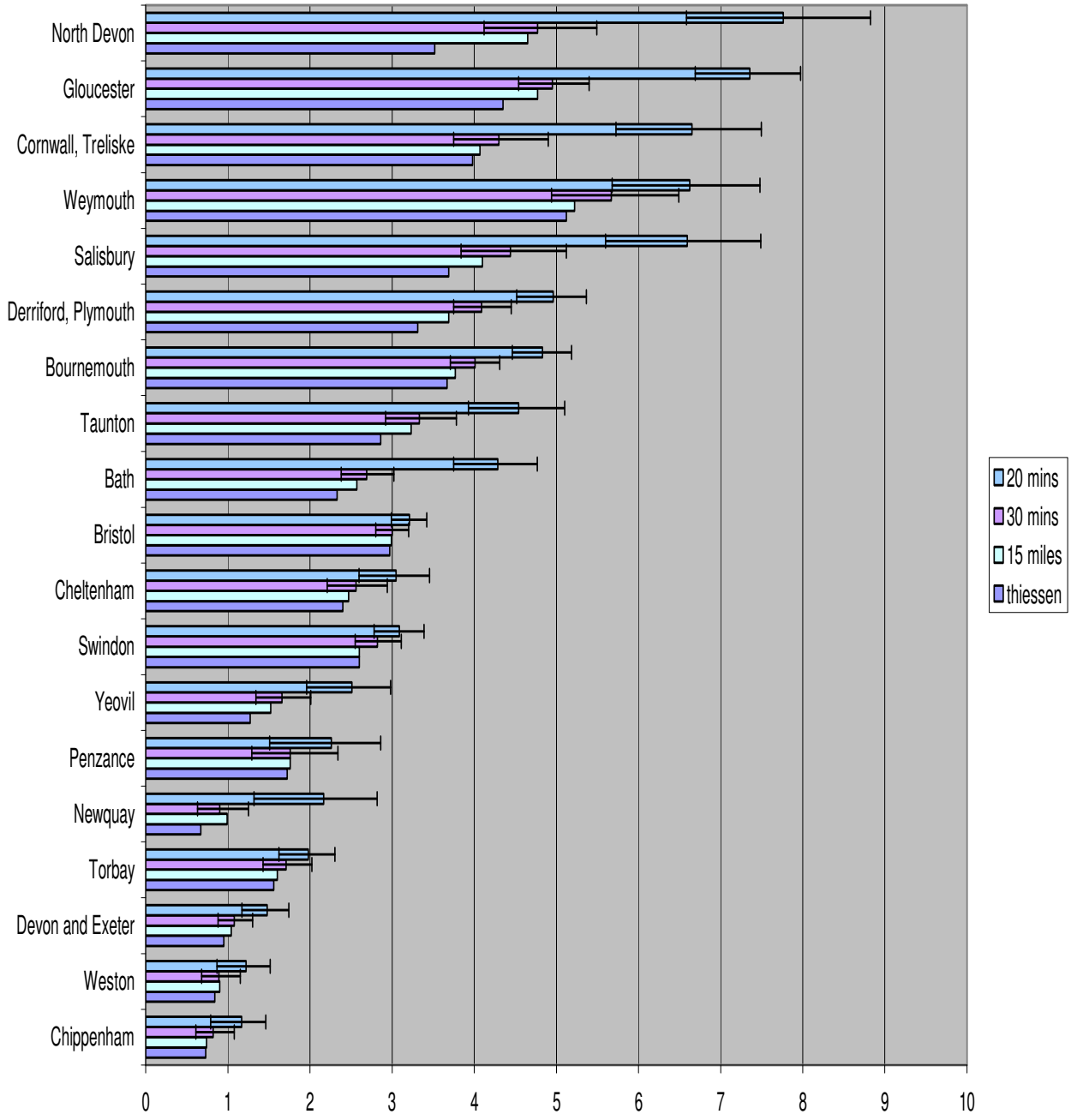


Figure 2.26 Comparison of gonorrhoea rates in the Southwest, including 20 minute drive time threshold

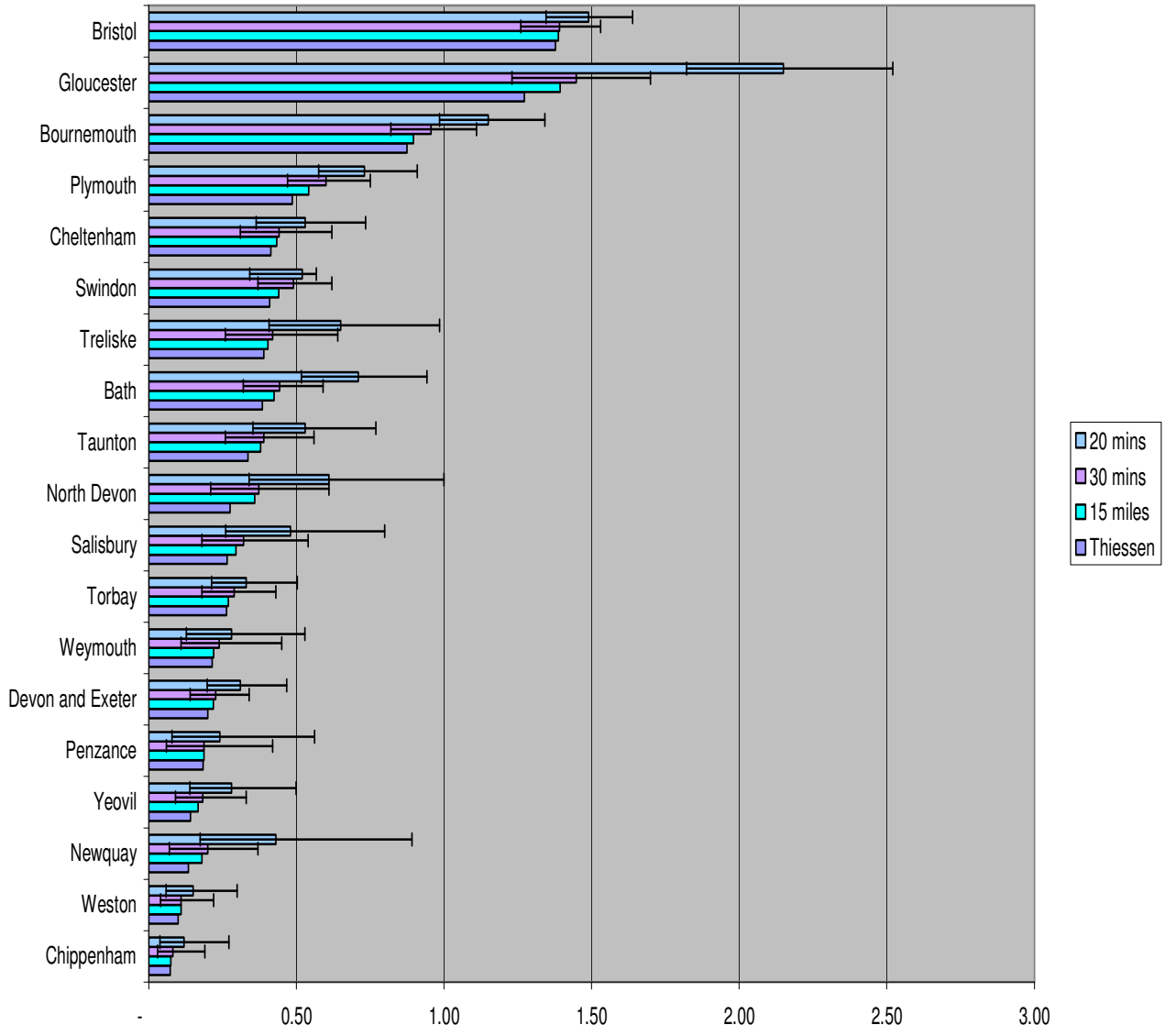


Table 2.13 Chlamydia and gonorrhoea rate in 2001 for population aged 16-44 years for Southwest clinics - 20 minute drive time

Clinic	Chlamydia rate per 1,000 population aged 16-44 years	Gonorrhoea rate per 1,000 population aged 16-44 years
Chippenham Community Hospital	1.17	0.12
Weston General Hospital	1.22	0.15
Royal Devon and Exeter Hospital	1.48	0.31
Torbay Hospital	1.98	0.33
Newquay and District Hospital	2.16	0.43
West Cornwall Hospital, Penzance	2.26	0.24
Yeovil District Hospital	2.51	0.28
The Great Western Hospital, Swindon	2.82	0.52
Cheltenham General Hospital	3.05	0.53
Bristol Royal Infirmary	3.21	1.49
Royal United Hospital, Bath	4.28	0.71
Taunton and Somerset Hospital	4.54	0.53
Royal Bournemouth Hospital	4.83	1.15
Derriford Hospital Level 5, Plymouth	4.96	0.73
Salisbury District Hospital	6.59	0.48
Weymouth and District Hospital	6.62	0.28
Royal Cornwall Hospital, Treliske	6.65	0.65
Gloucester Royal Hospital	7.36	2.15
North Devon District General Hospital	7.76	0.61

2.4.4 CONCLUSION OF MODELLING EXERCISE

The method used to calculate the denominator made very little difference to the rates that we obtained. The impact of trying to account for crow-fly and travel time measures of distance was greater in the Southwest than in the Northwest or the East Midlands and it resulted in marginally higher rates. However, this change to the rates was insubstantial. Using the simple Thiessen polygon approach seems

to be as good in all three regions as using more complex models and has the advantage of requiring us to make fewer assumptions about travel patterns.

Having said that, further research is required in order to determine whether the thresholds that we have chosen to use here are the most appropriate to measure accessibility of clinics. Results in the Southwest, and to some extent the East Midlands, are sensitive to whether a 20 or 30 minute drive time is used and the more complex drive time model may be justified should further studies show that a 20 minute threshold is more representative of the journeys that individuals are actually prepared to make.

But if the primary interest is not the point estimate of the rates but their relative magnitudes, i.e. which areas have relatively higher or lower rates, then the method chosen seems to make little difference. Whilst the point estimates change with the method chosen, the rates at certain clinics remain consistently higher than others regardless of method. For example, on all three methods Gloucester Royal Hospital and Weymouth and District Hospital have substantially higher chlamydia rates than the other clinics in the Southwest.

The rates in the Southwest were found to be much lower than were observed for the Northwest. The East Midlands had a narrower range of rates than either of the other two regions. And in all cases, the rates for gonorrhoea were far lower than those for chlamydia.

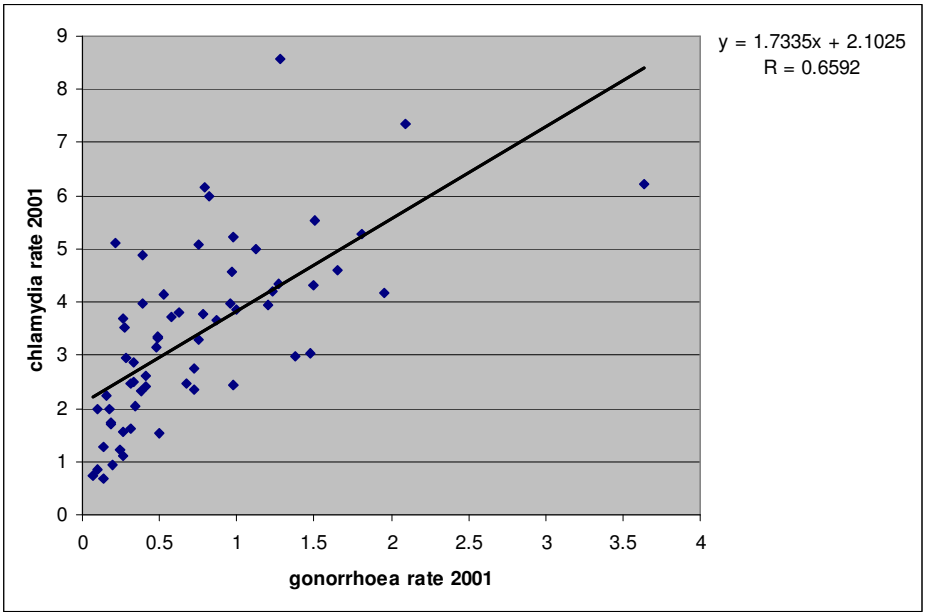
It is possible to compare the chlamydia rates we have calculated with those estimated by the Health Protection Authority for the whole region. Based on our calculations, the average chlamydia rate for the whole Southwest region is 2.67 per 1000 population aged 16-44 years. For the Northwest, the rate is 3.90 per 1000 population aged 16-44 years and for the East Midlands it is 3.64 per 1,000 population aged 16 – 44 years. For the East Midlands, this figure rises to 3.72 if we exclude the 2 clinics for which zero diagnoses were recorded. The Health Protection Authority (HPA) estimates for these regions similarly show the

Southwest rates as lower than those in the Northwest or the East Midlands, with a rate of 1.46 per 1000 for the Northwest and 1.39 in the East Midlands, compared with 1.03 per 1000 for the Southwest (Health Protection Authority, 2005). These rates are calculated using a different exposed to risk, i.e. per 1000 resident population rather than per 1000 population aged 16-44 years. When we recalculated our average rates using the same population exposed to risk as the HPA, we were able to replicate their rates. This is as we would expect as this study uses the same data sources for both the numerator and denominator as the HPA calculations. The only difference is that this study has defined the population exposed to risk differently.

The HPA estimated rate for all of England was 1.38 per 1000 (Health Protection Authority, 2005). Although the Southwest region has much lower rates on average than the rest of the country and the Northwest and East Midlands have somewhat higher rates, this varies considerably by clinic. Further research is needed in order to determine the source of these variations.

It is possible that the source of these variations is the same for both chlamydia and gonorrhoea. Alternatively, as these infections are caused by different bacteria and chlamydia is far more likely to be asymptomatic, it is possible that there may be different or competing explanations. However, in the Northwest there is a strong positive correlation between clinics with high rates of chlamydia and those with high rates of gonorrhoea. Although the relationship is less strong in the Southwest and East Midlands, it is still a moderate positive correlation. Using data from all the clinics, as shown in Figure 2.27, gives a correlation coefficient of 0.66, a sign of strong positive correlation. If clinics tend to have a high rate (or low rate) for both infections, it suggests that there may be a similar underlying reason. Further investigation of this is required.

Figure 2.27 All Northwest, Southwest and East Midlands clinics - Graph of 2001 chlamydia and gonorrhoea rates calculated using Thiessen polygon method



2.4.5 SPATIAL CLUSTERING

In the quartile maps of the rates using the Thiessen polygon approach shown above, there did not seem to be any initial evidence of clustering. Table 2.14 shows the Moran's *I* and p-values for each region. None of the p-values is significant so we can conclude that there is no evidence of spatial autocorrelation for either chlamydia or gonorrhoea rates.

Table 2.14 Spatial autocorrelation statistics

	Chlamydia		Gonorrhoea	
Region	**Moran's *I***	**p-value**	**Moran's *I***	**p-value**
Northwest	0.0510	0.20	0.1004	0.11
East Midlands	-0.1672	0.33	-0.2615	0.16
Southwest	-0.2600	0.12	-0.1924	0.17

2.5 DISCUSSION

This study has shown that it is possible to calculate rates of chlamydia and gonorrhoea infection for individual GUM clinics in the Northwest, East Midlands and Southwest regions of England. Were the data available, it would be possible to extend the methods used here to calculate rates for all UK clinics based on their KC60 returns.

Our calculations were based on the application of three different techniques of varying complexity to derive the population exposed to risk. It was found that the technique selected had little impact on the results and therefore we recommend that future studies use the simplest method of calculation, i.e. the Thiessen polygon approach. This method also has the advantage of requiring us to make fewer assumptions about individuals' travel patterns than the other two methods. This recommendation is especially appropriate if we are mainly interested in identifying areas which are chlamydia or gonorrhoea "hot spots". Although the point estimates of the rates changed depending on the method used, the clinics with higher rates calculated on one method tended to be also have high rates when calculated using the other methods.

However, the drive time model highlighted issues surrounding the accessibility of GUM clinics in the Southwest. Point estimates of the rates in the Southwest region were very sensitive to the drive time threshold used. Approximately 10% of the population lives more than 30 minutes from their nearest clinic and the exclusion of these individuals from the exposed to risk did not affect the rates in a statistically significant way. But if a 20 minute threshold is used, the changes to the rates were much more substantial, as 30% of the population live more than 20 minutes from their nearest clinic. And although the clinics in the East Midlands were highly accessible using the 30 minute measure, a full 18% of the population lived more than 20 minutes from their nearest clinic. We have used the 30 minute threshold in this study, as this threshold has been used in previous research.

However, its selection seems to have little basis in empirical evidence and it seems that further research is required to confirm how individuals access sexual health services.

Regardless of the measure used, there is evidence that individuals in some areas have longer journeys to access health services. Work by Damiani et al. suggested that 15% of the population of England could not access a hospital within 30 minutes of their home (Damiani et al., 2005). The study highlighted longer journey times in the same areas as our study, including Devon, East Anglia and parts of Lincolnshire and Cornwall. Since not all hospitals provide GUM services, it is possible that an even greater proportion of the population is affected than their calculations suggest.

It may be that the perception of remoteness varies by area. People living in especially rural locations in the Southwest of England may be used to travelling long distances to access all kinds of services and therefore the prospect of a 40 or 50 minute journey to reach the GUM clinic might not seem daunting to them. For example, our study has highlighted that access to the Plymouth clinic may be problematic, with many users having to travel more than 30 minutes. But if people living in the areas surrounding Plymouth are used to having to travel more than 30 minutes to get petrol for their cars or to visit their nearest supermarket, then the time taken to get to the clinic might not be off-putting.

A study which assessed the accessibility of a clinic in Plymouth for patients found that 20% of users reported travelling more than 30 minutes to reach the clinic and only 69% reported that they found the clinic location “convenient” (Malu et al., 2003). This suggests that longer travel times are not simply relative and that the time taken to travel to the clinic might be putting off some potential patients. The Southwest Health Protection Authority has observed that, within their region, a large proportion of sexually transmitted disease diagnoses are being made by GPs or in clinical settings other than GUM clinics (Health Protection Authority South West, 2005). They do not venture an explanation for this phenomenon but this

study suggests that one of the reasons may be the difficulties people in this region face in accessing GUM services.

If people are seeking treatment in settings other than GUM clinics, then an important investment may be in ensuring that health practitioners in these settings have received appropriate training to deal with all aspects of sexual health and that they have the time and resources to devote to its detection and treatment. For example, a survey of GPs and nurses in Dyfed Powys, a health authority in rural southwest and central Wales, found that the majority were in favour of further training and support to help them manage the treatment of chlamydia infection properly (Griffiths and Cuddigan, 2002).

Treatment seeking in settings other than GUM clinics has implications not only for health practitioners in these settings but also for the commissioning of services as most decisions are based on data from the KC60 returns. Since these only reflect cases diagnosed in GUM clinics, they may vastly underestimate the burden of sexually transmitted disease in the wider community.

However, the currently available data leave administrators little choice other than to base service allocations and commissions on KC60 data. The Health Protection Authority and the Department of Health are looking at ways of ensuring that data collected about sexually transmitted diseases are more accurate and more readily available. The Common Data Set for Sexual Health (CDSSH) is currently in its second pilot stage (Department of Health, 2007a). Once released, it will provide information on diagnoses from a variety of healthcare settings including both GP surgeries and GUM clinics. It will record patient demographic information, including postcode of residence, and a full sexual history (Department of Health, 2007b).

But as yet, there is no final release date for the CDSSH and it remains unclear who will have access to the data. In the interim, deriving rates calculated using a sound methodology represents the first step in getting more out of the existing

data available from the KC60 returns. Although these data cannot provide information on service settings other than GUM clinics, they do represent the best data currently available and allow us to explore differences in rates of sexually transmitted disease between groups, locations or over time. Moreover for areas such as the Northwest, where accessibility is generally good, the additional call on GP and other services is likely to be limited, making GUM clinic rates a more valid estimate of the true population rates.

Sexual health was highlighted as one of the key target areas in “Choosing Health” White Paper in 2004. Making progress on tackling sexually transmitted diseases will therefore require that we analyse existing data to help us to answer such fundamental questions as “Why are chlamydia (or gonorrhoea) rates higher in some areas than in others?”. Chapter 4 will explore one possible explanation for this, examining correlations between the rates derived here and data on sexual behaviour. Such analyses will assist us in targeting interventions so that they not only reach the locations and individuals who most need them, but also address the underlying reasons for the higher risk to these populations.

2.6 REFERENCES

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3. DEFINING RISKY SEXUAL BEHAVIOUR IN THE UK: A LATENT CLASS APPROACH

ABSTRACT

This chapter aims to define risky sexual behaviour in the UK with respect to the two most common bacterial sexually transmitted diseases: chlamydia and gonorrhoea. Using data from the National Survey of Sexual Attitudes and Lifestyles II, a nationally representative survey of sexual behaviour in Britain, this study aims to identify patterns of behaviours associated with increased disease risk by applying latent class techniques. A three class solution was obtained, splitting the sample into individuals with no sexual partners in the last year (8%), one sexual partner in the last year (71%) and the risky group, who had two or more sexual partners in the last year (21%). The study then explores the prevalence of risky behaviour by ethnic group, age group, sex and marital status.

3.1 INTRODUCTION

In the White Paper "Choosing Health", published in November 2004 (Department of Health, 2004a), the Government highlighted sexual health as one of its key target areas. In an accompanying statement, the then Health Secretary John Reid announced that £130 million would be spent to modernise Genitourinary Medicine clinics, £80 million to roll out a national chlamydia screening program, £50 million on a sexual health advertising campaign aimed at those aged under 25 years and £40 million to upgrade prevention services (Department of Health, 2004b).

Prevention services and advertising will be aimed at the groups that the Government has identified as a particularly "at-risk" due to high incidence of sexually transmitted diseases: young people aged under 25 years and black and ethnic minority populations (Health Protection Agency, 2005). But why are these groups particularly at risk? Is it because their behaviour differs in key ways from other individuals? And are there other groups that are also "at risk" that should be included in targeted campaigns to prevent sexually transmitted disease?

In order to answer these questions, we need to understand which behaviours are risky and how these are distributed in the population. By doing so, we will be able to design more effective public health campaigns. Observational studies can help us to determine which behaviours are associated with increased risk and in which population groups the odds of infection are highest. But it can still be difficult to determine what constitutes risky behaviour. For example, is someone with two partners who never uses condoms behaving in a risky way? What if those partners are not concurrent? Is someone in a new relationship who uses condoms safer? To truly understand what constitutes risky sexual behaviour, it would be useful to explore whether these behaviours cluster together in any particular way. This can be explored in a conventional logistic regression analysis but there is often a high degree of collinearity

among the variables. Moreover, it is often difficult and time-consuming to test for a large number of interactions between variables.

Latent class analysis is a technique that can help to identify groups of individuals who share similar interests, values, characteristics or behaviours (Magidson and Vermunt, 2004a). This study will apply this technique to data from the National Survey of Sexual Attitudes and Lifestyles II (NATSAL II), with the aim of identifying sexual behaviour which puts an individual at risk of contracting a sexually transmitted disease (STD). This information will be used to develop a simple measure of risky sexual behaviour. It may also be used to inform policies aimed at reducing the incidence and prevalence of STDs in the general population.

It has been argued that current behaviour is more relevant to the study of incidence and prevalence rates of bacterial infections than viral infections. "Infections such as gonorrhoeal and chlamydial infection (short duration infections) are in general acquired as a result of recent sexual behaviours whereas infection with HIV and HSV-2 (long duration infections) may be acquired through behaviours that took place decades earlier" (Aral, 2004, p. 10). As NATSAL II is a cross-sectional study which asked individuals about their current behaviours, this chapter will concentrate only on the two most common bacterial sexually transmitted diseases: chlamydia and gonorrhoea.

This chapter therefore aims to define risky sexual behaviour with reference to chlamydia and gonorrhoea.

The study objectives are:

- to review the existing literature on behavioural risk factors associated with the two most commonly diagnosed bacterial STDs (*Chlamydia trachomatis* and *Neisseria gonorrhoeae*) to determine which are associated with increased disease risk in observational studies and which groups within the population have the highest risk of STD infection;

- using latent class analysis, to analyse survey data on sexual behaviour drawn from the general population to determine whether there are clusters of individuals within the data with similar sexual behaviours;
- to use these findings to develop a simple variable to measure risky sexual behaviour with respect to the risk of contracting chlamydia or gonorrhoea infection;
- to determine the prevalence of risky sexual behaviour in key groups within the study population; and
- to explore any implications of these findings for policies targeted at reducing the incidence/prevalence of bacterial STDs in the UK.

3.2 LITERATURE REVIEW

3.2.1 BACKGROUND

Latent class analysis explores how behaviours group together. It does not, however, include any measure of the outcome of which an individual engaging in those behaviours may be at risk. For example, a latent class analysis will not include a variable to measure whether an individual tested positive for chlamydia. So if we are interested in the clustering of behaviours that put an individual at risk of chlamydia infection, we need to identify from the outset which behaviours those are.

For example, two distinct groups may differ in their smoking habits. But if smoking is not a known risk factor for any bacterial STD, then the analysis may not be usefully identifying from the data groups engaging in risky sexual behaviour. However, if further research were to determine that smoking was a key risk factor for STD infection and we had excluded it from our analysis, then our latent class analysis would be missing a key aspect of risky behaviour and our results would probably not be valid.

Epidemiological studies provide quantitative estimates of the levels of risk at which certain behaviours place individuals of contracting a bacterial STD. A review of the literature was undertaken in order to determine which sexual behaviours have been associated with increased risk of STD infection in previous studies and therefore which variables should be included in the latent class analysis.

3.2.2 STUDY SELECTION

3.2.2.1 Study identification

The search was conducted by reviewing the online databases PubMed, Popline, and the Cochrane Collaboration's Controlled Trials Register. Online searches were also carried out using conventional search engines such as Google, Google Scholar, Yahoo!, etc. As relevant papers were identified, their reference lists were reviewed and followed up.

3.2.2.2 Eligibility criteria

- Papers must have been published in English. Unpublished studies were not included.
- Study participants must have been drawn from the general population (i.e. not from specific "at risk" groups such as sex workers, gay men, etc.).
- The study must have considered the odds of disease infection for at least one of the diseases of interest (i.e. *Chlamydia trachomatis* or *Neisseria gonorrhoeae*)
- The outcome measure must have been disease-specific and clearly identified. Different diseases may have different risk factors and the results of the review might be skewed by including results where the outcome measure was not clear.
- The study must have examined the odds of STD infection for one or more behavioural variables.
- Studies must have reported odds ratios and 95% confidence intervals for their estimates or have provided sufficient data to allow these measures to be calculated.

Systematic reviews were eligible for inclusion but only those studies in the reviews which met the above criteria were included.

3.2.3 SELECTED STUDIES

The 24 studies which met the selection criteria are summarised in Tables 3.1 and 3.2 below. This included one systematic review which provided data from a further four studies.

Table 3.1 Epidemiological studies of behavioural risk factors for chlamydia infection

First author and year of publication	Type of study	Study size	Study population
Fenton et al. (2001a)	Cross-sectional	11,161	From NATSAL II
Gershman and Barrow (1996)	Cross-sectional	12,926	Females attending family planning clinics in Colorado
Hart (1992)	Cross-sectional	3,533	Females attending STD clinic in Adelaide, Australia
Hart (1993)	Cross-sectional	7,992	Men attending STD clinic in Adelaide, Australia
Hughes et al. (2000a)	Cross-sectional	18,238	STD clinic patients in London and Sheffield
Jonsson et al. (1995)	Cross-sectional	611	Sample of women living in Umea, Sweden
Latino et al. (2002)	Cross-sectional	3,314	Women in Turin, Italy
Niccolai et al. (2005)	Retrospective	1,455	Medical records from an STD clinic in Connecticut, USA
Radcliffe et al. (2001)	Case-control	1,351	Patients attending STD clinic in Birmingham, UK
Ramstedt et al. (1992)	Cross-sectional	5,274	Women seeking contraceptive advice in Gothenburg, Sweden
Vuylsteke et al. (1999)	Cross-sectional	2,784	Sample of women living in Antwerp, Belgium
Weinstock et al. (1991)	Cross-sectional	1,348	Women seeking contraceptive advice in San Francisco, California
Zenilman et al. (1994)	Cross-sectional	1,155	STD clinic attendees in Baltimore, USA

Table 3.2 Epidemiological studies of behavioural risk factors for gonorrhoea infection

First author and year of publication	Type of study	Study size	Study population
Austin et al. (1984)	Case-control	Not available	STD clinic, USA
Barlow (1977)	Cross-sectional	Not available	STD clinic, UK
Bjekic et al. (1997)	Case-control	800	Hospital patients in Belgrade, Yugoslavia
D'Oro et al. (1994)*	Systematic review	Not available	Not available
Hart (1992)	Cross-sectional	3,533	Females attending STD clinic in Adelaide, Australia
Hart (1993)	Cross-sectional	7,992	Males attending STD clinic in Adelaide, Australia
Hughes et al. (2000a)	Cross-sectional	18,238	STD clinic patients in London and Sheffield
Mertz et al. (2000)	Case-control	307	Male STD clinic patients in Newark, USA
Pemberton et al. (1972)	Cross-sectional	Not available	STD clinic Ireland
Rosenberg et al. (1992)	Retrospective	Not available	STD clinic USA
Upchurch et al. (1990)	Cross-sectional	607	STD clinic patients in Baltimore, Maryland

*Provided data from the following studies: Austin, Barlow, Pemberton, Rosenberg.

3.2.4 RESULTS

Where studies provided results for both males and females, these have been presented separately. This was to explore whether there were important

differences between the sexes with respect to risk factors. If so, the latent class analysis would have to be performed separately for males and females.

It was not considered appropriate to combine the study results and present a meta-analysis as the risk factors measured were not consistently defined across studies (Egger et al., 1997). The definitions used in each study are presented in the appendix to this chapter. The results presented in Figures 3.1 and 3.2 are those following multi-variable regression models, which aimed to control for the possible confounding effects of other variables as well as demographic and socioeconomic factors such as age and socioeconomic status. Not all studies included the same variables in the analysis.

The review found that having multiple partners, not using a condom with all partners and having had a short-term relationship were all associated with increased risk of chlamydia or gonorrhoea infection. The odds of chlamydia infection were also increased in girls who had their first sexual experience before age 16 years. These were the only statistically significant variables found in the majority of studies.

Though several studies noted that the odds of chlamydia or gonorrhoea infection increased if an individual had been previously diagnosed with an STD (Fortenberry et al., 1999; Gunn et al., 2000; Hughes et al., 2000b), no studies presented odds ratios and confidence intervals to quantify this increased risk. A number of studies have also found a high prevalence of reinfection with either chlamydia or gonorrhoea (Burstein et al., 2001; Whittington et al., 2001; Rietmeijer et al., 2002; Mehta et al., 2003). Therefore it seems probably that a previous STD diagnosis is a risk factor for chlamydia or gonorrhoea infection.

Several studies considered whether individuals who drank alcohol were more at risk than those who were non-drinkers. Although odds ratios and confidence intervals were not presented, these studies did not find any significant difference in the odds of infection with either chlamydia or gonorrhoea

(Zenilman et al., 1994; Bjekic et al., 1997; Vuylsteke et al., 1999; Radcliffe et al., 2001).

Only one study considered whether individuals with concurrent partnerships were at higher risk of chlamydia infection and found an increased risk for males (OR = 2.84), though the risk for females was not significant (Fenton et al., 2001a). However, several studies which examined the risk of infection in adolescents, rather than the general population, found that having concurrent partnerships significantly increased the risk of sexually transmitted infections in both males and females (Rosenberg et al., 1999; Kelley et al., 2003). Moreover, in studies of sexual partnership networks and their influence on the incidence of chlamydia and gonorrhoea, the prevalence of concurrent partnerships has been found to be a key factor (Ghani et al., 1997; Potterat et al., 1999)

Figure 3.1 Reported odds of chlamydia infection in the selected studies

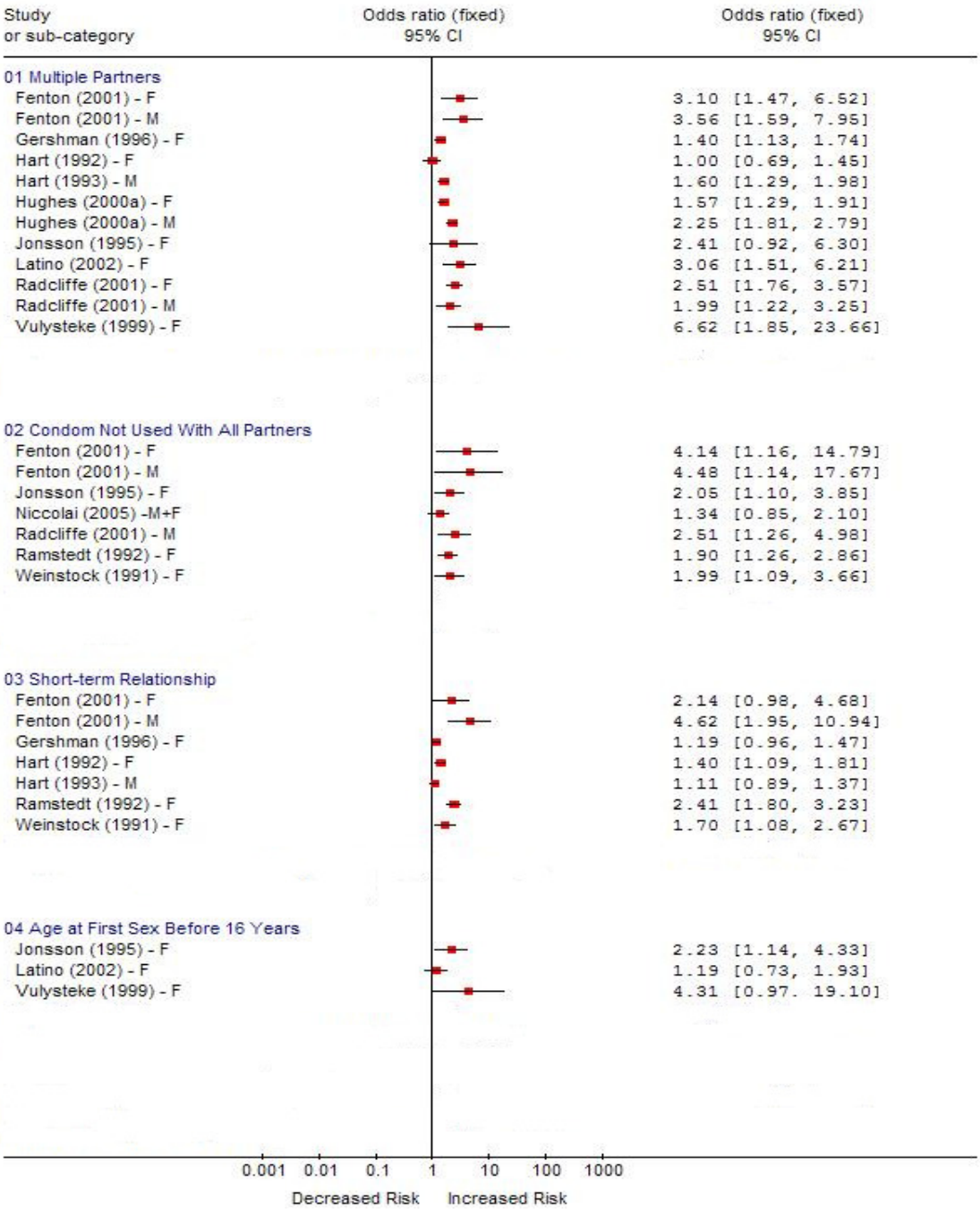
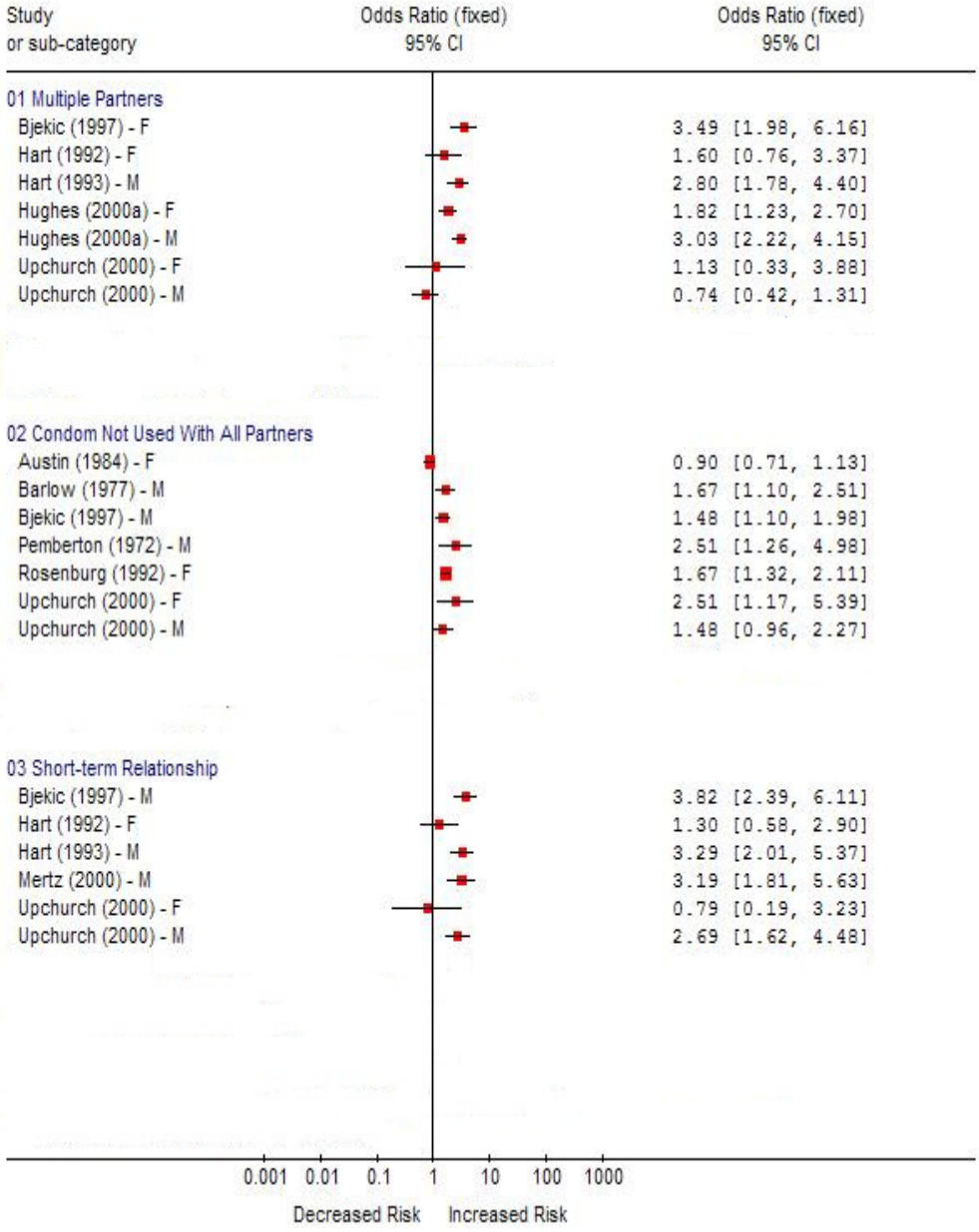


Figure 3.2 Reported odds of gonorrho*ea* infection in the selected studies



3.2.5 CONCLUSIONS

The literature review found the following behavioural risk factors associated with chlamydia and gonorrhoea infection:

- multiple partners,
- short term partnerships,
- non-use of condoms,
- age at first sex before 16 years old,
- previous STD diagnosis, and
- concurrent partnerships

These variables were taken forward and considered for inclusion in the latent class model.

No evidence was found of differences between men and women in terms of the key behavioural variables and therefore the latent class analysis is not run separately for males and females.

3.3 DATA AND METHODOLOGY

3.3.1 DATA SOURCE

The data used in this study were drawn from the National Survey of Sexual Attitudes and Lifestyles II (NATSAL II). NATSAL II is a nationally representative survey of sexual behaviour in Britain. Modelled on the first NATSAL survey conducted in 1990-1991, NATSAL II aims to provide a detailed understanding of the sexual behaviour patterns.

Using a combination of computer assisted personal interview (CAPI) and computer assisted self-interview (CASI), NATSAL II gathered data on sexual attitudes and behaviours from 12,110 individuals aged 16-44 years (11,161 from the general population and 949 from an ethnic minority boost sample) (Erens et al., 2001). Interviews began in May 1999 and were fully completed in February 2001. The general population sample was drawn using a multi-stage stratified probability sampling method. However, it was necessary to oversample in inner and outer London to compensate for predicted lower response rates and because NATSAL I showed a higher prevalence of HIV risk behaviours in London than elsewhere in Britain. It was thought that oversampling these areas would increase the precision of HIV prevalence estimates (Erens et al., 2001).

A sub-sample of individuals was asked to provide a urine sample to test for *Chlamydia trachomitis*. Half of the addresses at all sample points were selected for participation. Only those aged 18-44 years were eligible to participate. Approximately 70% of those asked to provide a urine sample did so, providing a sample of 3,608 individuals (Erens et al., 2001).

The ethnic minority boost sample was also selected using a multi-stage process. To ensure adequate numbers for analysis, selection was based on a combination of full screening and focused enumeration in areas identified in the 1991 census where at least 6% of the population were ethnic minorities (Erens et al., 2001).

Further details of the NATSAL II sampling methodology can be found in the survey's technical report (Erens et al., 2001). A response rate of 63.9% was achieved overall in the general population sample and 59% in the ethnic minority boost sample. This was slightly below the 64.7% response rate for NATSAL I.

The NATSAL II sample was compared with the mid-1999 population estimates on age, sex and Government Office Region. In spite of oversampling in London, London residents were still underrepresented, as were men aged 25-29 years. It was determined that additional weightings were required as these differences might have been due to differential non-response. Following the application of all relevant weightings, the characteristics of the NATSAL II sample closely reflected those of the general population (Erens et al., 2001).

3.3.2 LATENT CLASS ANALYSIS

Sometimes we cannot directly observe the construct in which we are interested. For example, it is unlikely that the direct question "Do you engage in risky sexual behaviour?" would elicit useful responses. However, we can more easily measure variables which we believe are characteristic of risky sexual behaviour. For example, we might expect people with risky sexual behaviour to have more partners, not to use condoms, to have previously had an STD, and so on. We can then frame questions to elicit useable data about these characteristics. Since these observable, or "manifest", variables are caused by the underlying, or "latent" variable, we expect a high degree of covariation among them (McCutcheon, 1987).

Latent class analysis studies the interrelationships between these manifest variables to help us to understand the latent variable. It can help us to identify classes of people who share similar interests, values, characteristics or behaviours (Magidson and Vermunt, 2003). It can also help us to highlight

which behaviours differ between groupings and hence which are key to understanding risky sexual behaviour.

3.3.3 MODEL FORMULATION

The calculations that underlie latent class analysis are based upon the principle of conditional independence, i.e. in a correctly specified latent class model, all the covariation between the observed variables will be explained by the latent variable. Within each latent class that is identified, the manifest variables are all assumed to be statistically independent of one another (Uebersax, 2001).

The latent class model is a simple parametric one. It uses the observed data to estimate two sets of parameters: the conditional response probabilities and the latent class prevalences.

The conditional response probabilities give the probability that in a particular latent class, for a given manifest variable, a randomly selected member of that class will give a particular response (Uebersax, 2001). For example, the conditional response probability tells us the probability that an individual in latent class 1 would have more than one partner. Comparing the response probabilities allows the examination of how latent classes differ from one another. If, for example, there is no difference between the probabilities of condom use between those in latent class 1 and those in latent classes 2 or 3, then condom use is probably not a key differentiating feature between people who engage in risky behaviour and those who do not.

The other parameters, the latent class prevalences, tell us the proportion of the population which falls into each latent class. They tell us how common certain groupings are in the study population.

Using these two sets of parameters, the probability of obtaining a specific response pattern can be expressed as the product of the conditional probabilities and the latent class prevalence. For example, if we have three

manifest variables (or items) A, B and C, then the probability that a person who gave response i to item A, response j to item B and response k to item C will be in latent class t is $\Pi_{ijkt}^{ABCX} = \Pi_{it}^{A|X} . \Pi_{jt}^{B|X} . \Pi_{kt}^{C|X} . \Pi_{t}^{X}$, where X is the latent variable, t indexes the classes of the latent variable X, Π_{t}^{X} is the probability of a randomly selected case being at level t of the latent variable X and $\Pi_{it}^{A|X}$, $\Pi_{jt}^{B|X}$ and $\Pi_{kt}^{C|X}$ are the conditional probabilities of obtaining the ith, jth and kth responses to items A, B and C respectively from members of class t (Magidson and Vermunt, 2004b).

3.3.4 PARAMETER ESTIMATION

The parameters in the latent class model are estimated by the maximum likelihood (ML) method. The ML estimates are the ones that give the highest probability to the observed data. Estimation requires iterative computation, and is usually undertaken using a computer program.

Several methods are available for calculating the ML estimates. The Expectation-Maximization (EM) Algorithm was derived by Goodman (1974). It considerably simplified the process which had previously been achieved through matrix manipulation and the calculation of solutions to simultaneous linear equations (Uebersax, 2001; McCutcheon, 1987). Although it can be slower than some of the more recently developed methods, the EM method is very stable and works well with sparse or incomplete data (Vermunt, 1997). As such, this is the method employed by most available latent class analysis programs including LEM, the program used in this analysis (Vermunt, 1997).

If the likelihood does not have a single global maximum, the results may depend upon the starting value selected. Magidson and Vermunt argue that the best way to proceed in this case is to estimate the model with different sets of random starting values. “Typically, several sets converge to the same highest log-likelihood value, which can then be assumed to be the ML solution” (Magidson and Vermunt, 2004a, p. 5).

3.4 RESULTS

3.4.1 SELECTING MANIFEST VARIABLES

Based on the results of the literature review, six variables were selected from NATSAL II as possible manifest variables for the latent variable “risky sexual behaviour. These variables were checked for association with self-reported incidence of chlamydia and gonorrhoea in the last year in NATSAL II. Because only nine individuals reported a gonorrhoea diagnosis in the last year before the survey, we also considered a diagnosis in the last five years. The p-values for the chi-squared univariate associations are reported in Table 3.3 below, showing that, at the 5% level, all the variables identified by the literature review were associated with both chlamydia and gonorrhoea diagnosis.

The manifest variables were therefore as follows:

- Number of sexual partners in the last year (none, 1, 2, 3-4, 5+)
- Ever previously diagnosed with a sexually transmitted disease, excluding thrush (Yes, No)
- Concurrent relationship in the last year (Yes, No, 2+ Partners but unknown concurrency, not applicable, not answered)
- Number of new sexual partners in the last year (none, 1, 2+)
- Number of sexual partners in the last year with whom a condom was not used (0, 1, 2+)
- First sexual intercourse before age 16 (Yes, No)

Each of these corresponds to one of the variables identified on page 91 as being associated with chlamydia and gonorrhoea infection.

Table 3.3 Univariate association between six possible risk factors and self-reported chlamydia and gonorrhoea diagnosis in last one and five years

Variable	p-value for chlamydia last year	p-value for chlamydia last five years	p-value for gonorrhoea last year	p-value for gonorrhoea last five years
Number of sexual partners in the last year	<0.0001	<0.0001	<0.0001	<0.0001
Ever diagnosed with an STI	<0.0001	<0.0001	<0.0001	<0.0001
Concurrent relationship in the last year	0.0722	<0.0001	0.2943	0.5217
Number of new partners in the last year	0.0003	0.0001	0.0004	0.0066
Number of sexual partners without using a condom	0.0006	<0.0001	0.0051	0.0367
First sexual experience before age 16 years	<0.0001	<0.0001	<0.0001	<0.0001

3.4.2 SELECTING COVARIATES

Some groups within the UK population have a higher observed incidence of chlamydia or gonorrhoea infection than others. In 2005, the Health Protection Agency identified higher incidence of both chlamydia and gonorrhoea in black ethnic minority groups and people under 25 (Health Protection Agency, 2005). Previous studies have also found that Black Africans and Black Caribbeans have higher odds of infection when compared to Whites and Asian groups. Married people have been observed to be less at risk than their single counterparts and younger people have much higher odds of disease than older

age groups (Lacey et al., 1997; Winter et al., 2000; Fenton et al., 2001a; Low et al., 2001; Radcliffe et al., 2001; Fenton et al., 2005). Moreover, the initial analysis of the NATSAL II data indicated a higher prevalence of chlamydia amongst males than females.

These variables are therefore included in the latent class analysis as covariates. By analysing the data for the population stratified by these variables, the latent class analysis can help us to identify any differences in the prevalence of risky behaviour. Recent Health Protection Agency estimates suggest that a third of gonorrhoea infections diagnosed in the UK are in men who have sex with men (Health Protection Agency, 2005). Although this group may be at increased risk of infection, we were unable to include a variable measuring sexual orientation as a covariate. In the NATSAL II sample, only 1% of the population (51 people – 44 male and 7 female) identify themselves as exclusively homosexual. Even if we extend the definition of homosexuality to include individuals who report that they engage primarily (but not exclusively) in relationships with someone of the same sex, we only increase the percentage to 2% of the population. This leaves insufficient data to subdivide into groups as part of the latent class analysis

Table 3.4 summarises the distribution of the sample population by age group and marital status. About half of the single people were in the youngest age group and only 16% were in the oldest group. Marriage, and widowhood, separation and divorce (respondents having experienced one of the last three and not having remarried being combined into a “previously married” group for convenience) are more common in the older age groups. About half of all people who were cohabiting were in the age group 25-34 years.

Table 3.4 Age composition of different marital statuses

Marital status	Age group		
	16-24 years	25-34 years	35-44 years
Married	3.44%	40.54%	56.03%
Cohabiting	19.95%	50.49%	29.55%
Single	50.57%	33.65%	15.79%
Previously Married	2.02%	34.89%	63.09%

NATSALII asked respondents to identify the ethnic group that they consider themselves to belong to. The variable derived from this information identified the following groups: Black, White, Indian, Pakistani, Bangladeshi, Chinese, Other Asian and Other. The Bangladeshi, Chinese and Other Asian groups were too small to be used in further analysis. The Other group was also disregarded as it was unclear what the ethnic origin was of individuals who had been allocated to this group, except that it was not one of the ones listed. We therefore included four ethnic groups in the analysis: Black, White, Indian and Pakistani.

These ethnic group classifications are not without their problems. Firstly, there is no allowance for the possibility of mixed ethnicity, even though this group was estimated in the 2001 UK Census to account for 1.2% of the population and to make up 15% of the ethnic minority population (Lupton and Power, 2004). And secondly, these broad categories can disguise substantial differences. For example, rather than using "Black" as an ethnic group classification, the 2001 Census included as separate categories Black Caribbean, Black African and Other Black group (Office for National Statistics, 2003). Within these groupings there may be important differences with respect to the behaviours and attitudes about which the NATSAL survey wishes to elicit information.

Of course, a balance must be struck between using meaningful categories of ethnicity and creating so many possible groupings that the resulting variable has categories which are all too small to be useful. This is particularly true

within survey work where only a small proportion of the total population will be sampled. Moreover, if we wish to include ethnic group within our analysis, the categories gathered by the NATSAL II survey are the only information available to us. Therefore, we have decided to use the categories available, whilst accepting that there are clear limitations.

The age distributions were fairly similar across all four ethnic groups. The Pakistani group was slightly younger than the others with 25% in the 16-24 year age group, compared with 17-18% of the Indian and Black group and 21% of the White group. The largest age group among Blacks was 35-44 years (44% of Blacks were in this age group); in the other ethnic groups the largest age group was 25-34 years (Table 3.5).

Table 3.5 Distribution of ethnic group by age group

Ethnic group	Age group		
	16-24 years	25-34 years	35-44 years
White	20.82%	40.10%	39.09%
Black	17.74%	38.33%	43.93%
Indian	16.94%	45.18%	37.87%
Pakistani	25.31%	50.61%	24.08%

Unlike the age distribution, the marital status distribution differed substantially between ethnic groups (Table 3.6). The Black group had the highest percentage single (49%) whilst the Pakistani group had the lowest (18%). On the other hand, 61% of Indians and 66% of Pakistanis were married, which was higher than in the other groups, with Blacks having the lowest proportion married at only 28%. Cohabitation was most prevalent amongst the white group (17%) and rare amongst Indians and Pakistanis.

Table 3.6 Distribution of marital status by ethnic group

Ethnic group	Marital Status			
	Married	Cohabiting	Single	Previously married
White	38.57%	16.56%	35.18%	9.69%
Black	28.48%	10.18%	48.61%	12.73%
Indian	61.46%	2.66%	28.90%	6.98%
Pakistani	65.98%	2.46%	18.44%	13.11%

As shown in Table 3.7, the distribution of marital status was fairly similar for both males and females. Males were most likely to be single (46.35%) and whilst females were most likely to be married (39.29%). A similar proportion of both sexes were cohabiting. Females were more likely than males to be married or previously married, though the difference in each case was about 5 percentage points

Table 3.7 Distribution of marital status by sex

Sex	Marital Status			
	Married	Cohabiting	Single	Previously married
Male	33.53%	13.22%	46.35%	6.89%
Female	39.29%	14.99%	34.41%	11.31%

The distribution of ethnic group varied little by sex. The White ethnic group was by far the largest for both sexes at approximately 86% for both.

Table 3.8 Distribution of ethnic group by sex

Sex	Ethnic Group			
	White	Black	Indian	Pakistani
Male	86.01%	7.31%	3.23%	3.45%
Female	86.06%	8.01%	3.16%	2.78%

Males and females also showed a fairly similar age distribution and most participants were aged over 25 years.

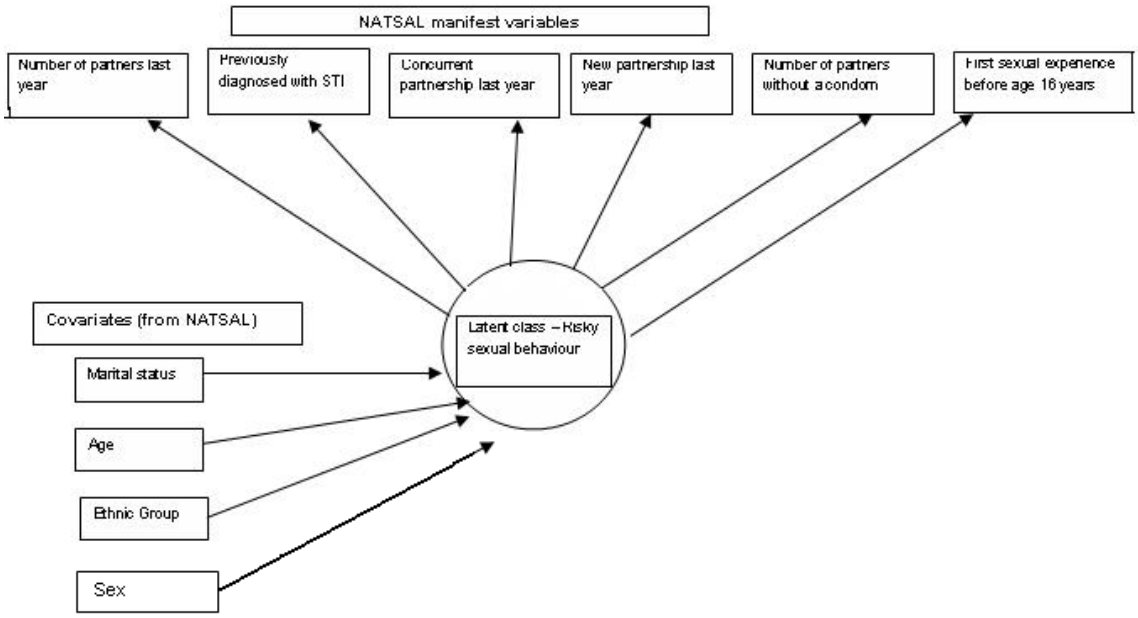
Table 3.9 Distribution of age group by sex

Sex	Age group		
	16-24	25-34	35-44
Male	26.53%	37.50%	35.97%
Female	22.57%	39.59%	37.84%

3.4.3 THE MODEL

The model proposed for latent class analysis is illustrated in Figure 3.3.

Figure 3.3 Latent class analysis model for risky sexual behaviour



Initially a one-class model was fitted and then one extra class was added at a time, considering all elements of model fit, until a suitable model was found. It was decided not to fit more than five classes. One of the aims of this study was

to develop a simple measure which would aid in the understanding and analysis of risky sexual behaviour. If we needed as many or more latent classes than we had manifest variables in order to explain risky sexual behaviour, then it was deemed that the latent class analysis was not helpful and another technique should be considered.

The data were cleaned to eliminate 172 individuals who had not provided any responses to any of the six manifest variables under consideration. Any individuals who had not had a sexual experience at the time of the survey were excluded as they would not have been exposed to the risk of contracting a sexually transmitted disease. This removed a further 706 individuals. The final sample size was 11,232. A further 236 individuals were identified as having given inconsistent answers (or example, they claimed only one partner during the last year but indicated two or more partners without a condom during the same period). The latent class analysis can deal with these inconsistencies and allocates these individuals to the latent class in which they have the highest posterior membership probability (Vermunt, 1997). Therefore no amendments were made to the data for these individuals.

Missing data are assumed to be missing at random. That is, it is assumed that the probability that a response is missing is unrelated to the value of that response (Allison, 2002). For example, some individuals will not report the number of partners that they had in the last year. These data can be viewed as missing at random provided this is not done differentially on the basis of number of partners – e.g. as long as individuals with more partners were not more likely not to answer than people with fewer partners. Although it is possible that in a survey of sexual behaviour values may not be missing at random, we had no information regarding any patterns in missing responses and have therefore assumed that the data are missing at random. In this case, the class allocation is made by calculating the posterior membership probability using the data which are available (Vermunt, 1997).

The program used for the analysis was LEM, developed by JK Vermunt specifically for the analysis of categorical data. The maximum likelihood estimates are computed using the Expectation Maximisation algorithm (Vermunt, 1997).

3.4.4 RESULTS

3.4.4.1 Number of latent classes

There is no single statistical test to determine the number of latent classes a model should have. Selecting the "best" model requires the consideration of statistical measures of model fit and the substantive interpretation of model usefulness. For example, statistical model fit is often improved by adding an additional latent class; but the additional class may not improve our understanding of the characteristics of the underlying variable and may make comparing the conditional response probabilities more difficult (Storr et al., 2004)

The most common methods of selecting a model are as follows:

- comparing the model fit to the observed data using a chi-squared test,
- finding the simplest model using parsimony indices,
- comparing to a baseline model, and
- considering the level of classification error.

3.4.4.1.1 Chi-squared test statistic

Probably the most common and most familiar method of assessing model fit is the likelihood ratio chi-squared test statistic. This compares the observed data to the frequencies expected by the model. The test statistic is taken from the chi-squared distribution with a number of degrees of freedom equal to the number of different response patterns minus the number of estimated parameters. The formula used by LEM to calculate the likelihood ratio test statistic is:

$L^2 = 2\sum_i n_i \log \frac{n_i}{m_i}$, where n_i is the observed cell count and m_i is the expected cell count.

A significant result on the chi-squared test indicates that the model fits the data well (Uebersax, 2001). However, in latent class models with sparse data, the likelihood ratio does not always conform to the chi-squared distribution and the resulting test statistic becomes a less reliable measure (Storr et al., 2004; Magidson and Vermunt, 2004a). As a result, the chi-squared test statistic alone is often not enough.

The p-value for a one-class model, as calculated by LEM, indicated that this model did not fit the data well. However for the two-, three-, four- and five-class solutions, the chi-squared test statistic had a p-value of $p<0.0001$. This means that potentially any of these solutions provide a good fit to the observed data. However, with five manifest variables and several categories of response to each, the data may well have been sparse in some response cells. Therefore, this measure was not considered to be reliable

3.4.4.1.2 Parsimony indices

Instead of looking at the way that the model fits the observed data, we might consider which model (two-class, three-class, etc) can most simply model the data – a sort of mathematical approach to Occam's razor. Adding additional parameters will often improve model fit. However, we wish to balance good fit with model simplicity. Parsimony indices penalise more complex models for their additional parameters whilst taking into account how well the models fit the data. The Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) are two parsimony indices and the relevant formulae are:

BIC = L^2 – degrees of freedom * number of cases

AIC = L^2– 2*degrees of freedom

Models with lower AIC and BIC values are preferred because these indicate a better balance between the number of parameters estimated and the fit to the observed data.

Table 3.10 shows the BIC and AIC values for the models of risky sexual behaviour. The BIC and AIC both fall as additional latent classes are added until we reach four latent classes. As we increase from four to five latent classes, the BIC rises again, though the AIC continues to fall slightly. The parsimony indices suggest that the four-class solution is the simplest and hence most acceptable. However, the change from a three-class model to a four-class model is less than 1%, as it is from a four-class model to a five-class model. Since the differences are so small, it is worthwhile considering other measures of model fit before selecting a model.

Table 3.10 Akaike and Bayesian Information Criteria values for the latent class models

Number of latent classes	AIC	BIC
2	82963	83395
3	75508	76050
4	75238	75890
5	75163	75924

3.4.4.1.3 Comparing to a baseline model

Adding latent classes complicates the model and its interpretation. It is worthwhile only if it adds to our total understanding of the latent variable and helps to explain the total association between the latent and manifest variables. Comparing to a baseline model gives an indication of how much of the total association is explained by adding another latent class. "In covariance structure modelling, a common choice of baseline model is a model imposing independence among the response variables" (Skrondal and Rabe-Hesketh, 2004, p. 270). Since a one-class solution means that all the manifest variables are independent of one another, this is usually chosen as the baseline (Magidson and Vermunt, 2004a).

As shown in Table 3.11 below, moving from two to three latent classes explains an extra 25% of the association. But the addition of a fourth and a fifth latent class adds less than 1% each time.

Table 3.11 Proportion of total association accounted for by the model

Number of latent classes	Percentage of association explained
2	53.4%
3	80.3%
4	81.3%
5	81.7%

3.4.4.1.4 Classification error

When classes are well-differentiated, it is not difficult to determine in which latent class an individual belongs. However, when two or more latent classes have similar response probabilities, it can be difficult to determine where to allocate an individual (Nyland, 2005). For analytical purposes, it is useful to have a model with clearly defined classes and hence a low level of possible misclassification. For a full discussion of how the level of misclassification is determined, see Skrondal and Rabe-Hesketh (2004).

In the two- and three-class models the classification accuracy was very high and thus the classes were well-differentiated. This deteriorated with the addition of further latent classes. Under the four-class model, approximately 15% of people were subject to potential misclassification whilst in the five-class model almost a third may have been incorrectly classified.

Table 3.12 Percentage of the sample correctly classified in each latent class model

Number of latent classes	Percentage of sample correctly classified
2	99.93%
3	99.97%
4	88.75%
5	68.00%

3.4.4.1.5 Conclusion

The parsimony indices seemed to indicate that the four-class model might be the best solution as it is the simplest. However, taking all the measures into account, it was determined that, on balance, a three-class model was preferable. It offered intuitive clarity, allowing us to classify people as “risky” or “faithful” or “alone” (see below). Although it had a slightly higher AIC and BIC than the four-class model, the difference was negligible (about 1%). It also explained approximately the same amount of the total association and had a lower level of classification error. Furthermore, a four-class model did not offer any additional insight into the “risky” group. Rather it further subdivided the “faithful” group based on whether they used condoms with their partner. Whilst this is an interesting insight, it was not deemed to be helpful in furthering our understanding of risky behaviour. Therefore a three-class model was selected.

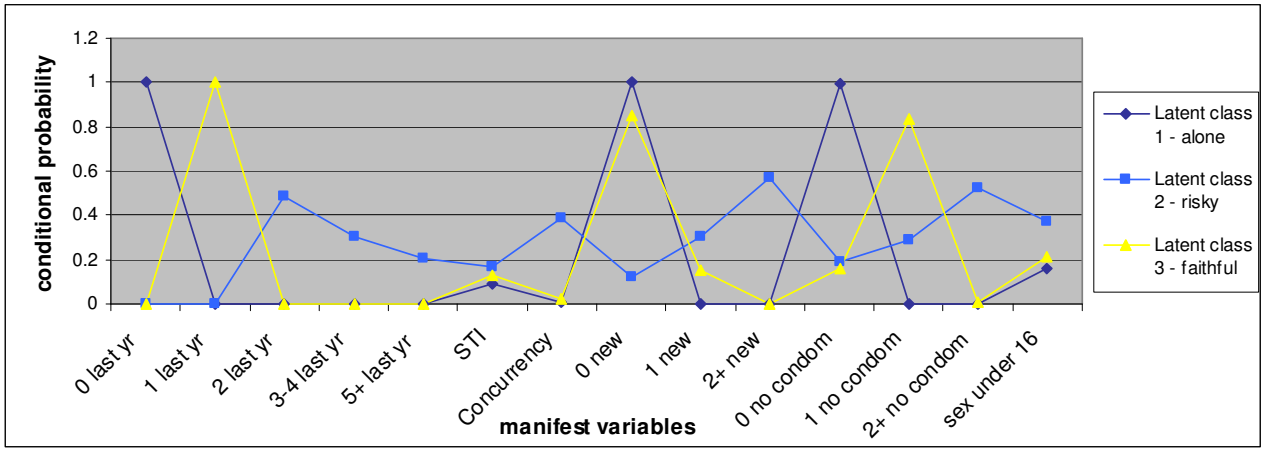
3.4.4.2 Class description

3.4.4.2.1 Three-class model – total population

In the three-class model, 8% of the study population were allocated to latent class one, 21% to latent class two and 71% to latent class three.

Figure 3.4 shows the conditional probabilities based on a positive response to one of the key variables. The full list of conditional probabilities is shown in Table 3.13. By comparing the differences between the conditional probabilities in the three latent classes, we can explore the features of each latent class and how their behaviours differ.

Figure 3.4 Comparison of Latent Class One, Latent Class Two and Latent Class Three on responses to key manifest variables



Number of partners in the last year seems to be the key differentiating feature between the classes. Individuals in latent class one universally had no sexual partners in the last year, although they had been sexually active previously and individuals in latent class three all had one sexual partner in the last year. Individuals in latent class two had at least two sexual partners in this period, with 20.7% claiming five or more partners in the last year.

Since latent class allocation is based on the number of partners in the last year, the conditional probabilities on many of the other variables follow from this result. It is only those individuals in latent class two who have had concurrent partnerships, multiple partners, multiple new partners and multiple partners without a condom. They had the highest rates of previous STD diagnoses, 17%, compared to 13% in latent class three and 9% in latent class one. Furher, 37% of this group had their sexual debut before the age of 16, compared with only 21% in latent class three and 16% in latent class one.

As a result, latent class two has been named the “risky” class. Since latent class one exclusively includes those with no partners over the period, we have named them the “alone” group. Following a similar approach, latent class three has been named the “faithful” group. These names are used in the rest of this chapter for ease of reference.

Table 3.13 Comparison of Latent Classes One, Two and Three on responses to key manifest variables

Variable	Latent Class One (alone)	Latent Class Two (risky)	Latent Class Three (faithful)
Total number of sexual partners last year			
• 0	1.000	0.000	0.000
• 1	0.000	0.001	1.000
• 2	0.000	0.485	0.000
• 3-4	0.000	0.307	0.000
• 5+	0.000	0.207	0.000
Ever diagnosed with an STD (excluding thrush)			
• No	0.906	0.833	0.873
• Yes	0.094	0.168	0.127
Concurrent partnership in last year			
• No	0.002	0.384	0.956
• Yes	0.009	0.388	0.020
• 2+ partners but unknown concurrency	0.000	0.207	0.000
• Not applicable	0.879	0.000	0.000
• Not answered	0.110	0.022	0.025
Number of new partners last year			
• 0	1.000	0.120	0.847
• 1	0.000	0.307	0.153
• 2+	0.000	0.573	0.000
Number of partners without a condom			
• 0	0.994	0.188	0.157
• 1	0.006	0.291	0.832
• 2+	0.000	0.522	0.010
Had sexual intercourse before age 16 years			
• No	0.838	0.632	0.786
• Yes	0.162	0.369	0.214

3.4.4.2.2 Three Class model – stratified by covariates

As Table 3.14 shows, individuals aged under 25 years were more than twice as likely to be allocated to the "risky" group than those in the older age groups. The prevalence of risky behaviour falls as age rises. It is unclear whether this is an age effect (are younger people always more risk-seeking than older people?) or a cohort effect (are younger people now more risk-seeking than young people used to be?). The probability of being allocated to the "faithful" group rises as age increases, as does allocation to the "alone" group, perhaps indicating the rise in divorce and widowhood with age.

The latent class prevalences by marital status are shown in Table 3.15. Single people were most likely to be allocated to the "risky" group with almost 40% in this class. The prevalence of risky behaviour was much lower amongst married and cohabiting individuals (5.7% and 13.1% respectively) perhaps reflecting their more stable partnerships.

Table 3.14 Latent class probability by age

Age group	Probability of being in "alone" class	Probability of being in "risky" class	Probability of being in "faithful" class
16-25 (N=2331)	5.71%	38.35%	55.93%
25-34 (N=4543)	6.44%	20.45%	73.11%
35-44 (N=4358)	9.80%	12.78%	77.41%

The previously married group resembles the single group more than the married or cohabiting groups; 31% of them fell into the "risky" category and previously married individuals who were not allocated to the "risky" group were much more likely than any other group to be "alone".

Table 3.15 Latent class probability by marital status

Marital status*	Probability of being in "alone" class	Probability of being in "risky" class	Probability of being in "faithful" class
Married (N=4,366)	1.12%	5.69%	93.19%
Cohabiting (N=1,703)	0.45%	13.12%	86.43%
Single (N=4,027)	13.99%	38.70%	47.31%
Previously Married (N=1,115)	20.30%	30.90%	48.81%

*The sum of the Ns does not equal 11,232 as 21 individuals did not provide details of their marital status

The latent class prevalences by ethnic group are shown in Table 3.16 below. The highest probability of being in the "risky" class is among the Black ethnic group at 25%, followed by the White ethnic group at 21%. The corresponding probability in the Indian and Pakistani groups is much lower with 14% and 13% respectively. The White group had the lowest probability of being in the "alone" class whilst the Black ethnic group were the least likely to be in the "faithful" class.

Table 3.16 Latent class probability by ethnic group

Ethnic group	Probability of being in "alone" class	Probability of being in "risky" class	Probability of being in "faithful" class
White (N=9,301)	7.03%	21.01%	71.96%
Black (N=826)	11.87%	25.49%	62.63%
Indian (N=301)	10.48%	13.76%	75.76%
Pakistani (N=245)	11.35%	12.64%	76.01%

Finally, table 3.17 shows the latent class prevalences by sex. The prevalence of risky behaviour amongst males is substantially higher than amongst women. Almost double the number of males are likely to engage in risky behaviour

compared to females (28.59% compared to 15.49%). Females and males showed a similar probability of being "alone" (7.92% and 7.11% respectively).

Table 3.17 Latent class probability by sex

Sex	Probability of being in "alone" class	Probability of being in "risky" class	Probability of being in "faithful" class
Male (N=4,745)	7.11%	28.59%	63.59%
Female (N=6,487)	7.92%	15.49%	76.59%

3.4.4.2.3 Standardisation

The results above tell us that the highest prevalence of risky behaviour is found amongst the Black ethnic group, individuals aged 16-24 years, single people and males. However, to isolate the independent effect of age, sex, ethnic group and marital status, we need to control for the possible confounding effects of the other covariates. For example, most individuals aged 16-24 years are single so is the high prevalence of risky behaviour in this age group in part explained by their single status?

Direct standardisation allows us to control for possible confounding effects by comparing the observed prevalence of risky behaviour for a given covariate with the results we would expect if the prevalence were determined purely by the potentially confounding covariates. Using the simple example above, direct standardisation would compare the observed prevalence of risky behaviour in the 16-24 year age group with the prevalence we should expect if risky behaviour in this age group were determined not by age but by marital status only. If the observed value is very close to the expected value, then the prevalence of risky behaviour is largely dependent on marital status, not age.

The standardised results are presented in Table 3.18 below. Whilst married and cohabiting people seem to behave in a way that is less risky than predicted by their age, sex and ethnic group profiles, single and previously married people behave in a way that is more risky. Married and previously married people

have a very similar age, sex and ethnic group distribution so their expected prevalence of risky behaviour is also similar. However, the actual prevalence shows a large gap, indicating that not being married any more has a very large effect on risky behaviour, independent of age and ethnic group effects.

Young people are slightly riskier in their behaviour than we would predict from their marital status, sex and ethnic group profiles, whilst those aged 35-44 years are slightly less risky. Risky behaviour decreases with age even after controlling for the other covariates. This implies that the prevalence of risky behaviour is not just decreasing, for example, because as people get older they are more likely to settle down into stable partnerships. There is a further effect that is related to age, though it is still not clear whether this is a cohort effect or a true age effect.

For the Black and White ethnic groups, the prevalence of risky behaviour is almost exactly as we would predict given their age, sex and marital status profiles. This means that the higher prevalence of risky behaviour amongst Blacks and Whites can be explained by their marital status and age distributions. The Indian and Pakistani groups, however, do show an effect of ethnic group with the actual prevalence of risky behaviour about 5% lower than the prevalence predicted by the age, sex and marital status profiles.

Risky behaviour remains more prevalent amongst males even after controlling for the age, marital status and ethnic group profile of the sample. Whilst females show an actual prevalence of risky behaviour that is almost 5% lower than would be predicted by their age, marital status and ethnic group profiles, males show an actual prevalence that is almost 5% higher than predicted. This suggests that there is an independent effect of being female that is protective, whilst the effect of being male is more risky.

Table 3.18 Standardised and observed percentages in "risky" class

	Percentages expected	Percentages observed
Marital status		
Married	16%	6%
Cohabiting	21%	13%
Single	28%	39%
Previously married	15%	31%
Age group		
16 – 24 years	33%	38%
25 – 34 years	20%	20%
35 – 44 years	16%	13%
Ethnic group		
Black	24%	25%
White	21%	21%
Indian	18%	14%
Pakistani	18%	13%
Sex		
Male	23%	29%
Female	20%	16%

3.4.5 TESTING THE RESULTS – LOGISTIC REGRESSION

The analysis above allows us to conclude that it is not necessary to create a latent variable in order to measure risky behaviour as it can be reliably identified using a single manifest variable - the number of partners in the last year. This one behaviour acts as a marker for a number of other risky behaviours that cluster with it and by knowing how many partners a person has had in the last year, we can determine the probability that they will have engaged in other risky behaviours. It is thus a simple and effective way of identifying individuals who may be putting themselves at increased risk of chlamydia or gonorrhoea infection. Although not everyone identified as engaging in risky behaviour will eventually contract an infection, these individuals should represent the group from which those who do become infected are most likely to have been drawn.

However, as we noted in Section 2, latent class analysis does not include any independent measure of disease risk. Our designation of a particular class as risky is made purely on the basis that this class includes the known risk factors from previous studies. In order to be certain that we have truly identified a marker for the risk infection with either chlamydia or gonorrhoea, we might wish to test how well we can predict an individual's disease status if we know their number of partners in the last year.

NATSAL II included a urine sample to test for chlamydia, which gives us an independent outcome measure. An attempt was made to verify the results using Classification and Regression Tree (CART) analysis, a technique developed by Breiman, Friedman, Olshen and Stone (Breiman et al., 1984). This approach starts from the outcome variable (the chlamydia test result), and partitions the data into subgroups such that each subgroup is as homogeneous as possible. A tree that split the outcome variable for those who had had more than two partners and those who had had fewer than two partners in the last year would confirm that the latent class analysis had identified a good predictive variable for measuring risky behaviour with respect to chlamydia infection.

However, CART does not work well when the outcome is highly skewed (Berk, 2006). In the NATSAL sample, only 2% of individuals tested positive for chlamydia. This means that 98% of the sample can be correctly classified simply by assuming the more common outcome for the whole sample. It will be difficult to find predictive values that reduce heterogeneity by a substantial amount and hence no classification tree can be generated.

We therefore tried an alternative approach, testing the latent class model using a logistic regression model. The chalmydia test results in the NATSAL II data have previously been analysed using a logistic regression model by Fenton et al. and were published in the Lancet in 2001. The results were presented separately for males and females and are reproduced below in Figures 3.5 and

3.6 (Fenton et al., 2001a). The calculations indicated that for males the odds of infection were higher amongst those who reported more than 1 new partner in the last year, a concurrent partnership in the last year, 2 or more sexual partners in the last year or not using a condom with all partners in the last year. For females, having 2 or more sexual partners in the last year or not using a condom with 2 or more sexual partners was associated with higher odds of infection.

Figure 3.5 – Results of analysis of NATSAL II chlamydia urine test result for males by Fenton et al. (2001)

Men	Prevalence (95% CI)	Odds ratio (95% CI)	p‡	Adjusted odds ratio (95% CI)*	p
All respondents†	2·2 (1·5–3·2)	..	..	..	..
Age (years)			0·12		
18–24	2·7 (1·2–5·8)	1·00		..	
25–34	3·0 (1·7–5·1)	1·12 (0·42–2·99)		..	
35–44	1·0 (0·4–2·5)	0·38 (0·11–1·27)		..	
Region			0·78	..	
Rest of Britain	2·1 (1·4–3·3)	1·00		..	..
Greater London	2·5 (0·9–6·3)	1·16 (0·40–3·40)		..	
Marital status			0·06		
Married	0·9 (0·4–2·3)	1·00		..	..
Single	2·4 (1·4–4·4)	2·63 (0·87–7·95)		..	
Cohabiting	3·8 (1·8–7·7)	4·14 (1·24–13·8)		..	
Separated/widowed/divorced	5·4 (1·7–15·7)	6·04 (1·33–27·41)		..	
Social class§			0·88		
I and II	2·2 (1·2–4·2)	1·00		..	..
IIINM	1·6 (0·5–5·5)	0·72 (0·17–3·05)		..	
IIIM	2·8 (1·4–5·2)	1·26 (0·49–3·23)		..	
IV and V	2·2 (0·9–5·1)	0·98 (0·32–2·98)		..	
1+ new partner in the past year			0·0006		0·0005
No	1·0 (0·5–2·0)	1·00		1·00	
Yes	4·6 (2·7–7·5)	4·95 (2·00–12·27)		4·61 (1·94–10·96)	
Concurrent partner in the past year			0·004		0·018
No	1·7 (1·0–2·9)	1·00		1·00	
Yes	6·2 (3·1–11·9)	3·76 (1·52–9·28)		2·84 (1·20–6·76)	
Number of sexual partners in past year			0·001		<0·0001
0–1	1·1 (0·6–2·1)	1·00		1·00	
2–4	4·3 (2·2–8·1)	3·98 (1·55–10·24)		3·57 (1·60–7·96)	
5+	8·7 (3·4–20·6)	8·42 (2·55–27·81)		8·89 (2·89–27·33)	
Number of heterosexual vaginal/anal sex partners without condom in past year			0·0001		0·002
0	0·4 (0·1–1·7)	1·00		1·00	
1	1·7 (1·0–3·0)	4·12 (1·04–16·38)		4·47 (1·14–17·60)	
2+	7·3 (4·2–12·7)	18·72 (3·99–87·75)		15·62 (3·21–76·01)	

Figure 3.6 – Results of analysis of NATSAL II chlamydia urine test result for females by Fenton et al. (2001)

Women	Prevalence (95% CI)	Odds ratio (95% CI)	p‡	Adjusted odds ratio (95% CI)*	p
All respondents†	1·5 (1·1–2·1)	..	..	..	..
Age (years)			0·007		
18–24	3·0 (1·7–5·0)	1·00		..	..
25–34	1·7 (1·0–2·8)	0·57 (0·27–1·20)		..	
35–44	0·6 (0·3–1·4)	0·20 (0·07–0·54)		..	
Region			0·53		
Rest of Britain	1·5 (1·0–2·2)	1·00		..	..
Greater London	1·9 (1·1–3·3)	1·25 (0·62–2·51)		..	
Marital status			0·0002		
Married	0·6 (0·3–1·3)	1·00		..	..
Single	3·6 (2·4–5·4)	6·23 (2·53–15·36)		..	
Cohabiting	1·9 (0·9–4·3)	3·26 (1·04–10·22)		..	
Separated/widowed/divorced	0·6 (0·2–2·5)	1·02 (0·20–5·22)		..	
Social class§			0·90		
I and II	1·5 (0·8–2·9)	1·00		..	..
IIINM	1·7 (1·0–2·8)	1·10 (0·47–2·56)		..	
IIIM	2·0 (0·6–6·9)	1·32 (0·31–5·57)		..	
IV and V	1·2 (0·5–2·8)	0·79 (0·27–2·32)		..	
1+ new partner in the past year			0·0004		0·06
No	0·9 (0·6–1·5)	1·00		1·00	
Yes	3·3 (2·0–5·4)	3·66 (1·79–7·46)		2·14 (0·97–4·72)	
Concurrent partner in the past year			0·22		0·83
No	1·20 (0·8–1·9)	1·00		1·00	
Yes	2·2 (1·0–5·1)	1·85 (0·70–4·89)		1·12 (0·41–3·07)	
Number of sexual partners in past year			<0·0001		0·008
0–1	0·9 (0·6–1·5)	1·00		1·00	
2–4	4·4 (2·6–7·5)	4·90 (2·30–10·44)		3·11 (1·47–6·58)	
5+	4·7 (1·7–12·3)	5·22 (1·64–16·59)		2·94 (0·92–9·40)	
Number of heterosexual vaginal/anal sex partners without condom last year			0·001		0·038
0	1·0 (0·4–2·8)	1·00		1·00	
1	1·4 (0·9–2·1)	1·40 (0·44–4·47)		1·87 (0·52–6·69)	
2+	5·1 (2·8–9·2)	5·45 (1·56–19·03)		4·15 (1·17–14·70)	

The analysis by Fenton et al. uses slightly different categories for the variables than those used in the latent class analysis due to small numbers in some groups. It also does not include information on the odds of infection for two of the variables included in the latent class analysis: whether an individual has ever been diagnosed with an STI and whether their first sexual experience was before the age of 16. It is possible replicate the calculations used in the article in order to provide these figures. Similarly we could calculate the odds of infection for the whole sample rather than for males and females separately. This approach would allow us to quantify the relationship between testing positive for chlamydia and each of the behavioural variables.

However, because of the small sample size, the odds ratios presented in the study are only adjusted for sociodemographic variables because " a fully adjusted logistic regression model was unstable due to the data table being too sparse." (Fenton et al., 2001a, p 1852). Therefore, it is not possible to present the independent effect of a particular behavioural variable after controlling for the effects of the other behavioural variables. The logistic model will not allow us to examine which behavioural variables have the largest independent effect on the outcome, nor to explore the interrelationships between behavioural variables.

It is, however, still possible to test the latent class analysis results using a logistic regression framework. If, as the latent class analysis suggests, number of partners is the key determinant of risky behaviour then a logistic regression model using this as the only explanatory variable should be as good, or nearly as good, at predicting whether a person will test positive for chlamydia as a model into which we introduce all the other risk factors as variables.

The baseline model for comparison is the null model. This is the model only including the outcome variable, the chlamydia test results. It is hypothesised that, based on the results of the latent class analysis, adding the variable "number of partners" to the model should have a substantial effect on the log-likelihood whilst adding additional variables should have relatively little additional impact on the loglikelihood.

The null model has a log-likelihood of -288.7. Adding the total number of partners in the last year to the model significantly increases the log-likelihood to -266.8 and this improvement is significant ($p<0.0001$ in a likelihood ratio test). Adding further variables to the model results in small and insignificant changes to the log-likelihood. These results are consistent with the findings of the latent class analysis. However, adding a variable to measure whether a person has previously been diagnosed with an STD is significant at the 5% level, though not at the 1% level. Due to the difficulties with the small sample size, it is not

possible to include all the variables in the logistic regression analysis simultaneously. However, the modelling exercise suggests that their contribution to explaining the outcome would not be significant. Table 3.19 shows the results of the modelling exercise.

Table 3.19 Results of logistic regression on NATSAL II chlamydia urine test results

Model	Log-likelihood	Likelihood ratio test result comparing to model with number of partners only
Null model	-288.7	
Model with number of partners	-266.8	<0.0001
Model with number of partners and new partnership	-265.9	0.44
Model with number of partners and STD diagnosis	-264.3	0.03
Model with number of partners and concurrency	-266.5	0.74
Model with number of partners and condom use	-264.9	0.16
Model with number of partners and sexual experience before age 16	-266.7	0.65

3.5 DISCUSSION

3.5.1 MAIN FINDINGS

The results of the latent class analysis showed that the key factor in determining whether an individual engages in risky sexual behaviour with respect to the risk of chlamydia and gonorrhoea infection is the number of partners he or she has had in the last year. Approximately 21% of the study population fell into this "risky" category having had two or more partners in the last year (suggesting that risky behaviour is relatively prevalent in the general population), 8% had not had any sexual partners in the last year, whilst 71% had one partner.

On further analysis by age group, risky behaviour was more prevalent in the youngest age group, 16-24 years, than in the older age groups of 25-34 years and 35-44 years. The prevalence of risky behaviour decreased with age from 38% in the youngest group to 20% in the middle group and 13% in the oldest group. This trend remained even after controlling for sex, ethnic group and marital status, although it could not be determined whether this was an age effect or a cohort effect.

Single people had the highest prevalence of risky behaviour (39%) but were closely followed by those who had been previously married (31%). Married and cohabiting individuals were well below the population prevalence of 21% with 6% and 13% respectively. After controlling for the effects of age, sex and ethnic group, this strong effect of marital status remained. Married and cohabiting people had a much lower prevalence of risky behaviour than would be predicted by their age/ethnic group distribution. In contrast, single and previously married people had a much higher prevalence of risky behaviour than their age/ethnic group distribution would predict.

Amongst the four ethnic groups identified in the study, the highest prevalence of risky behaviour was in the Black ethnic group (25%). This was closely followed by the White ethnic group (21%). The prevalence in the Indian and Pakistani groups was much lower, 14% and 13% respectively. The chance of falling into

the “risky” class in the Black and White groups could be predicted almost exactly using their age, sex and marital status distributions. This suggests that for the White and Black ethnic groups, ethnicity may not be a key factor in predicting risky sexual behaviour. For the Indian and Pakistani groups, however, the actual prevalence of risky sexual behaviour was lower than would have been predicted from their age and marital status distributions. For these groups, there may be something about their ethnicity which is protective.

Finally males had a higher prevalence of risky behaviour than females and this persisted even after controlling for the effects of age, marital status and ethnic group. Almost a third of men (29%) were allocated to the “risky” group.

3.5.2 OTHER STUDIES

The literature review presented in Section 3.3 identified a number of studies which had found that having multiple sexual partners was an important risk factor for bacterial STD transmission, although no studies were found which had applied latent class methods to arrive at this conclusion. This study agrees with those results but would actually go further and argue that not only is number of sexual partners in the last year an important variable, it is the key variable in differentiating between those engaging in risky behaviours and those who are far less likely to be engaging in behaviours which place them at risk of infection.

In the primary analysis of the NATSAL I data, Johnson et al.(1994) reported that the highest prevalence of “unsafe sex” was found in the group of widowed, divorced and separated individuals when compared to other marital status groups, with the previously married individuals six times more likely to report unsafe sex than those who are married. They defined having unsafe sex as having two or more partners in the last year but never using a condom in that time. This definition included condom use as a variable, which the results of the latent class analysis do not. However, it arrived at similar conclusions regarding the increased risk of the previously married group.

3.5.3 FURTHER RESEARCH

The aim of this study was to define risky sexual behaviour with reference to chlamydia and gonorrhoea in the UK. An obvious area for further research would be to extend this work to look at risky sexual behaviour in the context of other diseases and other countries. For instance, it might be interesting to explore whether the differences in transmission and duration of viral STDs translate into a different risky behaviour profile to the one that we have found for bacterial STDs. The picture might also look different if we were looking at a country other than the UK. In developing countries where HIV has become endemic, condom use might emerge as far more important than the number of partners.

For this study, data were only available on the behaviour of individual respondents to the survey. However, it might be interesting for another study to explore the effect of partnership networks on STD risk. An individual may be engaging in what they think is safe behaviour because they think that their partner is safe. However, if the partner is engaging in risky sex, then by only measuring the individual's sexual behaviour we would be underestimating their disease risk.

This study seems to highlight a large discrepancy between married and previously married people in the same age group and ethnic group. There seems to be something about not being married anymore which is associated with riskiness. Is it because divorced people suddenly find themselves free and single again? Is it because in their efforts to find a new partner, they feel too unsure of themselves to negotiate safe sex? Or is it their risky behaviour which prompted the divorce in the first place? Qualitative work to explore the effect of the transition from being married to being divorced and its effects on behaviour could shed light on the risky behaviours of a group that has not previously been targeted by interventions to reduce risky behaviour.

It was noted above that although the prevalence of risky behaviour seems to decrease with age, it was not clear whether this was an age or a cohort effect. It is hoped that time series data will become available which will allow further analysis in the future. Another round of NATSAL is planned in 2010 and perhaps that will allow us to begin looking at trends over the 20 years since NATSAL I in 1990.

3.5.4 DATA LIMITATIONS

3.5.4.1 Participation bias

Because sexual behaviour research requires the provision of personal and often intimate information, some people may be more willing to participate in the research than others. This can lead to participation bias if there are systematic differences, for example in age, sex or social class, between those who agree to participate and those who do not (Fenton et al., 2001b).

In NATSAL II there were more female than male respondents, with males in the 25-29 age group particularly under-represented. However, this group generally tend to be under-represented in surveys, and also in the UK census (Office for National Statistics, 2001). Further, in spite of efforts to over-sample for predicted non-response in London, London residents were still under-represented (Erens et al., 2001).

The studies detailed in Section 3 were also subject to participation bias, as the majority of them were carried out in sexually transmitted disease clinics. People will generally attend an STD clinic if they think that they have an STD. Thus this group may have a higher prevalence of risky behaviours than the general population and also may differ in important socio-demographic ways. As a result, the findings might not be representative of the wider target population (Fenton et al., 2001b; Aral, 2004).

3.5.4.2 Item response bias

Even amongst those who agree to participate in a study, not all questions will be answered. Item response bias can arise where the people who choose not to answer a question have risk behaviours which are systematically different from those of the people who elect to answer it (Fenton et al., 2001b).

A detailed study of the NATSAL I responses showed that those who were older, had problems with comprehension and came from certain ethnic groups were more likely to skip the more intimate questions. However, these groups were also more likely to be engaged in lower risk behaviours (Copas et al., 1997).

No study has been done to determine whether, or to what extent, the questions asked in the studies in the literature review suffer from item response bias. Although it is impossible to estimate how they might have been affected by item response bias, it is likely that to some extent they do. Where responses were sought in face to face interviews rather than using questionnaires or CASI, it is possible that there may have been increased bias and a decreased tendency to disclose personal information.

3.5.4.3 Recall bias

Cross-sectional surveys, such as NATSAL II and the studies included in the review, ask people to recall their recent behaviours. The reliability of the responses received can vary between people in important ways. Previous studies have found that the accuracy of recall varied by age, number of partners, ethnicity, number of sexual partners and how far back participants were asked to remember (Fenton et al., 2001b).

A particular problem has been identified in the recall of condom use. Individuals often struggle to recall, except over very short intervals, how often they used a condom with their partners and whether a condom was used with all partners. Questions on condom use triggered the largest numbers of inconsistencies in the NATSAL data, where for example individuals reported no condom use in the

last year but then did report condom use with an individual partner. Zenilman et al. (1995) noted that not only do individuals struggle to recall condom use accurately but they also may only report on "use" rather than "correct use". So condom breakages or slippages, for instance, which would increase STD risk would not be reported and the strength of any association diluted.

3.5.4.4 Publication bias

An additional source of bias in the literature review is publication bias. Researchers who find significant associations are more likely to pursue publication and possibly to be published. Thus it is possible that studies which find increased or decreased risk are not being balanced out by those that indicate no change in the level of risk. This would lead us to believe that there is stronger evidence for an association than may actually be the case.

3.5.4.5 Implications for results

None of these potential forms of bias will affect the response patterns uncovered by the latent class analysis. However, participation and item-response bias might affect the generalisability of the latent class prevalences to the general population if a study was not deemed to be representative.

Every effort was made to reduce participation bias in NATSAL II through methods to increase the response rate. For example, advance letters were sent to all homes, interviewers made repeated calls, and small rewards were offered for participation. Ultimately NATSAL II achieved a response rate of 64% and a sample that was broadly representative of the British population as compared to mid-1999 population estimates.

Methods were also employed in NATSAL II to improve item response rates. As noted in Section 3.3 above, the implementation of CASI improved data quality and reduced the number of skipped questions.

Whilst there is no way to be certain that individuals have accurately reported their past experiences, the survey questions were carefully designed and piloted in order to maximise reliability of responses. NATSAL included 158 internal consistency checks to help researchers assess the reliability of responses received. These checks have shown that respondents tended to complete questions consistently. Around 70% of respondents had no inconsistencies.

Even if a small amount of uncertainty remains about the generalisability of the prevalence estimates or the reliability of the information received, NATSAL II is still an extremely useful tool. It is one of the only sources of information on sexual behaviour designed as a probability sample survey of the general population. Whilst it is important to be aware of any biases that may arise in using it, efforts have been made throughout the design process to address potential sources of bias and issues regarding reliability.

The results of any systematic review are only as good as the studies from which they are drawn. Every effort was made only to select high quality studies published in peer-reviewed journals. Any bias in the original work, however, will have made its way into the results of this review. There was no way to correct for this at the review stage and it must simply be acknowledged that there are some threats to the generalisability and reliability to consider when looking at the results. Similarly, there is no way to predict how or to what extent the review is subject to publication bias.

3.5.5 METHODOLOGICAL LIMITATIONS

As discussed in Section 3.3, a number of weights were applied to the NATSAL study population to control for the under- or over-representation of certain groups. However, it was not possible to apply these weights to the data in the latent class analysis. Although this would not have had an effect on the specification of the classes and the conditional probabilities of class

membership, it might have affected the latent class prevalences, though it is not possible to tell in which direction.

3.5.6 IMPLICATIONS

This study has found that the key to determining whether an individual engages in risky sexual behaviour is the number of partners that he or she has had in the last year. This has important implications for how researchers interested in bacterial STDs conduct future studies.

For some categorical variables, there is a clinical guidance that helps us to decide how to define the categories. For example, hypertension is a diastolic blood pressure reading above 90 mm/hg and a systolic pressure reading of greater than 140 mm/hg (Carretero and Opartil, 2000). The threshold for obesity starts from a Body Mass Index (BMI) of 30, whilst a BMI of 25 or more means a person is overweight (World Health Organisation, 2000). Of course this does not mean that there is no debate about these definitions but they are generally held to be clear guidelines and a study that chooses not to use these measurements will generally justify this decision.

Things are less clear for non-clinical variables. What is a risky number of partners – is it more than one or more than three? Different studies have used different definitions (see Appendix) and this can make comparisons between studies difficult. What the latent class analysis in this study makes clear is that individuals engaging in risky behaviour can be identified as those who have more than one partner in a year. Adopting this definition, as we have done with BMI or blood pressure, could ensure that when researchers talk about risky behaviour, they are all talking about the same measure.

Being able confidently to use this single measure rather than a combination of measures would also make life easier for researchers and participants, ensuring that fewer and less personal sexual behaviour questions have to be asked. Intrusion into personal lives is really only ethical if it adds substantially to our

understanding of risk behaviours. This study suggests that it does not and that by simply asking people “How many sexual partners have you had in the last year?” we can predict their risk of chlamydia and gonorrhoea infection almost as well as if we probed further into condom use, concurrency, etc.

As a measure, any variable is useful only to the extent that it is accurately reported. It may seem to be a key variable in a latent class analysis but if it is not a valid or reliable measure then it is not a useful indicator. Recall of the number of partners in the last year is generally good. “Test-retest” studies have investigated whether people are able consistently to give the same response on different occasions. These have found that a high percentage of people are consistent in their responses about the number of partners they have had, especially if they have had one partner or no partners (Van Duynhoven et al., 1999; Jaccard et al., 2004).

Information on sexual behaviour is useful in clinical practice as well as research. On 27 February 2007, the National Institute for Health and Clinical Excellence (NICE) issued guidance for UK health professionals advising that they identify individuals whose sexual history puts them at increased risk of disease and undertake one-to-one structured discussions aimed at behaviour change (National Institute for Health and Clinical Excellence, 2007).

But GPs and other health professionals do not always find it easy to discuss sexual health with their patients. Gott et al. describe raising such issues as “opening a can of worms” - problematic because of the sensitivity of the issues but also because of constraints on time with each patient (Gott et al., 2004). If taking a full sexual history poses particular problems, then being able to ask only one question, “How many sexual partners have you had in the last year?”, should substantially simplify the process. It can help health professionals to quickly, easily and with minimum embarrassment, identify those individuals who, according to the NICE guidelines, require one-to-one interventions.

The usefulness of this study extends beyond its call to adopt a simple, uniform measure for risky sexual behaviour. It also expands our understanding of the distribution of risky sexual behaviour within key groups, which can in turn inform efforts to reduce STD prevalence or incidence through public policy.

Current Government policy with respect to STDs includes measures to specifically target groups which they have identified as “at risk” especially young people and black and ethnic minority groups (Health Protection Agency, 2005). This study has shown that young people are indeed a key group with a higher prevalence of risky behaviour than their older counterparts.

The story is quite different for Black and ethnic minority groups. The prevalence of risky behaviour in the Black ethnic minority group was slightly higher than in the White group but this prevalence could be predicted by their age and marital status alone. There seems to be no indication that being Black implies riskier behaviour.

However, the National Chlamydia Screening Program and the Gonococcoal Resistance to Antimicrobials Surveillance Programme both found a substantially higher infection rate amongst Black participants than other ethnic groups. (Health Protection Agency, 2005). This study has indicated that a higher prevalence of risky behaviour is not likely to be the explanation, which has important implications for the design of interventions to reduce the infection rate. Considerations besides behaviour change are needed. For example, Laumann and Youm (1999) found that the higher rates of bacterial infections amongst African Americans could be explained by the patterns of sexual networks between different ethnic groups. African Americans who report one or no partners in a year are more likely than White Americans to have had a partner who reported four or more partners in the last year. Rates can also be affected by the prevalence of the disease in the population. With higher case rates, there is a higher probability that one individual in a Black couple is infected (and may not even know it).

The prevalence of risky behaviour was substantially higher amongst males than females. Since risky behaviour is defined based on the number of partners a person has had in the previous year, this finding is consistent with previous studies which have indicated that men consistently report a greater number of sexual partners than women. A detailed study of the responses in NATSAL I found that men reported a higher mean number of sexual partners than women. (Wadsworth et al., 1996). This may be due to a genuine higher prevalence of risky behaviour amongst men.

Alternatively, Wadsworth et al. (1996) found evidence for social acceptability bias. This occurs when society accepts different standards of sexual behaviour for men and women and can lead to differential reporting of the number of sexual partners. It is hypothesised that in the UK context, this leads to under-reporting by women and over-reporting by men (Wadsworth et al., 1996). Women with more than one partner may be revising their response down to one, incorrectly placing them outside the risky category whilst men may be revising their response upward, above one, incorrectly placing themselves in the risky category. It is therefore reassuring that the National Chlamydia Screening Programme provides free testing for both sexes and Government proposals do not distinguish between males and females.

But there is a key group missing from the Government's proposals. This study has identified that previously married individuals have a high prevalence of risky behaviour, as did the initial analysis of NATSAL I (Johnson et al., 1994). With 167,116 divorces in 2004, large numbers of people enter into this group every year and potentially place themselves at risk of an STD (Office for National Statistics, 2005). However, little is known about why this group behaves as it does and further research is needed to inform the design of effective interventions to reduce risky behaviour.

Although number of partners in the last year may be a good indicator with which to identify at risk groups, it may seem a poor one on which to base a public health intervention. A health campaign that encouraged “avoid chlamydia and gonorrhoea: only have one sexual partner each year” would be laughable. Partnership formation and breakdown is largely divorced from disease risk. It is determined by the nature of each relationship and concepts such as love, trust and fidelity. To try to discourage partnership turnover is likely to be an ineffective strategy.

However, awareness of the importance of partnership turnover is useful because it provides a simple way for each person to assess their own risk. For instance, encouraging people who have had more than one partner to get tested for chlamydia and gonorrhoea could be an effective way to reduce disease prevalence. To help reduce incidence, it could target the 52% of people who have more than one partner but do not use condoms to change their behaviour, combining the message on partnership turnover with condom use. Through the media, we receive messages about our health every day and it can be too easy to ignore them. It is not difficult to understand why the Government would prefer to target certain groups, ensuring that the message is marketed to them in the most effective way possible. However, using a single, simple measure, it is possible for everyone to assess their own risk of infection and, in light of this, to decide whether or not to seek testing and/or to make changes to their sexual behaviour.

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Appendix

Table A.1. Definitions of "multiple partners"

Studies	Definition
• ***Chlamydia***	
Fenton (2001a)	2-4 partners in the last year
Gershman (1996)	More than 1 partner in the last 90 days
Hart (1992)	More than 1 partner
Hart (1993)	More than 1 partner
Hughes (2000a)	3+ partners in the last year
Jonsson (1995)	2-3 lifetime partners
Latino (2002)	More than 1 partner in the last 6 months
Radcliffe (2001)	2+ partners in the last year
Vuylsteke (1999)	2+ lifetime partners
• ***Gonorrhoea***	
Bjekic (1997)	3+ partners in the last year
Hart (1992)	More than 1 partner
Hart (1993)	More than 1 partner
Hughes (2000a)	3+ partners in the last year
Upchurch (1990)	2+ partners in last month

Table A.2. Definitions of "short term relationship"

Studies	Definition
• ***Chlamydia***	
Fenton (2001)	1+ new partner in the last 12 months
Gershman (1996)	1+ new partner in the last 90 days
Hart (1992)	1+ partner, but no steady partner, in last 3 months
Hart (1993)	1+ partner, but no steady partner, in last 3 months
Ramstedt (1992)	1+ new partner in last 12 months
Weinstock (1991)	1+ new partner in last 3 months
• ***Gonorrhoea***	
Bjekic (1997)	1+ new partner in the last month
Hart (1992)	1+ partner, but no steady partner, in last 3 months
Hart (1993)	1+ partner, but no steady partner, in last 3 months
Mertz (2000)	Casual partner during preceding month
Upchurch (1990)	1+ new partner in the last month

Table A.3. Definitions of "alcohol consumption"

Studies	Definition
• ***Chlamydia***	
Radcliffe (2001)	More than 5 units of alcohol per week
Vuylsteke (1999)	Drinking at the weekend and several times during the week
Zenilman (1994)	Drank more than 2 times in the last week
• ***Gonorrhoea***	
Bjekic (1997)	Frequent alcohol consumption
Zenilman (1994)	Drank more than 2 times in the last week

4. SMALL AREA ESTIMATES OF RISKY SEXUAL BEHAVIOUR AND THEIR CORRELATION WITH ESTIMATES OF CHLAMYDIA AND GONORRHEOA RATES

Abstract

This chapter aims to explore the relationship between risky sexual behaviour and clinic-level rates of chlamydia and gonorrhoea. Using data from the National Survey of Sexual Attitudes and Lifestyles II and the 2001 Census, the study uses a synthetic regression model to obtain small area estimates of risky sexual behaviour for all English wards. The results of this exercise show that the prevalence of risky behaviour is higher in urban areas and prevalence can be predicted by using the proportion of single individuals as a proxy measure.

The small area estimates are then compared with the estimated rates of chlamydia and gonorrhoea calculated in Chapter 2. There is a positive correlation for both infections but far stronger for gonorrhoea than chlamydia ($r=0.70$ and $r=0.41$ respectively). This suggests that although variations in the prevalence of risky sexual behaviour can help to explain some of the variation in the observed rates of chlamydia and gonorrhoea, further research is required in order to explore other possible sources of variation.

4.1 INTRODUCTION

Chlamydia and gonorrhoea infection are on the rise in the United Kingdom. Between 1998 and 2007, chlamydia infections rose by 150% and gonorrhoea infections by 42% (Health Protection Agency, 2008a). By 2002, more sexually transmitted infections were being diagnosed each year than at any time since the National Health Service began in 1948 (Terrence Higgins Trust, 2002). Consequently, in the 2004 "Choosing Health" White Paper, the Government made sexual health one of the five key areas it targeted for improvement. In this paper, it indicated that it believed there to be a link between the rise in sexually transmitted diseases and the observation that "sexual risk-taking behaviour is increasing across the population". (Department of Health, 2004b, p. 1)

John Reid, then the Health Secretary, pledged £50 million for advertising aimed at behaviour change saying, "We will run an advertising campaign which tells people, especially young people, of the consequences of irresponsible sexual behaviour and of sexually transmitted disease." (BBC, 2004) In 2006, the £4 million "Essential Wear" campaign was first aired. Its aim was, in the words of the Public Health Minister Caroline Flint, "to make carrying and using a condom among this age group (16-25 years) as familiar as carrying a mobile phone, lipstick or putting on a seatbelt." (Department of Health, 2006a).

It seems that the Government regards changing individuals' sexual behaviour as a vital part of reducing the headline sexually transmitted disease rates. Specifically, they have targeted an increase in condom usage due to its association with decreased risk of disease transmission (Warner et al., 2006). The second chapter in this thesis found that failure to use condoms with all partners was one element of risky behaviour but that individuals at risk within the general population could be better identified by the number of partners that they had had in the previous year. Those with multiple partners were more likely to be engaging in other forms of risky behaviour as well, such as having concurrent partnerships and not using condoms with all partners. It is

possible, therefore, that campaigns aimed at increasing condom use alone will not achieve the desired effect unless they manage to motivate consistent, correct condom use amongst those individuals who have multiple partners. Even more effective might be a campaign targeted specifically at changing the behaviour of those who have multiple partners.

But regardless of how "risky" sexual behaviour is defined, behaviour modification programs aimed at reducing the incidence of disease in the population are predicated upon the assumption that the incidence of disease in the population is highly correlated with the prevalence of risky behaviour. If this is true then reducing risky behaviour should lead to the desired reduction in disease incidence. However, if this is not the case, then reducing risky behaviour will have little impact on the population incidence and it is unlikely that these education campaigns will be judged money well spent.

It seems intuitive that individual risky behaviour should be related to individual risk of contracting a disease. Further, as we saw in the Chapter 3, it is possible to identify certain types of behaviour that place an individual at greater risk of contracting a disease. Since a population is made up of individuals, it would also seem reasonable to suggest that the population prevalence of disease is related to the population prevalence of risky behaviour. In Chapter 2, we observed variations in the rates of chlamydia and gonorrhoea diagnosed at clinics in the Northwest and Southwest of England. If this argument is true then the difference between clinics with high rates and those with low rates should be partly explained by differences in the prevalence of risky behaviour in their catchment areas. Areas with high levels of risky behaviour should see correspondingly higher rates of chlamydia and gonorrhoea than areas with low levels of risky behaviour.

However, as Geoffrey Rose observed in his highly influential article "Sick Individuals and Sick Populations", the causes of cases may not be he same as the causes of population incidence (Rose, 1985). He wrote, " 'Why do some individuals have hypertension?' is quite a different question from 'Why

do some populations have much hypertension, whilst in others it is rare?' The questions require different kinds of study, and they have different answers."

If Rose is right, then we need to consider other possible explanations that might affect populations rather than individuals. In this we are assisted by the literature on the mathematical modelling of disease. "The central role of mathematical models in the study of epidemiology and control of sexually transmitted diseases is to further knowledge of the interplay between the variables that determine the typical course of infection within an individual, and those that determine the pattern of infection in the community." (Anderson et al., 2000).

Both chlamydia and gonorrhoea are infectious diseases that are transmitted almost exclusively through sexual contact. Although antibiotic treatment is highly effective in most cases, it does not confer immunity. Thus in a given population, individuals may be either currently infected or susceptible to infection. The prevalence of the disease in the population will be determined by the average number of susceptible individuals to whom each infected person manages to transmit the disease. This is itself a function of a number of biological and behavioural factors.

Firstly, there is the probability of transmission. Within each partnership there is a probability of transmission from one partner to another. For example, the probability of a woman transmitting gonorrhoea to a male partner during a single sexual contact is estimated to be between 0.2 and 0.3. In contrast, the probability of transmission from a male partner to a female partner is 0.5 to 0.7 (Heathcote and Yorke, 1984). Thus a male partner is more than twice as like to infect a female partner than the other way around. However, it is unlikely that this transmission probability varies much across the UK and thus it is of little help in understanding regional variations.

Secondly, there is the mean duration of infection. The longer that someone is infected, the more opportunity they will have to pass it on. Thus the more quickly an individual seeks and receives treatment, the fewer other individuals

he or she will be able to infect. Whilst symptomatic individuals are likely to seek treatment shortly after noticing symptoms, asymptomatic individuals may infect many partners before finally being diagnosed and treated. Thus the mean duration of infection can affect the regional prevalence in several ways. There might be regional differences in the time taken to access treatment after noticing symptoms. Detecting and treating asymptomatic individuals is harder. Some GPs or health regions may take a more proactive approach in encouraging individuals to get tested. This may increase the recorded incidence of the disease as more individuals will be diagnosed. However, it may simultaneously decrease the overall incidence in the population as asymptomatic individuals will have their infections detected and treated before they manage to infect a large number of partners.

Finally, there is the average rate of sexual partner change. Not everyone has the same risk of acquiring or passing on a sexually transmitted disease, and individuals with a greater number of partners have a greater risk. However, the type of partnership is also important. In a population where all individuals are mutually monogamous, any sexually transmitted infection will eventually die out because it cannot be passed on, i.e. there is no contact between the infected and the susceptible populations. Where at least one individual in each relationship is monogamous, the infection can be transmitted but it will not be passed on. So if one non-monogamous person has hundreds of partners, they can infect hundreds of people. However, provided these partners have no other partners, the disease cannot be passed on further. Thus the conduit for sexually transmitted diseases to spread in the population must be where there are mutually non-monogamous pairs. The way in which individuals interact in sexual networks is therefore key to understanding how sexually transmitted diseases spread within a population.

Thus we have a number of possible determinants of population prevalence, of which individual risky behaviour is only one. Ideally, this chapter would explore all of these competing measures and determine the extent to which they explain the regional variations in the rates of chlamydia and gonorrhoea that we observed in Chapter 2. Unfortunately, the data are only available to

explore one aspect, i.e. the relationship with risky sexual behaviour as defined in Chapter 3. If a strong relationship is found, then this lends support to the Government's programs aimed at individual behaviour change. If not, it suggests that attention should perhaps be directed elsewhere in the fight to reduce sexually transmitted disease prevalence.

The objectives of this study are:

- To calculate estimates of risky sexual behaviour at ward level for all regions of the UK
- To aggregate the ward-level estimates to correspond with the areas surrounding each clinic for which we have an estimate of the chlamydia and gonorrhoea rate
- To determine the level of correlation between the estimates of risky behaviour and the estimates of the STD rates for the areas surrounding each clinic

4.2 METHODS

4.2.1 DATA

As in Chapter 3 of this thesis, we will be using data from the National Survey of Sexual Attitudes and Lifestyles II (NATSAL II), a nationally representative survey of sexual behaviour in Britain (Erens et al., 2001).

4.2.1.1 Risky behaviour

In Chapter 3, we explored the NATSAL II data to determine how best to define "risky sexual behaviour" in the UK context. The latent class model indicated that the best measure was one based on the number of partners an individual had had in the preceding 12 months. Those individuals who had had more than one partner were deemed to have engaged in risky behaviour with respect to chlamydia and gonorrhoea infection. This result will be used throughout this chapter to define risky behaviour.

4.2.1.2 Rates of infection at clinic level

In Chapter 2, we derived rates of chlamydia and gonorrhoea infection for clinic catchment areas in the Northwest and Southwest of England. These rates will be used in this study as the outcome variable in a regression model with risky behaviour estimates for these same catchment areas as the independent variable. This will allow us to explore whether a correlation exists between the two.

4.2.1.3 Census

In this study we will also use data from the 2001 UK Census. Although only a limited number of questions can be asked, the Census provides the most complete information about the UK population available. Cross tabulations and counts of individuals who fall into particular sociodemographic groups have been provided by the Office for National Statistics as part of their Key Statistics and Standard Tables series.

We will be using the smallest geographical unit for which much of these data are available: the "standard table" ward. These are the electoral wards as set out on 31 December 2002 (when the Census statistics were being produced).

Wards with fewer than 1000 individuals or 400 households have been merged to ensure confidentiality. This affects 113 wards in England and Wales. Our analysis will be restricted to England, where there are 7,932 standard table wards (Office for National Statistics, 2008).

4.2.2 SMALL AREA ESTIMATION

4.2.2.1 Direct estimators

To estimate the national level prevalence of risky behaviour is relatively straightforward because NATSAL was designed to give representative estimates at the national level. We simply calculate the proportion of individuals who have had more than one partner in the last year. Because individuals in the sample had unequal selection probabilities, we ensure that we apply the relevant design weights to the data. This direct estimate, often called a Horvitz-Thompson estimator, is simple to calculate and theoretically unbiased, since the expected value of the estimate for each small area is equal to the true population value (Brakel and Bethlehem, 2008).

However, direct estimates become less reliable when we try to estimate proportions for smaller geographic areas, such as wards or local authorities. This is because the survey was not designed to produce accurate or efficient estimates at this level. NATSAL has only 12,000 respondents, which means that many areas will contain only a few individuals. Trying to calculate a direct estimate from one or two people would lead to unreliable results with a very high variance.

Moreover, due to the clustered sample design, many small areas will not have been selected for the sample and will contain no observations. For these areas it will be impossible to calculate any direct estimates. Overall, only 466 postcode sectors out of the 9650 UK postcode sectors were selected as primary sampling units (Erens et al., 2001). Therefore, NATSAL includes only about 5% of areas.

This problem is not unique to NATSAL. Budget and other constraints often prevent the allocation of large enough samples to small areas, or the domains

of interest are frequently specified after the fact (Pfefferman, 2002). As a result, a number of methods exist to allow estimates to be made for smaller areas by combining survey data with other data sources, such as the census. These have been applied to a number of surveys in the UK already. For example, Office for National Statistics (ONS) produce small area estimates for the General Household Survey, in which only 3% of postcode sectors are sampled. The National Centre for Social Research has similarly produced estimates for the Health Survey for England, which also has a clustered survey design (Bajekal et al., 2004).

4.2.2.2 The generalised regression estimator (GREG)

The GREG attempts to combine information directly from the sample with aggregated data from another source in order to improve the sample estimates. The direct survey estimates are adjusted based on known differences between the survey estimates and estimates available from auxiliary data (Bajekal et al., 2004). For example, if we know that age is a good predictor of smoking, and we know that age in a particular ward is higher than average, then we would adjust the smoking estimate upwards to account for this difference.

This method should be more accurate than using the direct estimator alone because it makes use both of what we know about the relationship between the outcome and the predictor variables and the information that we have from auxiliary data sources about the predictor variables (Heady et al., 2003).

However, the GREG still requires that we have a sample within every small area. Often this assumption is relaxed and it is assumed that in areas where the sample is too small, the mean for that area is equal to the mean for the whole study sample (Saei and Chambers, 2003). But even if we were to make this assumption, there is an additional problem with applying this method to NATSAL II data. In order to link the direct data for the small area in the survey to the auxiliary data in, for example, the Census, we need to be able to uniquely identify each small area. In order to know whether the age for a particular ward is above the average, we need to know which ward we

are looking at. This is not possible within NATSAL II. Although there are 466 sampled postcode sectors, for confidentiality reasons no information is made available to allow these sectors to be identified or linked to other data sources.

4.2.2.3 Indirect standardisation

Instead of using the NATSAL II data to derive direct estimates for small areas, it is possible to use it to produce estimates for larger areas and refine these estimates for smaller areas using auxiliary information. There are a number of methods that allow us to do this, the simplest of which is indirect standardisation. This would entail deriving a national estimate of risky behaviour for different groups of individuals and then applying this estimate to area-level population counts from the Census. For example, if 5% of married men aged 25-34 in the NATSAL sample engaged in risky behaviour, and there are 1000 married men aged 24-35 in ward A, then our estimate of the prevalence of risky behaviour for this subgroup would be 5% x 1000 = 50. Summing across all age, sex and marital status groups would give us a total estimated prevalence of risky behaviour for Ward A. This can then be repeated for all other wards. "Essentially, therefore, the national prevalence rates for each sub-group are weighted by the proportion of persons in that sub-group in the small area" (Pickering et al., 2004, p 6).

In addition to being straightforward to calculate, this approach is intuitively appealing. "It seems likely that the mean level of many variables in a population is likely to be highly related to the distribution of the population by such demographic variables as age, sex, race, income, residence, etc., which are the variables generally used in obtaining [indirect] estimates" (Levy, 1979, p 10). Moreover, both the estimates of the national level prevalence and the numbers in each subgroup are generally obtained from large samples, which are likely to have small sampling variances. This means that the overall estimate is also likely to have a relatively small variance (Levy, 1979).

But this approach assumes that the national level rates apply uniformly across small areas. In other words, we assume that any differences in the estimates

that we observe between areas are due solely to their different sociodemographic profiles. If two areas have the same sociodemographic profile, then they would have the same predicted prevalence of risky behaviour using this method. Previous research has shown that health behaviours are complex and may include variables that are measured at the area level as well as the individual level (Von Korff et al. 1992, Macintyre et al. 2002, Kawachi and Berkman, 2003). It is difficult to incorporate into indirect standardisation the techniques that allow us to adjust for area-level clustering that is a feature of many study designs, including NATSAL II.

4.2.2.4 Synthetic regression model

It is often easier to incorporate the clustered survey design within a regression modelling framework. But moving from a standardisation approach to a regression approach does not change the basic steps in our calculations. We will still be generating national level estimates and applying these estimates to census counts of the small area population. With indirect standardisation, the national level estimates were the proportions engaging in risky behaviour in specified subgroups. For a synthetic regression model, the estimates will be the coefficients from the regression equation. Before any weights are applied, if the same variables are used in the synthetic regression model as in an indirect standardisation, the same answer will be obtained. The advantage of the synthetic regression model is that the regression framework makes it easier to include more variables and to apply survey and sample weights.

The outcome variable is binary – an individual is "risky" if they have two partners or more in the last year and "not risky" if they have had one or zero partners. Therefore, a logistic regression model can be used to predict the probability that an individual engages in risky behaviour based on their characteristics using the equation :

Logit (probability of risky behaviour) = constant + β(sex) + β(age group) + β(marital status)

The coefficients from the model can then be applied to small area counts from the Census much in the same way as in the indirect standardisation approach.

It is always important to have a well specified regression model. We obviously want the independent variables to predict the dependent variable as well as possible. However, this is particularly important in small area estimation because our synthetic estimates are known to be prone to bias. We are trying to predict prevalence in a small area based on a relationship modelled at the national level. If that relationship varies widely at the small area level, then our estimates will be highly biased.

This problem can be illustrated from one of the earlier examples of small area estimation. In 1971, a study by Levy found that synthetic estimates of death rates from cardiovascular renal disease based only on age, race and sex were good predictors of the true death rates but that using the same covariates to predict motor vehicle accident death rates led to very poor predictions of the true rates (Levy, 1971). This is because age, race and sex are important risk factors for cardiovascular renal death but not for motor vehicle death. Where the regression model fails to capture and correctly specify the relationship between all the variables which are related to the parameter of interest, the estimates are likely to be prone to substantial bias (Koch, 1979). In contrast, a regression model that correctly captures the relationship between the dependent and independent variables is more likely to be unbiased regardless of the area of interest. This does not mean that a well specified model removes the possibility of large biases, merely that it reduces the likelihood of their occurring.

Ordinarily, specifying an appropriate logistic regression model would be relatively straightforward. Through stepwise regression we would examine those independent variables associated with the dependent variable and retain in the model those independent variables that significantly improve model fit. The challenge in our calculations is that we are severely limited in the range of variables that can be included in the regression model by the availability of data from the Census. For example, including information on sexual orientation might substantially improve the fit of the regression model,

but if we cannot obtain this information from the Census, then we cannot apply the coefficient for sexual orientation to a Census count.

Census cross-tabulations are only produced at ward level (the smallest available area) for a maximum of three variables. The regression model that we produce will therefore be fairly limited; in fact, it will not be much different from what we could produce with an indirect standardisation, apart from applying the appropriate weights to control for the clustered design of NATSAL II. If three variables are sufficient to generate a fairly robust model, then this is not a cause for concern. We therefore must scrutinise the model fit diagnostics very carefully. If it is not possible to specify a model that adequately represents the relationship between the dependent and independent variables within the limitations posed by the Census data, then it may not be possible to produce small area estimates that are fit for use.

4.2.2.5 The "Twigg" model and area level variables

In a paper published in 2000 in *Social Science and Medicine*, Liz Twigg, Graham Moon and Kelvyn Jones set out a synthetic regression model which incorporated not only individual level variables but also those measured at the health authority level (Twigg et al., 2000). The authors argued that health behaviours are predicted not only by individual characteristics but also ecological or area level factors. This is done by explicitly including area level variable in a multi-level modelling framework, rather than merely adjusting for clustering at the area level within a synthetic regression model. Although the modelling process is more complex than the standard synthetic regression model, if the authors are correct in their assumption regarding the importance of area level factors, the resulting small area predictors should be more accurate.

The literature has suggested a number of individual behaviours on which ecological variables appear to have an effect. With respect to smoking, for example, a number of studies have indicated that area-level deprivation remains a strong predictor of individual smoking status even after taking into account a number of individual characteristics (Kleinschmidt et al., 1995;

Duncan et al., 1998; Rejineveld S, 1998). These studies suggest that individuals in more deprived areas have a higher probability of being a smoker than would be expected purely based on their individual characteristics. The failure to include a measure of area-level deprivation in the calculation of small area estimates of smoking prevalence would lead to less accurate estimates. Similarly, we might review the literature to determine area level variables that have been consistently shown to be independently associated with individual risky sexual behaviour and include these in our model.

However, there are several problems using the NATSAL data to obtain area level variables. We could derive the variables directly from individual level survey responses by aggregating these responses to the area level at which it is believed that the effect operates. However, if the area is relatively small such as a Primary Sampling Unit (PSU) or ward, the estimate obtained would be subject to large biases. For example, there are only two individuals in PSU 47. One of these individuals might fall into the fourth quintile of the index of multiple deprivation whilst the other might be in the second quintile. So our estimate for the area might be that it falls into the third quintile. But clearly an estimate derived from a sample of two is likely to be highly inaccurate. Only in areas with large sample sizes would we be willing to trust these deprivation estimates. However, these are precisely the areas for which direct estimates of risky behaviour are also likely to be reliable.

Deprivation is often measured directly at the area level and scores for wards and other geographical areas could instead be obtained from auxiliary data sources rather than attempting to obtain some sort of mean score for the area from the individual survey responses. We are limited in this approach as we cannot identify the NATSAL PSUs for confidentiality reasons and thus cannot link them to external data sources. But we could use a higher level of aggregation than the PSU. In their study Twigg et al. use health authority areas. NATSAL provides data on Government Office Region (GOR) and it would certainly be possible to link these to external data sources to obtain a measure of deprivation or some other area level variable in which we were interested.

However, GORs represent quite large areas, such as the Northwest or West Midlands, and for most variables there is little variation across GORs so including the area level variable in the model is unlikely to add much. Moreover, it is difficult to see how the level of deprivation across a whole region might affect individual behaviour.

4.2.2.6 Composite estimators

Earlier we rejected the use of direct estimators because they are unreliable for small areas with relatively few or no survey respondents. Although theoretically unbiased, direct estimators can have very large variances. The opposite is true for synthetic estimators – using the full dataset to derive the estimates keeps the variance small but the bias may be large. Ideally, we would like to draw from the strength of both these types of estimators.

A composite estimator is one that aims to achieve a balance between the two approaches by taking a weighted average. The weights are defined such that if the sample size is large, more weight is given to the direct estimator. Further, in areas where the sample is too small to be reliable, more weight is given to the synthetic estimator (Schaible, 1979).

However, much like the problems encountered with the GREG described in section 4.2.2.2, because NATSAL does not provide information on the residence of respondents, it is not possible to identify auxiliary information for those areas where synthetic estimates might be more suitable. Therefore it is not possible to produce composite estimators.

4.2.2.7 Evaluating bias

All of the methods described above will produce ward level estimates of the prevalence of risky behaviour. But as discussed, many cannot be applied in this instance due to data limitations. As a result, this study will use a synthetic regression model with three individual level variables, in accordance with the limitations imposed by the Census data, and controlling for the clustered nature of the survey. With only three variables, an indirect standardisation

model would be able to produce the same results but would make it more difficult to control for the clustering within the design of NATSAL II.

Since we are forced by the nature of the NATSAL data to use a synthetic regression model if we wish to produce small area estimates, and since these estimates can suffer from bias, we must attempt to assess the validity of any estimates that we produce. A number of validation checks were proposed by Brown et al. (2001).

Direct survey estimates may be unreliable in some small areas but they are largely unbiased. To test whether the same is true of our synthetic regression estimate, we could plot them on the *x*-axis and the direct estimates on the *y*-axis. An ordinary least squares regression line is then fitted to the scatter plot. If the model predictions are unbiased, we would expect the slope of the line to be not significantly different from one (Australian Bureau of Statistics, 2006).

However, in our case it is impossible to carry out this diagnostic. As noted above, we cannot match direct and synthetic estimates due to the lack of identifiers in the NATSAL dataset. Moreover, even if we could identify small areas to carry out the comparison, the direct estimates for many small areas would be unreliable because of the very small sample sizes involved (Australian Bureau of Statistics, 2006).

Another way of assessing the small area estimates is to determine the extent to which they sum to direct estimates for appropriate levels of aggregation. Because the sample sizes are larger for higher levels of aggregation the direct estimates can generally be considered accurate. In our case, we might wish to aggregate the ward level estimates into GORs as data at this level are available from NATSAL. We can get an idea of how accurate the model estimates are by comparing the aggregated model estimates with the direct estimates. When considering two or three possible models, the one which most closely agrees with the direct estimates is preferred (Brown, 2001). Although we do not expect the model-based estimates to aggregate exactly to

the direct estimate, we would expect them to fall within the 95% confidence limits of the direct estimate (Heady et al., 2003).

4.2.2.8 Comparing with rates of disease

One of the aims of this chapter is to explore the correlation between the estimates of risky sexual behaviour derived from this modelling process with the rates of chlamydia and gonorrhoea calculated in Chapter 2.

The wards must be aggregated into areas that correspond with the Thiessen-polygon-based areas for which we have measured disease rates. We do this by determining the polygon in which each wards lies (based on population centre) and then weighting the contribution of each ward to the rate in each polygon by the ward population size.

4.2.2.9 Spatial autocorrelation

At both the ward level and at the aggregated clinic level, the data were tested for the presence of spatial autocorrelation. Spatial autocorrelation provides a measure of the extent to which there is clustering in the prevalence of risky behaviour. Positive spatial autocorrelation tells us that wards or clinics with a high prevalence of risky behaviour tend to be surrounded by other wards or clinics with similarly high levels or alternatively that wards or clinics with low prevalence are surrounded by similarly low wards or clinics. Negative spatial autocorrelation tells us that high values are generally next to low values (Fotheringham et al., 2002).

4.3 RESULTS

4.3.1 SELECTING THE VARIABLES

Variables used in the small area estimation must be available both in NATSAL and in the 2001 Census. The following variables were identified as being in both data sources and were able to be identically coded.

- Age (16-24 years, 25 – 34 years, 35 – 44 years)
- Sex (male/female)
- Marital status (married, cohabiting, single, previously married)
- Housing tenure (own, rent from council, rent privately, rent from housing association, lives rent-free)
- Social class (i/ii, iii non manual and manual, iv/v)
- Ethnic group (White, Black, Indian, Pakistani, other)
- Religion (None, Christian, Muslim, Hindu, Other)
- Perception of own health (good, fairly good, not good)

However, due to the requirement to maintain confidentiality in the Census, tabulations are only available using three variables. Therefore, only three variables from NATSAL can be selected. Of these three variables, one must be age. NATSAL only covers individuals aged 16-44 years whilst the Census data will include individuals of all ages. In order to restrict the Census data to the age interval which overlaps with the NATSAL data, we require data on age.

The first task, therefore, was to determine the two remaining variables that best explained an individual's probability of engaging in risky sexual behaviour, i.e. having more than one partner in the last year, using the NATSAL II data. Initially, each variable was cross tabulated with the outcome and the significance of any association explored using a chi-squared test. Table 4.1 below shows that with the exception of social class and individuals' perception of their health all the variables were significantly associated with the outcome at the 5% level. The two non-significant variables were dropped.

Table 4.1 Chi-squared test results for associations between dependent variables and number of partners in the last year

Variable	P-value for chi-squared test of association with number of partners in the last year
Marital Status	<0.001
Sex	<0.001
Housing tenure	<0.001
Social class	0.054
Ethnic group	0.012
Religion	<0.001
Perception of own health	0.185

Table 4.2 shows the results of the logistic regression analysis including all the significant variables identified above. The odds ratios indicate that marital status has a strong association with risky behaviour. Individuals who cohabit, were previously married or are single are significantly more likely to engage in risky behaviour. Being female is significantly protective, with women almost half as likely as men to engage in risky behaviour. Similarly being Christian is protective compared with having no religion, though other religions were not similarly protective. There seemed to be little effect of ethnic group. Being Black was marginally more risky than being White, whilst there was no effect for the other ethnic groups. Similarly there seemed to be little effect of housing tenure, though those renting privately were marginally more likely to engage in risky behaviour.

Table 4.2 Odds of engaging in risky sexual behaviour - logistic regression results

Variable	Odds ratio	95% CI	P-value Chi squared
Marital Status			
Married	1.00		
Cohabiting	1.94	(1.56,2.42)	<0.001
Previously Married	9.38	(7.55,11.66)	<0.001
Single	7.95	(6.58,9.61)	<0.001
Age group			
16 – 24 years	1.00		
25 – 34 years	0.70	(0.60,0.82)	<0.001
35 – 44 years	0.48	(0.40,0.58)	<0.001
Religion			
None	1.00		
Christian	0.83	(0.73,0.95)	0.01
Muslim	1.18	(0.63,2.26)	0.60
Hindu	0.64	(0.25,1.65)	0.36
Other	0.94	(0.54,1.66)	0.85
Housing tenure			
Own	1.00		
Rent from Council	1.05	(0.89,1.24)	0.54
Rent from Housing Association	0.98	(0.72,1.31)	0.87
Rent privately	1.26	(1.04,1.51)	0.015
Rent-free	1.50	(0.73,3.08)	0.27
Other	1.94	(0.79,4.77)	0.15
Ethnic Group			
Black	1.00		
White	0.74	(0.54,1.00)	0.05
Indian	0.77	(0.33,1.77)	0.54

Variable	Odds ratio	95% CI	P-value Chi squared
Pakistani	0.50	(0.20,1.21)	0.13
Other	0.80	(0.53,1.21)	0.30
Sex			
Male	1.00		
Female	0.51	(0.45,0.58)	<0.001

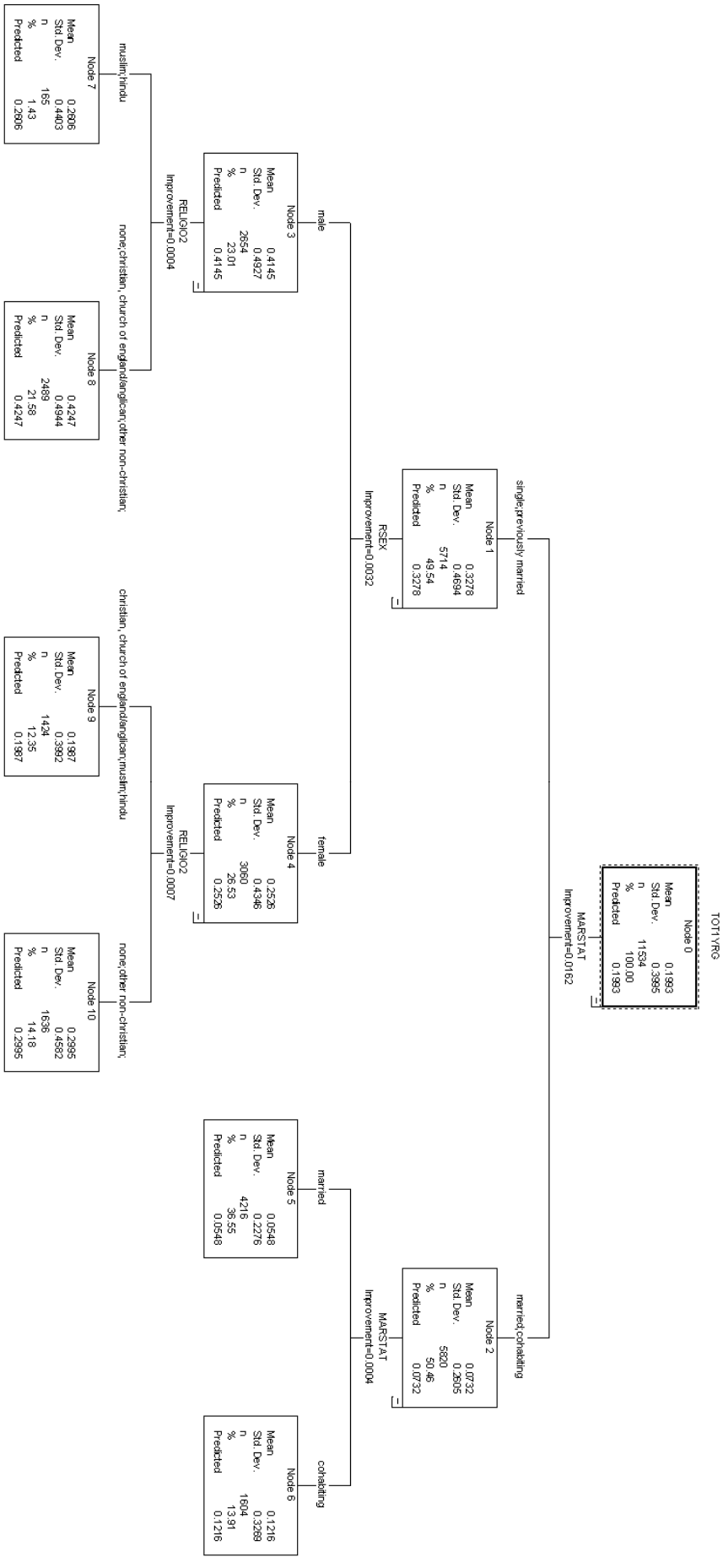
Thus far, it seems as though in addition to age the model ought to contain sex and marital status, as these seem to be the most strongly predictive of whether an individual engages in risky behaviour. Table 4 of the Census Standard Tables contains ward-level data on age by sex and marital status and these data are freely available to researchers on request whilst data on any other combination of variables would incur a fee to supply, even if the ONS were willing to release the data. The pragmatic approach would use one of the existing tables rather than attempting to commission a special table. However, since this regression model will form the basis of the small area calculations used in the rest of the study, it is important to ensure that the correct variables are chosen. Therefore another method of variable selection was also considered.

Whilst logistic regression may tell us which variables are significant with respect to the outcome, it can be difficult to rank the importance of these variables in the way required for our analysis. Classification and Regression Tree (CART) Analysis, a technique developed by Breiman, Friedman, Olshen and Stone (1984), can help to provide the sort of ordering of variables that we require. CART is a binary method of partitioning data into homogeneous groups. CART begins with the entire sample, which is heterogeneous - consisting of individuals who do and do not engage in risky sexual behaviour. It then splits up the sample into the most homogeneous sub-sample that it can find based on all the predictor values (Lewis, 2000; Yohannes and Hoddinott, 1999). Further details of the calculations used in this splitting process can be

found in the statistical appendix. The calculations were carried out using SPSS Answer Tree Version 2.0 (SPSS, 1998).

The results of the CART analysis are shown below. The tree indicates that the best split is made on the basis of marital status, followed by sex and finally religion. None of the other variables significantly improves the model's homogeneity.

Figure 4.1 CART diagram of predictors of risky sexual behaviour



Both the CART approach and the logistic regression model indicate that marital status is the single most important predictor in the model. Taking the two approaches together would indicate that the final variable should be either religion or sex. Sex is a better predictor on both methods. Moreover, this approach would mean that we would require Table 4, which is readily available from the Census. As such, it was decided to proceed with age, sex and marital status as the variables in the regression.

4.3.2 WARD-LEVEL ESTIMATES OF RISKY SEXUAL BEHAVIOUR

To control within the logistic regression model for the clustered nature of the NATSAL II survey design, the svylogit commands in STATA have been used to calculate the synthetic regression model for all age, sex and marital status groups.

The coefficients shown in Table 4.3 were obtained to for each of the age/sex/marital status categories. These coefficients can be transformed from logits to proportions, giving the proportion in each group who engage in risky sexual behaviour (Twigg et al., 2000). For each age, sex and marital status group the transformation takes the form: $\frac{\exp(\beta)}{1+\exp(\beta)}$.

Table 4.3 Synthetic regression results – proportions engaging in risky sexual behaviour for all age-sex-marital status groups

Category	Coefficient	Standard error	Proportion engaging in risky sexual behaviour (Transformed logit)
Males married 16 – 24 years	-1.354	0.465	0.205
Males cohabiting 16 – 24 years	-1.722	0.290	0.152
Males previously married 16 – 24 years	1.375	0.909	0.798
Males single 16 – 24 years	-0.038	0.099	0.490
Males married 25 – 34 years	-2.518	0.159	0.075
Males cohabiting 25 – 34 years	-1.872	0.187	0.133
Males previously married 25 – 34 years	-0.249	0.233	0.438
Males single 25 – 34 years	-0.228	0.118	0.443
Males married 35 – 44 years	-2.841	0.165	0.055
Males cohabiting 35 – 44 years	-1.975	0.236	0.122
Males previously married 35 – 44 years	-0.432	0.158	0.394
Males single 35 – 44 years	-0.981	0.147	0.273
Females married 16 – 24 years	-3.141	0.552	0.041
Females cohabiting 16 – 24 years	-1.739	0.197	0.149
Females previously married 16 – 24 years	0.204	0.563	0.551
Females single 16 – 24 years	-0.673	0.111	0.256
Females married 25 – 34 years	-3.411	0.189	0.032
Females cohabiting 25 – 34 years	-2.593	0.183	0.070
Females previously married 25 – 34 years	-0.889	0.153	0.297
Females single 25 – 34 years	-0.922	0.117	0.338
Females married 35 – 44 years	-3.378	0.168	0.032
Females cohabiting 35 – 44 years	-2.579	0.275	0.070
Females previously married 35 – 44 years	-1.424	0.143	0.291
Females single 35 – 44 years	-1.968	0.184	0.285

Having obtained the coefficients from the synthetic regression model, the next step is to obtain the ward-level counts from the 2001 Census data for each category and multiply by the relevant transformed logit. The result is the estimated number of individuals in each ward who engage in risky behaviour. Dividing by the total population in each ward provide the proportion of the population engaged in risky behaviour. An example of the calculations are shown for one ward in Table 4.4 below.

Table 4.4 Example calculation of risky behaviour estimate for one ward

Population subgroup	Population at 2001 Census	Transformed logit (from Table 3)	Population x transformed logit = estimated population engaging in risky behaviour
Males married 16 – 24 years	7	0.205	1.436
Males cohabiting 16 – 24 years	30	0.152	4.547
Males previously married 16 – 24 years	3	0.798	2.395
Males single 16 – 24 years	221	0.490	108.388
Males married 25 – 34 years	145	0.075	10.820
Males cohabiting 25 – 34 years	75	0.133	9.999
Males previously married 25 – 34 years	16	0.438	7.007
Males single 25 – 34 years	126	0.443	55.841
Males married 35 – 44 years	209	0.055	11.530
Males cohabiting 35 – 44 years	56	0.122	6.821
Males previously married 35 – 44 years	51	0.394	20.076
Males single 35 – 44 years	64	0.273	17.451
Females married 16 – 24 years	23	0.041	0.954
Females cohabiting 16 – 24 years	40	0.149	5.980

Population subgroup	Population at 2001 Census	Transformed logit (from Table 3)	Population x transformed logit = estimated population engaging in risky behaviour
Females previously married 16 – 24 years	6	0.551	3.306
Females single 16 – 24 years	251	0.256	84.808
Females married 25 – 34 years	155	0.032	4.951
Females cohabiting 25 – 34 years	85	0.070	5.912
Females previously married 25 – 34 years	34	0.297	9.907
Females single 25 – 34 years	112	0.338	31.870
Females married 35 – 44 years	215	0.032	7.094
Females cohabiting 35 – 44 years	41	0.070	2.891
Females previously married 35 – 44 years	98	0.291	19.020
Females single 35 – 44 years	66	0.285	8.090
Total	**2,129**		**441.093**

If we divide 441.093, the estimated number of individuals engaging in risky behaviour, by the total population of the ward, 2,129, we obtain 20.7%. This is the estimated prevalence of risky behaviour for this ward.

There are approximately 8,000 wards in England so the results have been grouped into quartiles and are illustrated on the map (Figure 4.2) below. These rankings represent the quartiles of the estimates themselves, rather than any ranking of the actual underlying prevalences. Because large cities such as London are made up a many small wards, seven of the largest cities in England have been magnified and illustrated in separate figures (Figures 4.3-4.6). From these figures it appears that urban wards tend to have a

higher prevalence of risky behaviour, with a large number falling into the highest quartile.

Figure 4.2 Proportion of the population aged 16-44 engaging in risky behaviour for all wards in England by quartile

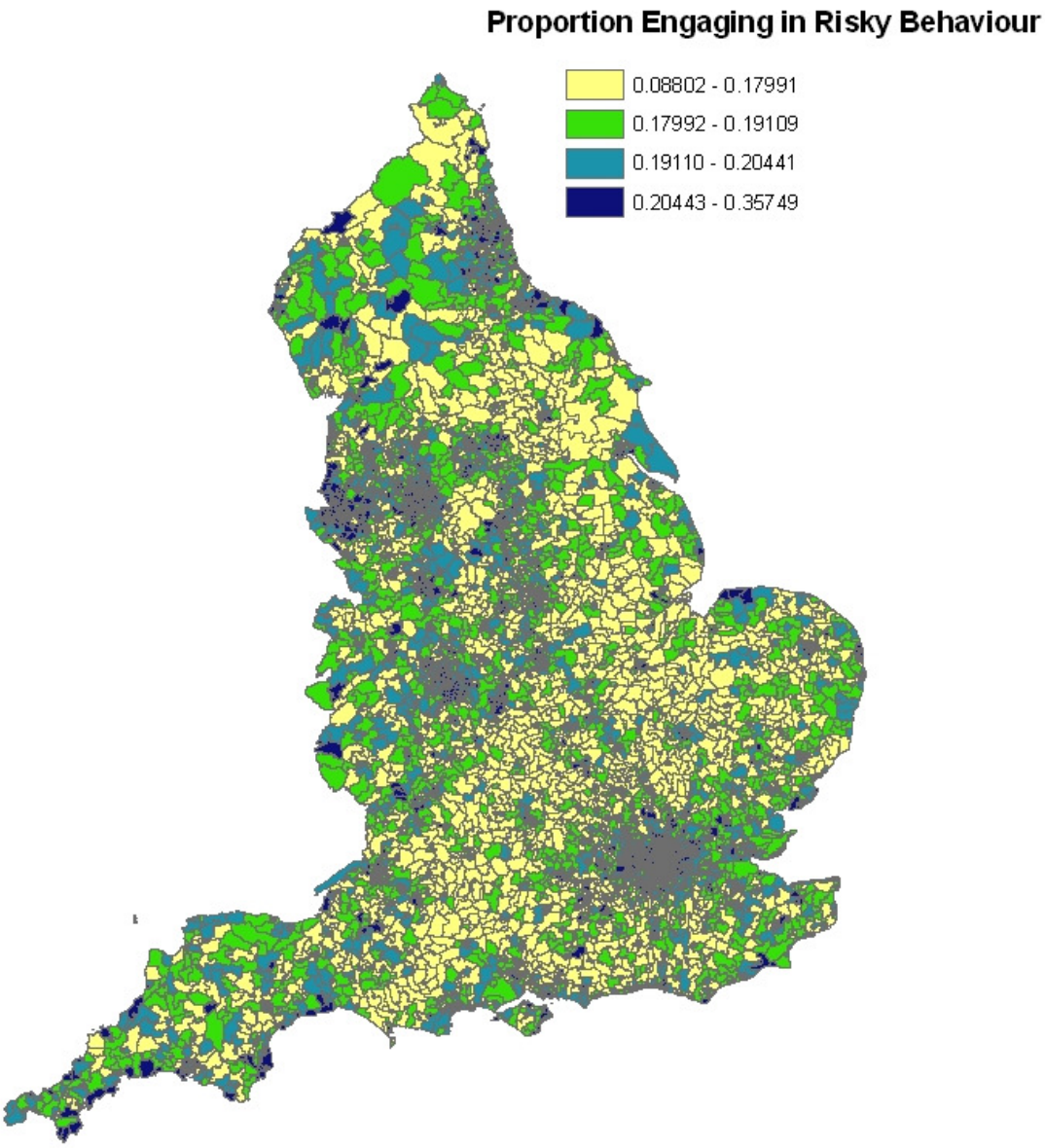


Figure 4.3 Proportion of the population aged 16-44 engaging in risky behaviour in London by quartile

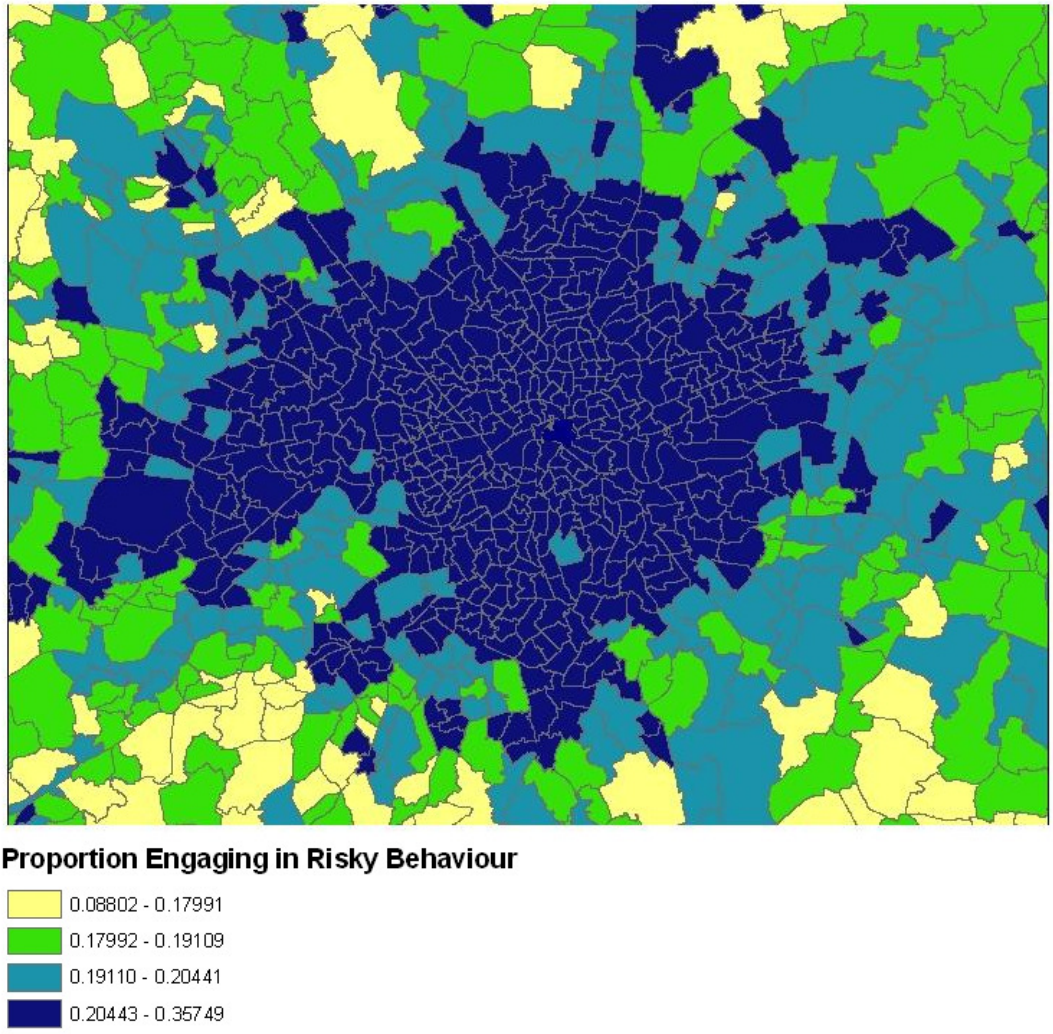


Figure 4.4 Proportion of the population aged 16-44 engaging in risky behaviour in Manchester and Liverpool by quartile

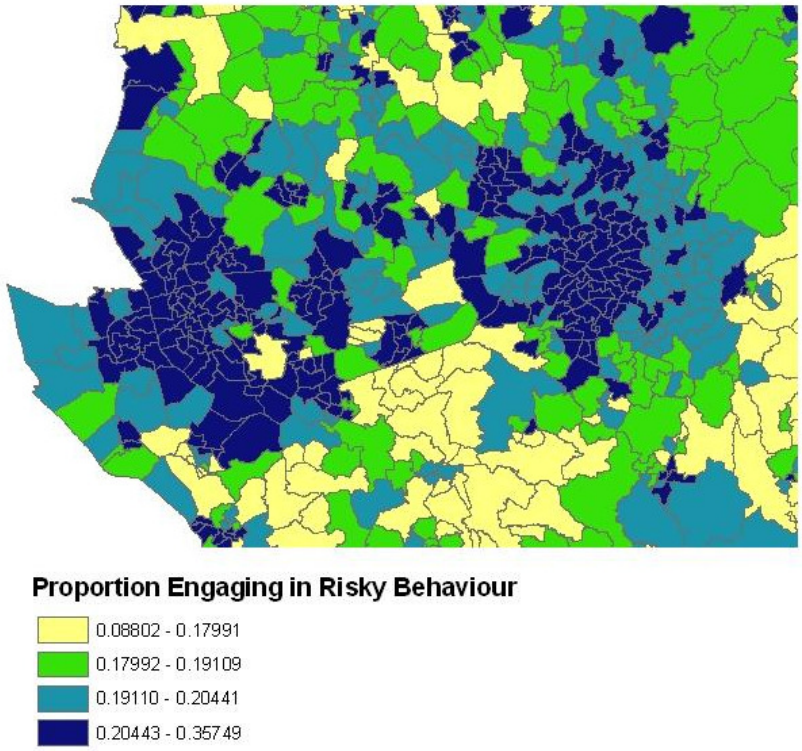


Figure 4.5 Proportion of the population aged 16-44 engaging in risky behaviour in Birmingham and Coventry by quartile

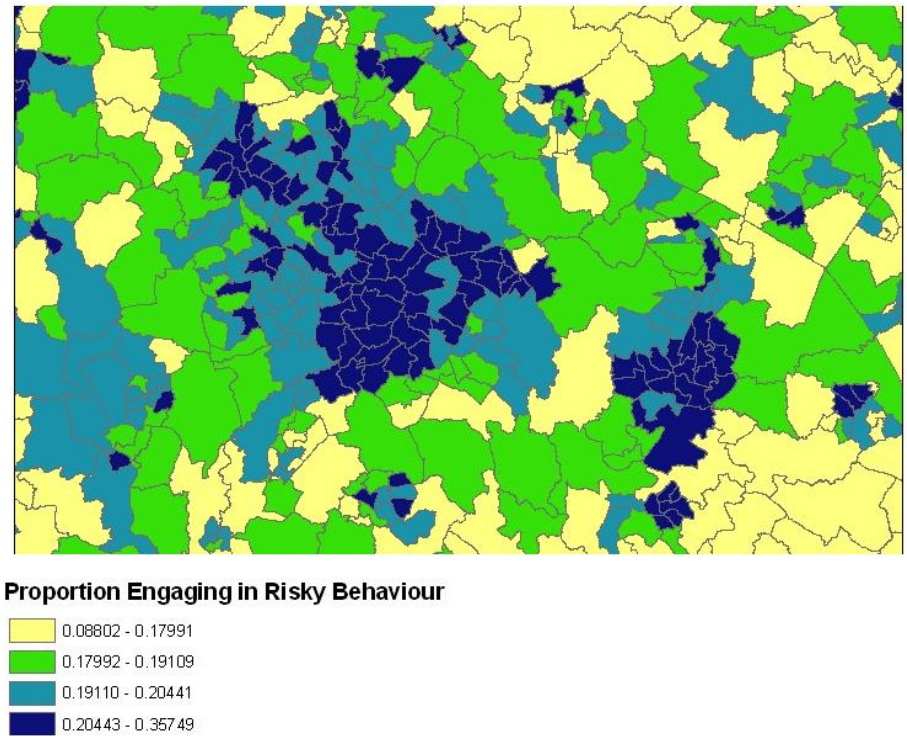
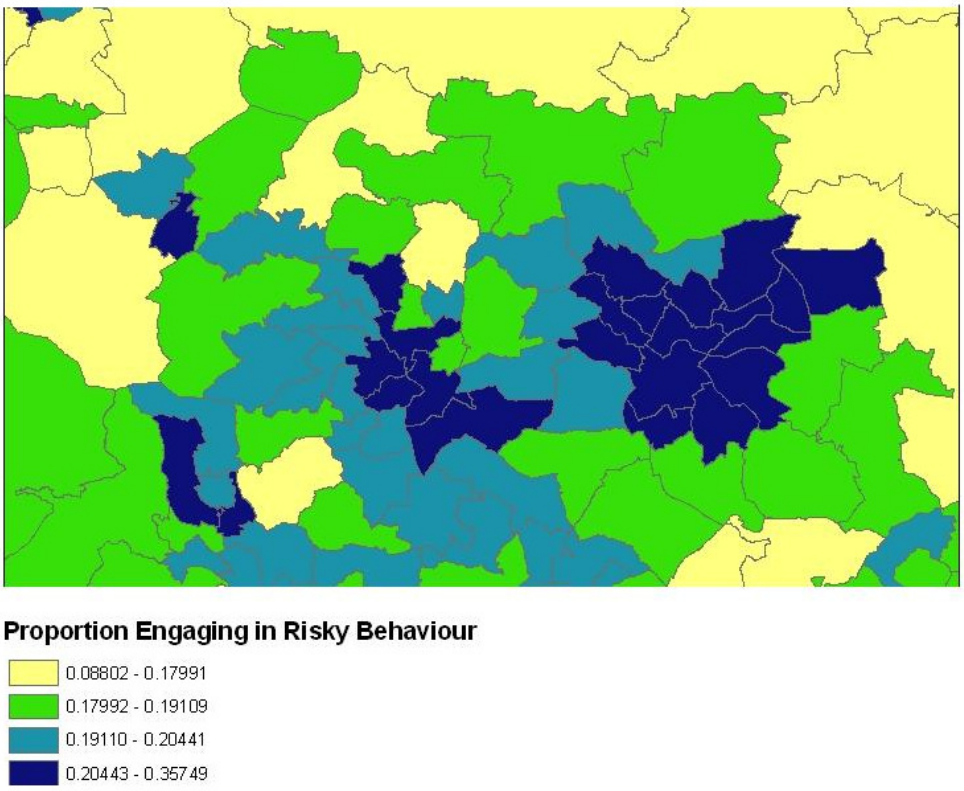


Figure 4.6 Proportion of the population aged 16-44 engaging in risky behaviour in Leeds and Bradford by quartile



As previously noted, it appears as though urban wards are more likely to have a high prevalence of risky behaviour. Figures 4.7 and 4.8 illustrate the distribution of the upper and lower 10% of wards. Again we can see that higher levels appear to be clustered around larger towns and cities whilst lower levels of risky behaviour appear to predominate in the middle of the country.

Figure 4.7 Top 10% of wards in England for the estimated proportion fo the population aged 16-44 engaging in risky sexual behaviour

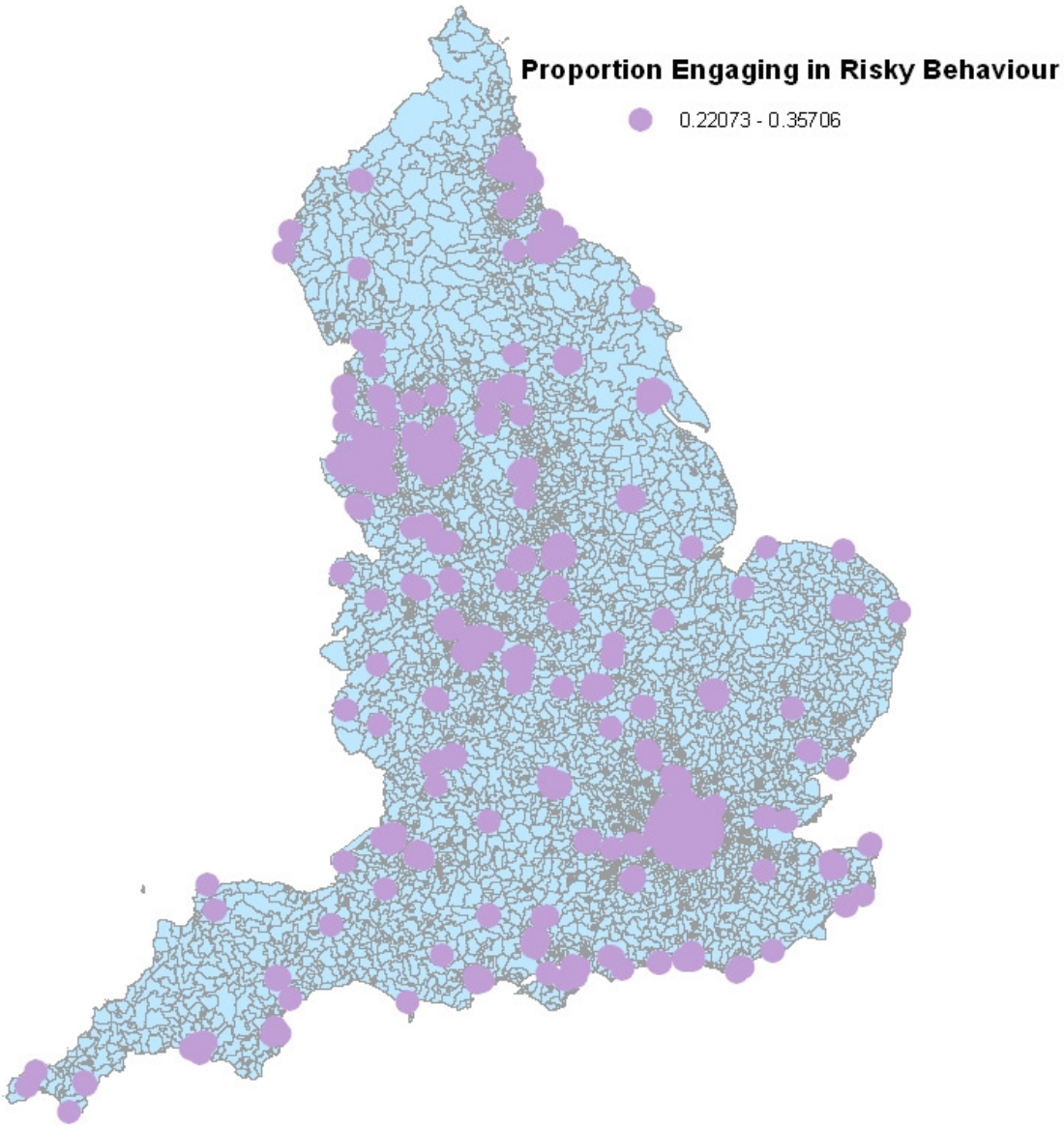
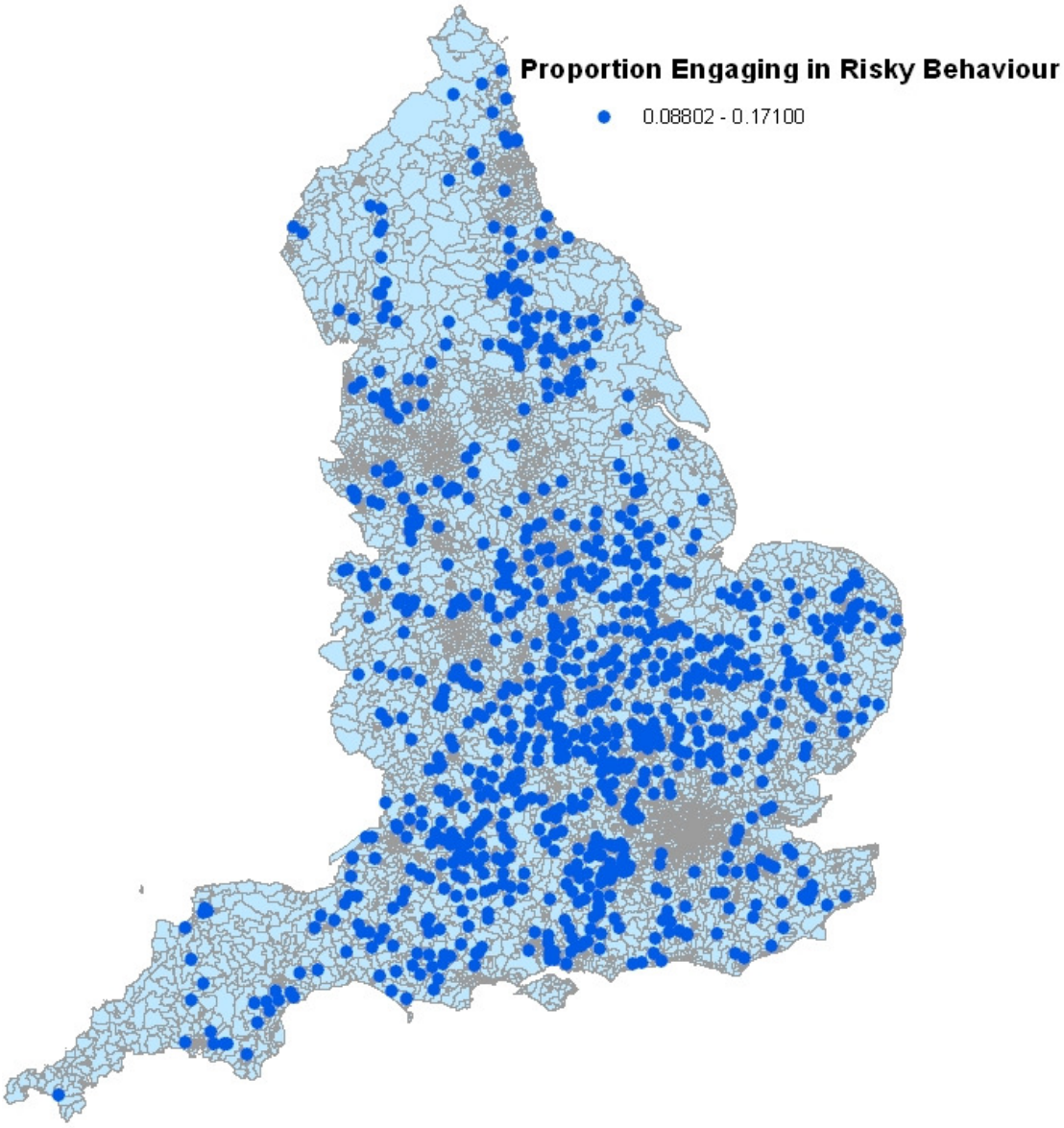


Figure 4.8 Bottom 10% of wards in England for the estimated proportion fo the population aged 16-44 engaging in risky sexual behaviour



We tested the data and found evidence of positive spatial autocorrelation (Moran's *I* = 0.078, p-value = <0.001). This suggests that areas with high levels of risky behaviour tend to be surrounded by other areas with high levels of risky behaviour whilst areas with low levels tend to also be surrounded by similar neighbours.

Some areas clearly have significantly higher levels of risky behaviour than others. While there is a concentration of risky behaviour in urban areas, some

rural areas also show relatively high estimate prevalence of risky behaviour. For example, Brancaster, a village on the north coast of Norfolk, has a predicted prevalence of 23.0%. This places it comfortably in the top 10% of wards. Similarly, the model predicts a risky behaviour prevalence of 23.6% for Grade-Ruan and Landewednack, a rural ward in southwest Cornwall.

All of the socio-demographic indicators that we originally considered for inclusion in the regression model have been identified in previous studies as being associated with the prevalence of risky behaviour. Differences in the prevalence of these indicators might lead to differences in the predicted prevalence of risky behaviour. In order to explore this further, we examined the correlation between the ward-level estimates of risky behaviour obtained from the model and the ward-level data available from the Census and the R-squared values are shown in Table 4.5 below.

Table 4.5 Proportion of variation in estimated risky behaviour explained by key socio-demographic indicators

Variable	R-squared
Proportion of the population aged under 25 years	0.6176
Proportion of the population single	0.9175
Proportion of the population previously married	0.0994
Proportion of the population not in a “stable” relationship (single + previously married)	0.9566
Proportion of the population not affiliated with any religion	0.1597
Proportion of the population from black ethnic minority groups	0.1581
Proportion of the population that is male	0.0044

The proportion of individuals in a ward who are single explains 92% of the variation in the estimated prevalence of risky behaviour. If we also include individuals who were previously married, this figure rises to 96%. This means that we can almost perfectly predict the level of risky behaviour in a ward

simply by knowing the proportion of individuals who are not currently in stable relationships. The two rural wards indicated earlier as having a high predicted prevalence of risky behaviour both have high proportions of the population aged 16-44 who are single or previously married (48% in both Brancaster and Grade-Ruan and Landewednack).

Similarly, large urban areas such as London have a high predicted prevalence of risky behaviour across all their wards. This is initially surprising as cities often have neighbourhoods which vary considerably with respect to their cultural, socioeconomic and demographic characteristics. Yet the model predicts that there is likely to be little variation between these areas with respect to the prevalence of risky sexual behaviour. This is because the key predictor of the prevalence of risky sexual behaviour for a ward is the proportion of single and previously married individuals and in this respect, wards vary little within cities Had other indicators such as ethnic group or religion been more important predictors than we might have seen more variation within urban areas.

Although sex was a highly significant predictor in our initial consideration of the NATSAL data (see Tables 4.1 and 4.2), here it explains very little of the variation between wards. This may be because there is very little variation in the sex distribution between wards. Most wards contain an approximately equal number of males and females.

4.3.3 VERIFYING THE ESTIMATES

The ward-level estimates were aggregated to obtain regional level estimates for comparison with those derived directly from NATSAL II. The results are shown in Table 4.6 below. The 95% error limits were obtained in STATA using a binomial model. For all regions, the estimate derived from the synthetic regression model lies within the 95% error limits of the direct estimate obtained from NATSAL II. Many of the aggregated estimates are relatively close to the direct estimate, especially in the Southwest, West Midlands and London, where the model provides an almost perfect prediction. Moreover, the overall magnitude of the estimates is approximately correct.

For example, both measures show the highest prevalence in London and the lowest in the East of England and Yorkshire and the Humber.

Table 4.6 Comparison of direct risky behaviour estimate from NATSAL II and aggregated small area estimates from synthetic regression analysis

Region	Estimated prevalence of risky behaviour	Prevalence of risky behaviour for NATSAL II (95% CI)
East Midlands	0.196	0.188 (0.161, 0.218)
East of England	0.192	0.180 (0.155, 0.207)
London	0.219	0.234 (0.219, 0.249)
Northeast	0.205	0.181 (0.148, 0.217)
Northwest	0.207	0.182 (0.160, 0.250)
Southeast	0.193	0.185 (0.165, 0.207)
Southwest	0.196	0.196 (0.169, 0.226)
West Midlands	0.201	0.199 (0.173, 0.226)
Yorkshire and the Humber	0.176	0.167 (0.143, 0.193)

4.3.4 RISKY SEXUAL BEHAVIOUR AND CLINIC-LEVEL RATES OF DISEASE

In Chapter 2, we derived the catchment areas for each of the GUM clinics in the Northwest, Southwest and East Midlands, based on Thiessen polygons. By aggregating the ward-level estimates of risky behaviour within these Thiessen polygons, we can get clinic-level estimates of risky behaviour. These can then be compared with the estimates of chlamydia and gonorrhoea infection from Chapter 2. Table 4.7 below shows these estimates for each clinic and Figures 4.9 and 4.10 show a linear regression of the behaviour estimates against the disease rates. At the aggregated clinic level there was no evidence of spatial autocorrelation and therefore this has not been taken into account in the regression.

It can be seen from the regression plot that both chlamydia and gonorrhoea are positively correlated with estimates of risky behaviour. However, this

correlation is far weaker for chlamydia rates (0.41) than gonorrhoea rates (0.70). The R-squared values show that the variation in risky behaviour explains 49% of the observed variation in gonorrhoea rates but only 17% if the observed variation in chlamydia rates.

Table 4.7 Risky behaviour estimate by clinic

Clinic	Risky behaviour estimate	Chlamydia rate	Gonorrhoea rate
East Midlands			
Lincoln County Hospital	0.194	5.09	0.76
Grantham and Kesteven Hospital	0.180	2.24	0.16
Pilgrim Hospital	0.182	2.50	0.33
Skegness and District Hospital	0.194	3.03	1.48
King's Mill Hospital	0.190	2.35	0.72
Retford Hospital	0.186	3.80	0.63
Nottingham City Hospital	0.218	4.60	1.65
Leicester Royal Infirmary	0.203	5.01	1.12
Loughborough General Hospital	0.196	2.00	0.10
Northampton General Hospital	0.198	4.57	0.97
Kettering General Hospital (Warren Hill Centre)	0.190	4.15	0.53
Chesterfield and North Derbyshire Royal Infirmary	0.191	4.88	0.39
Derbyshire Royal Infirmary (William Donald Clinic)	0.195	4.31	1.49
Northwest			
Royal Albert Edward Infirmary, Wigan	0.197	1.12	0.26
Arrowe Park Hospital	0.208	5.22	0.98
Ashton Community Care Centre	0.219	3.97	0.96
Baillie Street Health Centre, Rochdale	0.198	8.56	1.28
Royal Blackburn Hospital	0.197	3.79	0.78

Clinic	Risky behaviour estimate	Chlamydia rate	Gonorrhoea rate
Victoria Hospital, Blackpool	0.201	4.16	1.96
Royal Bolton Hospital	0.203	3.86	1.00
Burnley General Hospital	0.197	1.53	0.50
Countess of Chester Hospital	0.200	5.99	0.82
Chorley and South Ribble District General Hospital	0.195	2.96	0.29
Cumberland Infirmary	0.195	2.47	0.31
Fairfield General Hospital	0.198	3.28	0.75
Halton General Hospital	0.210	1.62	0.31
Hope Hospital	0.223	2.45	0.97
Leighton Hospital	0.185	2.46	0.67
Royal Liverpool Hospital	0.236	5.54	1.51
Macclesfield District General Hospital	0.190	3.73	0.58
North Manchester Hospital	0.223	5.28	1.81
Royal Oldham Hospital	0.199	3.96	1.21
Ormskirk Hospital	0.214	1.71	0.19
Royal Preston Hospital	0.204	4.20	1.23
Southport District General Hospital	0.198	6.17	0.80
Manchester Royal Infirmary	0.252	6.23	3.64
St Helens and Knowsley Hospital	0.207	3.16	0.48
Stepping Hill Hospital	0.194	1.22	0.24
Tameside and Glossop Sexual Health Centre	0.199	2.75	0.72
Trafford General Hospital	0.203	3.36	0.49
Warrington and District General Hospital	0.190	2.05	0.34
Withington Hospital	0.229	7.35	2.09
Workington Community Hospital	0.198	1.98	0.18
Southwest			
Royal United Hospital, Bath	0.201	2.33	0.38

Clinic	Risky behaviour estimate	Chlamydia rate	Gonorrhoea rate
Royal Bournemouth Hospital	0.201	3.67	0.88
Bristol Royal Infirmary	0.209	2.97	1.38
Cheltenham General Hospital	0.201	2.40	0.41
Chippenham Community Hospital	0.174	0.73	0.07
Royal Cornwall Hospital, Treliske	0.200	3.98	0.39
Derriford Hospital, Level 5, Plymouth	0.203	3.31	0.49
Royal Devon and Exeter Hospital	0.202	0.95	0.20
Gloucester Royal Hospital	0.188	4.35	1.27
Newquay and District Hospital	0.193	0.67	0.13
North Devon District General Hospital	0.192	3.52	0.28
Salisbury District Hospital	0.184	3.69	0.27
The Great Western Hospital, Swindon	0.183	2.60	0.41
Taunton and Somerset Hospital	0.190	2.86	0.34
Torbay Hospital	0.197	1.56	0.26
West Cornwall Hospital, Penzance	0.195	1.72	0.18
Weston General Hospital	0.189	0.84	0.10
Weymouth and District Hospital	0.187	5.12	0.22
Yeovil District Hospital	0.184	1.27	0.14

Figure 4.9 Linear regression – clinic-level chlamydia rates and small area estimates of risky behaviour

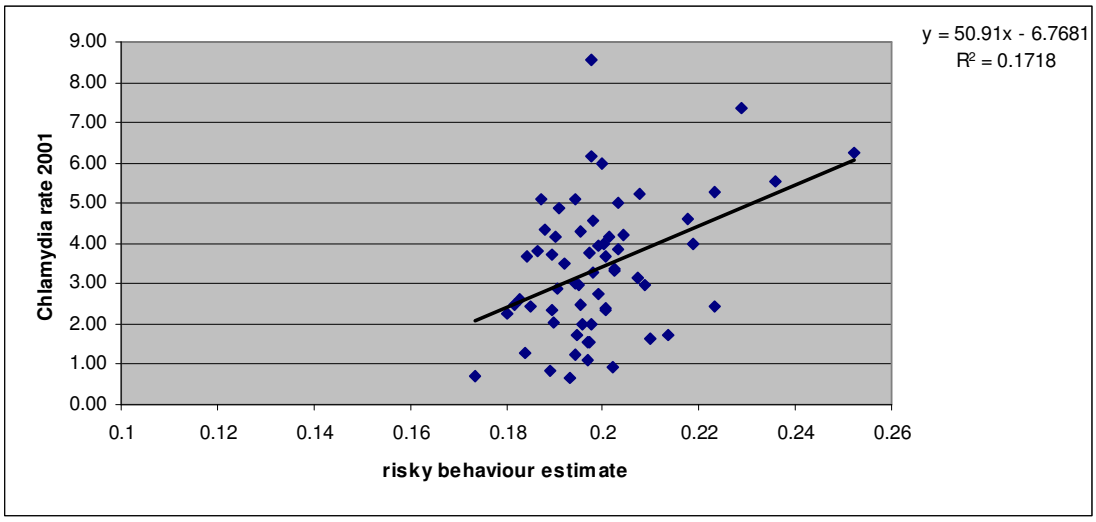
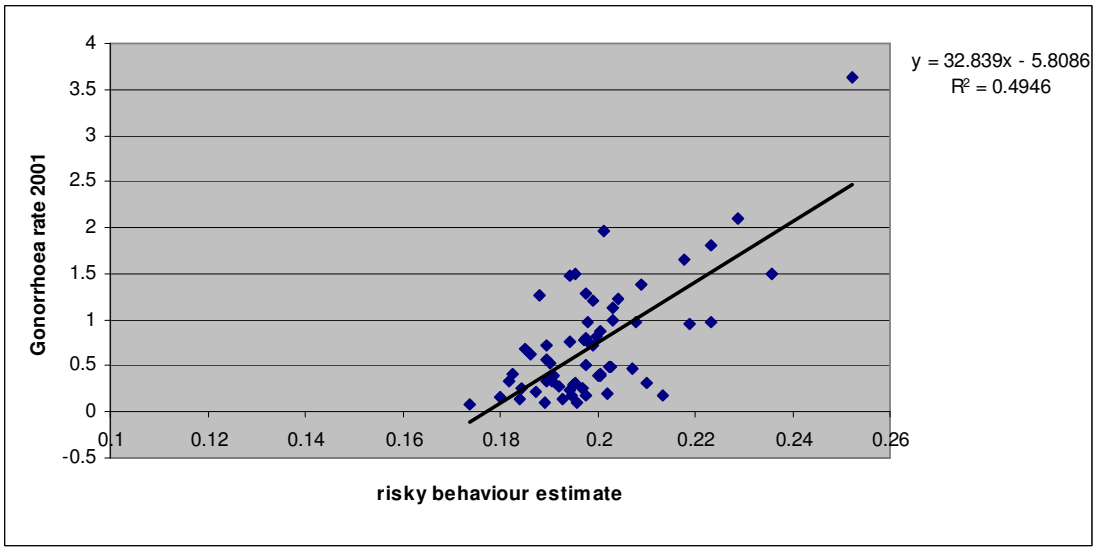


Figure 4.10 Linear regression – clinic-level gonorrhoea rates and small area estimates of risky behaviour



4.4 DISCUSSION

4.4.1 MAIN FINDINGS

This study has derived ward-level estimates of the prevalence of risky sexual behaviour and has shown that the most important predictor of this is the proportion of individuals who are single or previously married. There was an observed variation in the prevalence of risky behaviour between urban and rural areas, with higher rates in urban areas. This is likely to reflect the higher proportion of single and previously married individuals living in towns and cities.

When aggregated to obtain estimates of risky behaviour prevalence at clinic catchment area level, the rates showed a positive correlation with both chlamydia and gonorrhoea rates as estimated in Chapter 2. The relationship was stronger with gonorrhoea than chlamydia.

4.4.2 OTHER STUDIES

We are not aware of any other studies that have attempted to estimate risky sexual behaviour at the local or regional level. Nor were we able to identify any other studies that look at the correlation at the population level between risky sexual behaviour and rates of either chlamydia or gonorrhoea infection.

Similar techniques to those used here have been applied to the Health Survey for England (HSE) by the National Centre for Social Research to derive estimates of certain health behaviours such as the proportion of people smoking or the proportion who are obese. However, the HSE dataset allowed primary sampling units to be identified and thus more use could be made of methods of direct estimation and areal indicators.

4.4.3 FURTHER RESEARCH

Our estimates of the prevalence of risky behaviour have assumed that the same relationship between risky sexual behaviour and the predictor variables (age, sex and marital status) holds at both the national level and the local level. It would be

interesting to explore the extent to which this is true in several local studies. Obtaining local estimates and the opinion of local experts can be a good way to verify the extent to which there are local effects and to determine why such effects exist.

4.4.4 LIMITATIONS

Obviously the limitation imposed by the availability of Census data is an important one and one faced by all researchers. The predictive power of the synthetic regression model could be greatly improved by the ability to include more than three variables. Having said that, the three variables that we finally included were rigorously selected to explain as much of the variation in the outcome as possible.

It might also improve estimates to be able to identify PSUs within the NATSAL II dataset. Linking with auxiliary data sources would allow composite estimators or the GREG estimators to be calculated and compared to synthetic regression estimates.

Finally, we have compared the estimated prevalence of risky behaviour with rates of disease based on cases reported at GUM clinics. However, clinic rates are only an estimate of true prevalence. In the UK, a GUM clinic is one of a number of places an individual may choose to seek treatment for a suspected sexually transmitted disease. Moreover, chlamydia is often asymptomatic and as a result those affected may not seek treatment at all. Our estimates are therefore likely to be underestimates of the true rates in their respective areas. This is not a problem if all areas face similar proportions of individuals using different health services or not seeking treatment. However, this may not be the case. For example, it is possible that some clinics are better at attracting patients as they may have more convenient opening hours. This would push up the observed rate at this clinic more than at neighbouring clinics and thus distort the relationship between risky behaviour and rates of disease.

At the moment, there is nothing that we can do to account for this possible bias. It would be interesting to explore this relationship again in light of the data that will hopefully become available from the Common Dataset for Sexual Health. Since this dataset will contain information on diagnoses across health services it should be possible to obtain more accurate rates with which to compare the estimated prevalence of risky behaviour. If a similar level of correlation between behaviour and rates is found in that exercise as in this chapter, it suggests that the clinic-based rates are actually good estimates for their catchment areas. Alternatively, a very different correlation might suggest that there are big differences between clinics in terms of attracting patients, a finding which itself would require further exploration.

4.4.5 IMPLICATIONS

A key finding of this study was that 92% of the variation in risky behaviour could be accounted for by knowing the proportion of single people in a ward. The figure rose to 96% if we knew about the proportion single and previously married. This means that we can almost perfectly predict the ward-level prevalence of risky behaviour by asking a simple, non-intrusive question about living arrangements. Questions about sexual behaviour are not routinely collected by surveys and it is known that there are difficulties in obtaining good data. In contrast, most large scale surveys, including the Census, include questions about living arrangements. This study suggests that one simple demographic question can act as an excellent proxy, allowing us to predict that where there are high proportions of single/previously married individuals, there is likely to be a higher prevalence of risky behaviour. This can be hugely helpful for planning, especially at the local level where data on sexual behaviour are difficult to obtain.

This has further implications for the way in which policy addresses risky behaviour. Currently, the Government targets certain groups, particularly young people and black ethnic minority groups. However, these data suggest that age

and cultural background are far less relevant than whether a person is living with their partner. Young people and those from black ethnic minority groups may experience a higher prevalence of risky behaviour and/or sexually transmitted disease incidence, but this may well be due to a higher proportion of people in these groups who are not living in partnerships.

The current approach may lead certain individuals, for example older people who have recently divorced, to believe that sexual health is not a matter of concern for them. In fact, cases of sexually transmitted diseases are rising most quickly amongst the over-45s, with a doubling of cases in the past 8 years (Health Protection Agency, 2008b). The message that policy-makers and public health practitioners should be sending is that all individuals need to consider their sexual health, regardless of age or cultural background.

In terms of health promotion, a message that suggests that single people or those with more than one partner seek regular testing for sexually transmitted diseases is a simple and useful approach. However, from a funding and planning perspective, targeting particular geographic areas rather than population groups may be more useful. The study indicates urban areas have a high prevalence of risky behaviour, driven by their high proportion of individuals who are not in a relationship. If messages encouraging increased testing are successful, then urban areas are likely to see an increased demand for services. There will need to be more funding put in place to cover the extra cost of testing, treatment and ensuring staff are fully trained to provide sexual health care. Funds within the health service are limited and the targeting of urban areas could help to ensure that services are available where there is most likely to be a demand for them.

However, the aim of this study was primarily to determine whether risky sexual behaviour was correlated with higher population level rates of chlamydia and gonorrhoea infection. A strong correlation would justify the many efforts made to

encourage individual behaviour change whilst a weak correlation or no correlation would suggest that other approaches needed to be considered if the aim is to reduce the levels of disease diagnosed at GUM clinics.

Our results are mixed. Higher rates of risky behaviour were correlated with higher rates of both chlamydia and gonorrhoea. This is especially true for gonorrhoea where the correlation is much stronger than for chlamydia. This may be in part because reporting of gonorrhoea, which frequently causes noticeable (and painful) symptoms, is likely to be better than for chlamydia, which is often asymptomatic. As such, we would expect that efforts to reduce risky behaviour through individual behaviour change should result in lower rates of chlamydia and gonorrhoea. This bodes well for the Government initiatives such as the “Essential Wear” campaign to encourage condom use amongst those aged under 25 years.

However, the Government campaign is aimed specifically at condom use whilst our work has identified the total number of partners an individual has as being a more important factor. Whilst consistent condom use can significantly reduce the probability that an individual will transmit or contract either chlamydia or gonorrhoea, partnership turnover and mixing patterns have also been shown to be an important element in the prevalence of disease (Kretzschmar et al., 1996; Ghani et al., 1997; Anderson et al., 2000).

The high rate of partnership turnover is not addressed by the current and proposed campaigns. This may be because it is a difficult subject to broach. A change of partner is probably less likely to be viewed as related to health than to concepts such as fidelity or love. However, it is essential that individuals who have multiple partners recognise the increased level of risk that they are facing and seek testing and treatment as needed.

But by no means could all the variation in clinic-level rates of disease be explained by individual risky behaviour, especially for chlamydia, where 80% of the variation remained unaccounted for. Whilst partnership duration and sexual mixing patterns are clearly important, so are factors which influence the duration of the infection. If health professionals and/or media campaigns can persuade individuals to get tested and treated more quickly, then they will be far less likely to spread the infection to others. Ultimately, this means that the population prevalence of disease will be lower. There may be differences in this respect between clinic catchment areas which might account for some of the unexplained variation. However, it has not been possible to measure these factors either directly or indirectly in our study.

However, to suggest that the Government has ignored the service-side of the argument in favour of health promotion campaigns favouring individual behaviour change would be unfair. Efforts have been made to try to make sexual health services, especially GUM clinics, more accessible. In the 2004 "Choosing Health" White Paper, the Government made improving sexual health a priority and promised that "by 2008 patients referred to GUM clinics will be able to have an appointment within 48 hours" (Department of Health, 2004b, p15). This was reinforced in the 2007/08 NHS Operating Framework which stressed that "while progress has been made to improve access to sexual health services, more needs to be done, in particular to deliver 48-hour access to genito-urinary medicine (GUM) clinics." (Department of Health, 2006b, p. 11)

Unfortunately, concentrating on GUM clinics ignores the fact that many people will approach other health service sites for sexual health matters. The Southwest Health Protection Authority has observed that within their region, a large proportion of sexually transmitted disease diagnoses are being made by GPs or in clinical settings other than GUM clinics (Health Protection Agency Southwest, 2005). If people are seeking treatment in settings other than GUM clinics, then an important investment may be in ensuring that health practitioners in these

settings have received appropriate training to deal with all aspects of sexual health and that they have the time and resources to devote to its detection and treatment.

The recently implemented National Chlamydia Screening Programme is an alternative model to increase the accessibility of testing and treatment. It offers testing for those aged under 25 years at a variety of alternative sites such as pharmacies, youth clubs and colleges. Patients can indicate how they wish to be advised of their test results (letter, phone call, email or text message) and, if positive, will be advised of how to obtain free treatment. If this model proves successful, there may be an initial rise in chlamydia diagnoses as more people are tested; however, it is likely that we will ultimately see a reduction in the population prevalence of chlamydia.

However, such a model is predicated on the assumption that by targeting young people the majority of the “high risk” population will be reached. This study has suggested that age is not the key differentiating feature. Far more effective would be to open the programme to individuals regardless of age and to offer testing for a full range of sexually transmitted diseases. Although this approach might be more costly, it should help to reduce sexually transmitted disease rates.

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5. CONCLUSION

5.1 MAIN FINDINGS AND IMPLICATIONS

This thesis set out to explore the measurement of and the relationship between risky sexual behaviour and the population prevalence of chlamydia and gonorrhoea infection. This final chapter offers a brief summary of the findings set out in Chapters 2, 3 and 4 and considers their implications for health policy in the UK.

Chapter 2 considered three ways to derive rates of chlamydia and gonorrhoea infection at genitourinary medicine (GUM) clinic level: Thiessen polygons, 15 mile boundaries, and 30 minute drive times. The rates were relatively insensitive to the method chosen and therefore the simplest approach, using Thiessen polygons, is recommended. The analysis was limited by only being able to obtain data for the Northwest, Southwest and East Midlands regions. However the Thiessen polygon method can be easily applied by other researchers should they have access to additional data for other regions of the UK.

Having properly calculated rates can help us to identify those areas in which there are relatively high (or low) levels of chlamydia or gonorrhoea infection. The number of cases diagnosed is generally higher in areas where the population is higher. Controlling for this by using rates rather than absolute numbers of cases allows us to identify “hot spots” and “cool spots” which might otherwise be obscured. Considering what makes areas with high rates differ from those with low rates can help us to understand the individual behaviours and population characteristics that are associated with the population prevalence of these infections and can help us to design better and more effective interventions.

When considering how to calculate the rates, it was necessary to consider which GUM clinic individuals would attend should they require diagnosis or treatment. This highlighted issues regarding clinic accessibility. There were clear disparities

between regions. Accessibility was far better in the Northwest than the East Midlands, which in turn was better than in the Southwest.

Currently, services are commissioned and funds allocated on the basis of the information obtained from GUM clinics through KC60 returns. However, in areas where access to GUM services is poor, individuals may be accessing sexual health services in other settings. This can lead to an underestimate of the true burden of disease in the population and hence to an under-allocation of resources to these areas.

Funding for services can be problematic if, due to difficulties in accessing GUM services, individuals turn to other healthcare settings such as satellite clinics or primary care. It is important that investment is made to ensure that the health practitioners in these settings receive appropriate training to deal with all aspects of sexual health and that they have the time and resources to devote to detection and treatment.

In Chapter 3 we turned our attention from the measurement of sexually transmitted disease to the measurement of risky sexual behaviour. Whilst many behavioural risk factors for both chlamydia and gonorrhoea have been identified in previous studies, this chapter explored whether a single characteristic or set of characteristics could be used to help identify those individuals at risk of infection. Using latent class analysis, it was found that risky behaviours do tend to cluster together and that individuals who had more than one partner in the last year were more likely to be engaging in other risk behaviours as well. Those with no partners or only one partner in the last year were far less likely to be engaged in any of the behaviours known to increase chlamydia and gonorrhoea risk. Approximately 21% of the study population fell into a more “risky” category having had two or more partners in the last year, suggesting that risky behaviour is relatively prevalent in the general population.

Having a single, simple measure that can help to identify individuals at risk of infection can potentially be very useful. GPs and other health professionals do not always find it easy to discuss sexual health with their patients because of the sensitivity of the issues, but also because of constraints on time with each patient. Knowing that it is possible to identify those engaging in risky behaviour just by asking, "How many sexual partners have you had in the last year?", could help to simplify the process. It can help health professionals to quickly, easily and with minimum embarrassment, identify those individuals who, according to the NICE guidelines, require one-to-one interventions and further discussion. For these patients it may then be worth taking the full sexual history, especially exploring their pattern of condom use. But encouraging all people who have had more than one partner to get tested for chlamydia could be an effective way to reduce disease prevalence.

This chapter also explored the prevalence of risky behaviour by age, sex, marital status and ethnic group. It found that risky behaviour declined with age with the highest prevalence in the youngest age group, 16-24 years. Single people had the highest prevalence of risky behaviour (39%) but were closely followed by those who had been previously married (31%). Married and cohabiting individuals were well below the population prevalence of 21% with 6% and 13% respectively. The prevalence of risky behaviour was fairly similar in the Black and White ethnic groups, whilst the Indian and Pakistani groups had a substantially lower prevalence. Males had a much higher prevalence than females.

Understanding the distribution of risky sexual behaviour within key groups can inform efforts to reduce STD prevalence or incidence through public policy. Current Government policy with respect to STDs includes measures specifically to target groups which they have identified as "at risk" especially young people and black and ethnic minority groups. This study has shown that young people

are indeed a key group with a higher prevalence of risky behaviour than their older counterparts.

The prevalence of risky behaviour in the Black ethnic minority group was slightly higher than in the White group but this prevalence could be predicted by their age and marital status alone. There seems to be no indication that being Black per se implies riskier behaviour. Instead, the higher prevalence of chlamydia and gonorrhoea in this group may be due to its age, sex and marital status profile. Alternatively, it may be related to sexual partnership networks and sexual mixing patterns within this group.

Whilst the specific targeting of the Black ethnic minority group may be mistaken, another group seems to have been left out of health promotion proposals and targets altogether – previously married individuals. Large numbers of people divorce every year, entering this group and potentially placing themselves at risk of an STD. This may help to explain why the Health Protection Agency recently found that sexually transmitted diseases were rising most quickly in over 45s. Little is known about why this group behaves as it does and further research is needed in inform the design of effective interventions to reduce risky behaviour among the previously married.

Chapter 4 brought together the work on measuring both rates and risky behaviour. It considered the extent to which the variations in rates observed in Chapter 2 could be explained by the varying prevalence of risky behaviour (as defined in Chapter 3) over the same areas. In order to explore this correlation, it was necessary to first calculate the prevalence of risky behaviour in the relevant areas. Using a synthetic regression model, small area estimates were obtained for all wards in England. The results of this exercise show that the prevalence of risky behaviour is higher in urban areas and prevalence can be predicted by using the proportion of single individuals as a proxy measure.

This is an extremely useful finding. Relatively few surveys collect data about sexual behaviour but many, including the Census, collect data on living arrangements. This study suggests that one simple demographic question can act as an excellent proxy, allowing us to predict that where there are higher proportions of single/previously married individuals, there is likely to be a higher prevalence of risky behaviour. This can be hugely helpful for planning, especially at the local level where data on sexual behaviour are difficult to obtain.

These small area estimates were then aggregated into areas that corresponded with the Thiessen polygons used to derive the clinic-based rates. The variation in the prevalence of risky behaviour was able to explain 17% of the variation in chlamydia rates and 49% of the variation in gonorrhoea rates. Thus whilst the prevalence of risky behaviour clearly contributes to the variation in sexually transmitted disease rates, it by no means explains all of the variation. Further research is required to determine what other factors may be relevant.

The Government has tried to tackle one other possible cause of higher infection rates. If individuals cannot easily and quickly access sexual health services then they are more likely to infect a partner. By attempting to improve GUM service and ensure that every patient receives an appointment within 48 hours, the Government hopes to reduce disease transmission and hence infection rates. But as Chapter 2 showed, accessibility is not all about time to appointments and, in some areas, the burden may fall on other practitioners who are not being targeted with additional funding or training. Whilst the National Chlaymdia Screening Programme may make this less relevant for those under aged 25 years, the studies in Chapters 3 and 4 suggest that young people are not the only group at risk of infection.

Reducing sexually transmitted infections across all regions will require multiple approaches. Making all people, not just specific groups, aware of how their relationship patterns may place them at risk is perhaps the best way to ensure

that individuals take responsibility for their part in reducing the spread of sexually transmitted disease. In conjunction with this it is important to make testing programmes, such as the National Chlamydia Screening Programme, widely available to all age groups. Or, if that is not cost-effective, then the Government should at least ensure that sexual health services are available to all people, even those in more remote areas, and that the health practitioners that they do see are trained to deal with all aspects of sexual health.

5.2 FURTHER RESEARCH

Only a limited number of research questions can actually be discussed in this thesis and, during the process of answering these questions, others have arisen that we have not been able to address. Below are some of the possible avenues for further research that have suggested themselves.

Throughout this research programme the data available on sexually transmitted disease diagnoses have limited the questions that it has been possible to ask and explore. All clinics are required to report their diagnoses to the Health Protection Agency (HPA) using the KC60 form. Whilst the HPA holds these data for the whole UK, we were only able to obtain information on the Northwest, Southwest and East Midlands regions of England. If it were feasible to obtain additional clinic-level data, it would be possible to calculate rates across all of England, or possibly across the whole of the UK, for both chlamydia and gonorrhoea. Not only would this provide valuable additional insight into the variation of disease rates across the UK, but it would also improve the analysis of the relationship between the prevalence of these diseases and the prevalence of risky sexual behaviour. At the moment, we have calculated the correlation between these two using about 50 data points. By obtaining data for all clinics in England, for example, we would be able to increase this to 200 data points thereby improving the validity of any correlation found.

In examining the correlation between risky sexual behaviour and sexually transmitted disease rates, this thesis has considered only one of the potential sources of variation in the rates of disease diagnosed at GUM clinics. Very little information is currently available on the approach taken by primary care physicians and health care professionals when presented with an individual requiring sexual health services. However, a region in which GPs are proactive in referring individuals to GUM services is likely to see higher rates then one where the subject is never broached with patients. Similarly, if GPs in a particular area tend to carry out any required testing or treatment at the surgery rather than referring patients to a GUM clinic, that area may have substantially lower rates. Thus by studying the treatment practices with respect to sexual health of other local healthcare professionals we would be better able to understand the variation observed at clinic-level.

In Chapter 3, we used data from NATSAL II, which was carried out in 2001. In 2010, a third round of NATSAL will be undertaken. It will ask similar questions to those in the previous two NATSAL rounds but will increase the upper age limit to 74 years and will include more STD testing. It would be interesting to explore whether the nature and prevalence of risky behaviour has changed in the 10 years since the data used in Chapter 3 were released and to explore the prevalence in the older age groups not included in the previous rounds. Moreover with data from 1990, 2001 and 2010, it will be possible to explore trends in sexual behaviour over the past 20 years.

In Chapter 4, small area estimates of risky sexual behaviour were produced. However, the key word here is “estimates”. The prevalence of risky behaviour has been predicted through the use of other variables that are known to be associated with it. Sometimes this produces very good estimates. Other times, they are less accurate. Without good local data on the prevalence of risky sexual behaviour it has been impossible for us to evaluate our ward-level estimates. It would therefore be very interesting to examine the experience in several wards to

determine whether the synthetic regression model has produced estimates that reflect the true local prevalence. And if the estimates do differ from the local experience, it would be interesting to understand why.

Some of these possible avenues for further studies may be superseded by the release of the Common Dataset for Sexual Health. If this project delivers on its objectives, this dataset will provide information on all diagnoses, disaggregated by setting. It will allow the calculation of incidence rates both for the total population and for specific settings. It will also provide some sexual history data which should allow the relationship between risky sexual behaviour and disease incidence to be more fully explored. It is currently unclear when this dataset will become available and which individuals will have access to the data when it is released. However, it is to be hoped that it will be widely available to the academic community and that it will substantially improve our understanding of the local experience of sexually transmitted diseases and risky sexual behaviour. Until then, it is hoped that these three chapters have suggested some innovative approaches to using the existing data and have addressed some of the gaps in our knowledge about this relationship.

Statistical Appendix

Calculation of Moran's *I*

Moran's *I* compares the value of a variable at a particular location with the value at all other locations using the formula:

$$I = \frac{N\sum_i \sum_j W_{i,j}(X_i - \overline{X})(X_j - \overline{X})}{(\sum_i \sum_j W_{i,j})\sum_i (X_i - \overline{X})^2}$$

Where N is the number of cases

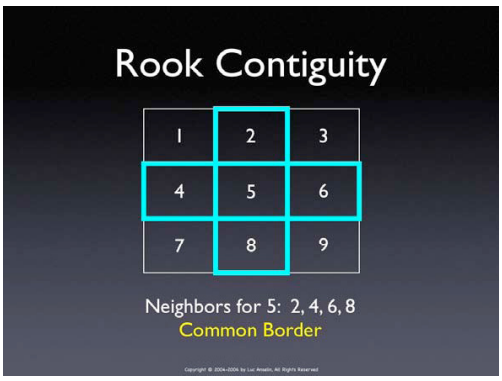
X_i is the value of the variable at a particular location i

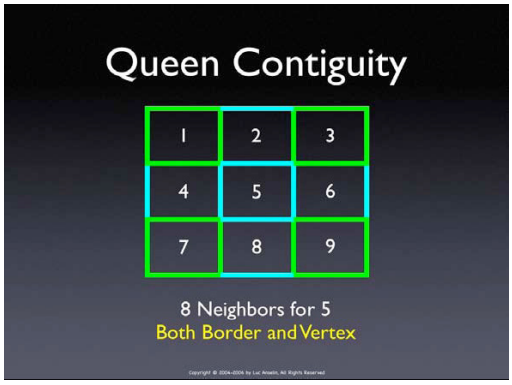
X_j is the value of the variable at another location j

$\overline{X}$ is the mean of the variable based on all locations and

Wij is a weight applied to the comparison between location i and location j (Voss and Ramsay, 2006).

The weight, Wij, can be calculated in a number of ways. Tobler's first law of geography says "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236). As the distance between clinics increases, the less impact they are likely to exert upon one another. We specify this in the calculation of *I* by creating a weights matrix. One approach to specifying the weights matrix is to base it on contiguity, i.e. one clinic can only influence another if it is in an adjacent polygon. The two most common measures of contiguity are Rook and Queen, based on the path taken by these pieces in a game of chess. This is illustrated in the figures below (Glavis, 2007).





Weights can also be based on the Euclidean distance between the clinics. Generally the weight given to each observation is the inverse of the distance between them. Alternatively, we can use the "nearest neighbours" approach. Every clinic will have a certain number of neighbours, no matter how far apart they are. It is usually best to experiment with weights matrices and then to select the one that produces the highest value of Moran's *I*. This errs on the side of caution, forcing you to explain the largest amount of spatial autocorrelation (Voss and Ramsay, 2006).

Classification and Regression Tree Analysis (CART)

The binary splits in CART analysis are made by assessing the Gini impurity function. A node that has no impurity would have no variability with respect to the dependent variable, i.e. everyone would have given the same response (0 or 1) on this variable. The Gini impurity function of the parent node is compared to the weighted average of the Gini impurity function of the two child nodes and the split is selected for which the difference between the two values is greatest. (Lemon et al., 2003).

The Gini impurity function is calculated as $2p_{i/j}(1-p_{i/j})$, where $p_{i/j}$ is the probability that the dependent variable is equal to i in Node j.

The weighted average of the impurity function of the two child nodes is calculated as: $p_1(\text{impurity function child node 1})\ p_2(\text{impurity function child node 2})$, where p_1 and p_2 refer to the proportions of the parent node that are included in each of the respective child nodes (Lemon et al., 2003).

The Gini improvement measure is then calculated by subtracting the weighted average from the parent node impurity function. The split of the variable which provides the largest value for the improvement measure will be the one selected at each step (Lemon et al., 2003)

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