Exploring area-based vulnerability to gambling-related harm:
Developing the gambling-related harm risk index

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MANCHESTER CITY COUNCIL

City of Westminster

Contents

Executive Summary

Background

- In the Gambling Act 2005, children, the young and the vulnerable are singled out for special regulatory attention, with the aim that they should be protected from being harmed or exploited by gambling.
- From April 2016 all industry operators have to undertake local area risk assessments to explore what risks gambling venues pose to the licensing objectives, including the protection of young and vulnerable people.
- To date, there has been very little examination of who is vulnerable to gambling-related harm, how these people can be identified and what might be done to protect them.

Aims of this study

- The first aim of this study was to consider the types of people who may be at greater risk of harm from gambling and where they might be located. Based on review of existing research evidence, a previous report (called *Exploring area based-vulnerability to harm: who is vulnerable?*) concluded that youths, those affected by substance abuse / misuse / excessive alcohol consumption, poorer mental health, those living in deprived areas, from certain ethnic groups, those with low IQs, personality/cognitive impairments, those seeking treatment for gambling problems and those who are unemployed are potentially more vulnerable to harm from gambling.
- Having identified these groups, this report brings this information together to create local risk indices, showing areas with greater concentrations of people who are more likely to be vulnerable to harm.
- Commissioned by Westminster and Manchester City Councils, this study used Westminster and Manchester as case study areas to develop local risk indices of gambling-related harm.

Methods

- For each characteristic of vulnerability identified, the availability of local level data was reviewed. For some characteristics, there were good data available (for example, unemployment rates from census records). For others there were no data available (such as low IQ). Therefore, the final characteristics of vulnerability included in our models were those where there was a strong theoretical and empirical basis for inclusion and good local level data available.

- Information from all different characteristics was brought together and visually displayed. Data were grouped into two different indices based on whether they related to:

    - the characteristics of people who live in a local area (the resident profile) and/or,
    - the location of local services which are likely to attract potentially vulnerable people to a specific place.

- Data from the two indices were then combined to produce an overall gambling risk index for each area. These results were displayed visually on maps for Westminster and Manchester to highlight the locations which had relatively higher risk profiles.

Results

- In Westminster, four broad areas of greater risk were identified. These are those to the north west of Westminster, around the Harrow Road, to the south, around Victoria and Pimlico, north-central areas around Paddington and the Edgware road and finally, the West End. The heightened risk in each area is driven by a range of different factors. For example, in Pimlico risk is higher because of a greater number of homelessness shelters and substance abuse treatment providers in this area. In the North West area, risk is driven by rates of unemployment, ethnic make-up and large numbers of resident young people.

- In Manchester, there are many different areas of risk which include areas around the city centre and the south of the city; around Rushholme and Longsight and an area around Cheetham. Risk in the city centre is driven primarily by the concentration of pay-day loans shops, education establishments, younger residents and support centres for problem gamblers. Relatively high levels of unemployment as well as ethnic mix are major driving factors in the other locations.

- Comparisons of the areas identified by our risk models with data on deprivation shows some overlaps but also some differences. For example, the City of Manchester has a relatively low score according to the Index of Multiple Deprivation (IMD) but was identified as higher risk of gambling harm in our models. This is because there are a range of services offered within the city that may draw potentially vulnerable people into the city centre. This is not represented in IMD scores which focus only on the profile of people living in an area. Because of this we believe IMD is not a sufficient proxy to represent risk to gambling-related harm at a local level.

Caveats

- Our models are probabilistic. Just because we have highlighted an area as being at greater risk, does not mean that all people in those areas will experience harm.
- Our models are based on current knowledge and available data. There were a number of potentially vulnerable groups (such as immigrants or those on probation) who were excluded from our models because of a lack of local level data. Our models are limited to areas where more research has been conducted and where good quality local level data are available.
- Finally, the evidence base used to develop the models shows those vulnerable to gambling problems rather than gambling-related harm. The models may be conservative as gambling-related harm is broader than problem gambling.

Recommendations

- The Gambling Commission's introduction of Local Area Risk profiles represents a new opportunity for Local Authorities (LA) and industry alike to think more deeply about the protection of vulnerable people from gambling-related harm. This means extending understanding of local area risk beyond mapping deprivation and considering a more nuanced range of factors.
- LAs interested in pursuing this approach should start to consider the different types of data they have available and how these can be used in local area profiles.
- LAs should also start to consider what data and/or evidence is missing and how they could fill these gaps, working with different departments within the authority to capture relevant information.
- The models developed are based on the best information currently available. An acknowledged limitation of gambling research is the paucity of evidence available. We recommend that the models developed for this project are periodically reviewed and updated to take into account growing knowledge, better data and changes in local areas.

1 Introduction

Overview of project

This project aims to explore area-based vulnerability to gambling-related harm, incorporating all types of gambling activity. Gambling behaviour and who experiences harm from gambling vary among different types of people. This variation is the result of characteristics relating to the person, such as their age or gender, those relating to personal circumstances, such as employment or income, and those relating to where people live, such as deprived areas. The political landscape in which gambling is provided and regulated will also have an effect.

The Gambling Act 2005 states that children and vulnerable people should be protected from being harmed or exploited by gambling. Yet to date, there has been little investigation about who may be vulnerable or why. Furthermore, how vulnerability and harm may vary at a local level has not been explored. This project aims to help fill this gap by:

- exploring and documenting the range of characteristics that suggest someone is vulnerable to harm from gambling,
- investigating how these characteristics can be measured at a local level, using a range of different data, and
- developing local area risk indices to show areas where those who may be more vulnerable to harm are located.

We have previously published a scoping report highlighting the kinds of people and/or characteristics that may mean someone is more vulnerable to gambling-related harm.[1] This current report builds on that work and looks at how we can use this insight to explore vulnerability at a local level, using a variety of local level data. Commissioned by Westminster and Manchester City Councils, we have worked with them to model area-based vulnerability to gambling-related harm. The resulting indices are displayed visually on maps for each region so that areas of potential risk are highlighted. This report outlines the methodology we used to create the local area risk indices and discusses the results. Our previous report sets out the theory underpinning the development of the indices.

[1] See Wardle, H (2015a) Exploring area-based vulnerability to gambling-related harm: Who is vulnerable? Evidence from a quick scoping review. London: Westminster. Available at: http://transact.westminster.gov.uk/docstores/publications_store/licensing/final_phase1_exploring_area-based_vulnerability_and_gambling_related_harm_report_v2.pdf

Policy context

The Gambling Act 2005 (the Act) gave Local Authorities (LAs) responsibility for issuing premises licences for gambling venues. The advice contained within the Act was that LAs should "aim to permit" premises licences so long as applications are reasonably consistent with the following objectives:

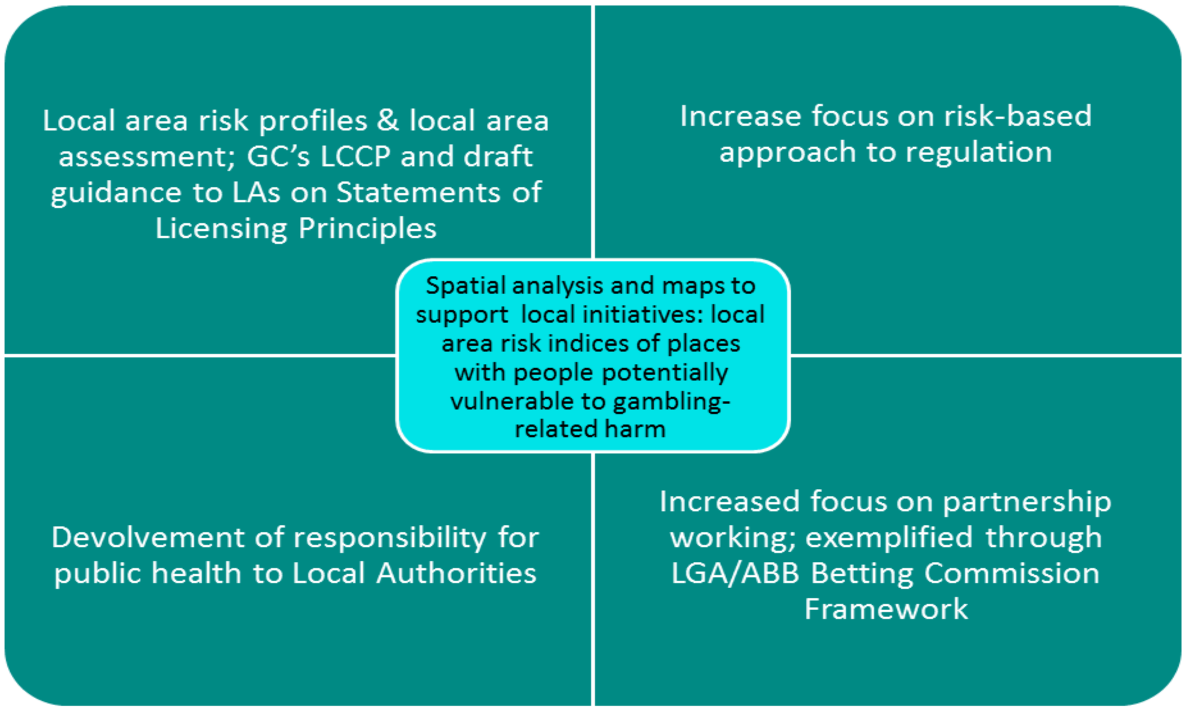
> (a) preventing gambling from being a source of crime or disorder, being associated with crime or disorder or being used to support crime,
> (b) ensuring that gambling is conducted in a fair and open way, and
> (c) protecting children and other vulnerable persons from being harmed or exploited by gambling.

More recently, there have been some changes in the recommended approach to gambling licensing and regulation, as expressed in various documents published by the Gambling Commission (GC, see GC, 2015; GC, 2012). These changes can be summarised into three broad themes:

- increased focus on risk and risk regulation;
- greater attention to local area risk, and
- encouragement of partnership and collaboration between stakeholders to mitigate risk.

In addition, a further change is the devolvement of public health to LAs and their new responsibility to protect the health and wellbeing of people in their local communities (see Figure 1).

Figure 1: Policy context for this project



Increased focus on risk regulation

A risk-based approach to regulation has been a key part of the GC's principles for licensing and regulation since 2009, meaning that resources are concentrated where they are needed most and can be most effective (GC, 2009; 2015). Greater pursuit and clearer demonstration of this risk-based approach was a key recommendation of the Culture, Media and Sport Select Committee inquiry into the impact of the Gambling Act (DCMS, 2012). This renewed emphasis on risk-based regulation can be seen in the GC's revised Licensing Conditions and Codes of Practice (LCCP) which encourages industry to consider the risk that their venues pose to the licensing objectives and to take appropriate action. This focus is underpinned by the GC's encouragement that stakeholders, including industry and local government, better consider risk, look at future risks and think about risk in a probabilistic way:

> "*Risk is not necessarily related to an event that has happened. Risk is related to the probability of an event happening and the likely impact of that event – in this case on licensing objectives*" (GC, 2015)

This focus is important especially when it comes to thinking about evidence-based policy and action as it highlights the importance of thinking probabilistically about risk. Here the onus is not to prove that action one way or another will have a certain effect or outcome but rather to think about the likely impacts that could happen, given what is known about a local area, and to think about the likelihood of these outcomes occurring. In short, it changes the burden of proof away from demonstrating that certain actions ***will*** have a stated outcome towards thinking that they ***may*** have certain outcomes because of a variety of influences. As some academics have noted, this shift in focus "*allows regulators to make decisions based on what they do know rather than what they don't*" (Philips & Goodman, 2004).

Local risk assessments

Greater focus on risk and probabilistic thinking arguably underpins the GC's new requirement that gambling industry operators should (from April 2016) conduct local risk assessments. The assessments are required for all premises and operators need to demonstrate that they understand local issues and show what measures they propose to introduce or currently have to mitigate against this risk (see Box 1).

Box 1: The new provisions for local risk assessment in the LCCP, 2015

Social responsibility code provision 10.1.1
Assessing local risk
All non-remote casino, adult gaming centre, bingo, family entertainment centre, betting and remote betting intermediary (trading room only) licences, except non-remote general betting (limited) and betting intermediary licences.

This provision comes into force on 6 April 2016

1. Licensees must assess the local risks to the licensing objectives posed by the provisions of gambling facilities at each of their premises, and have policies, procedures and control measures to mitigate those risks. In making risk assessments, licencees must take into account relevant matters identified in the licensing authority's statement of licensing policy.
2. Licensees must review (and update as necessary) their local risk assessments:
    a. to take into account significant changes in local circumstances, including those identified in a licensing authority's statement of licensing policy;
    b. when there are significant changes at a licensee's premises that may affect their mitigation of local risks;
    c. when applying for a variation of a premises licence; and
    d. in any case, undertake a local risk assessment when applying for a new premises licence.

The GC has also recommended that LAs consider producing local area profiles to support their licensing statements and principles. The intention is that these local area profiles draw on information from a wide range of local bodies to further understand the nature of potential risks in each LA and to develop more locally focused gambling policy:

> *"We are encouraging LAs to move away from a national template [of Statement of Licensing Principles] to something that is genuinely reflective of local issues, local data, local risk… The experts are each LA. They know their patch better than anyone. And of course they should engage with both responsible authorities such as the Safeguarding Board, the police and others as well as other expert bodies such as perhaps public health, mental health, housing as well as community groups who have a particular knowledge of parts of the area and the population of the area."* (GC, 2015)

The GC are recommending that local area profiles are built into LAs revised Statements of Licensing Policy, due to be implemented from January 2016. The emphasis for understanding local risk is therefore incumbent on both the gambling operator and the LA.

Partnership working

The introduction of local risk assessments into the LCCP reflects a broader policy movement which encourages LAs, the regulator and the industry to work in partnership to address local issues and concerns. This form of partnership working was enshrined within the Local Government Association's and the Association of British Bookmakers' Framework for Local Partnerships on Betting Shops. This framework recognised there are local concerns about betting shops and their impact. It drew on practice from alcohol licensing and local partnerships between the alcohol trade and communities to suggest a range of ways that industry, LAs, community safety teams, and the police could work together to address concerns. Suggestions included setting up local Betwatch schemes, as has been done in Ealing, or creating other bespoke solutions to deal with issues, like the responsible gambling partnership set up in Medway.

The GC is keen to see this form of partnership working extended. Part of the rationale for local area risk assessments is so that operators and LAs can work together to establish a range of practices that may mitigate potential harms in certain areas.

Devolvement of public health to LAs

A final important policy change is the devolvement of public health to LAs. The Health and Social Care Act, 2012 gave responsibility for health improvement to the LA. This gave each LA a new duty to take appropriate steps to improve the health of people in its area. Under this provision, new Directors of Public Health were appointed and units created to support the new public health functions of LAs. The intention was for LAs to have freedom to choose how they improve their population's health and it was hoped that this would create a new focus on improving health and reducing inequalities. These changes are important as gambling is often considered a public health issue. The Responsible Gambling Strategy Board (RGSB), the body responsible for providing advice to the GC and government about gambling, advocates that gambling be considered within a public health framework. Other jurisdictions, like New Zealand, have gone further and defined gambling as a public health consideration with policy responsibility residing with the Department of Health.

In Great Britain, policy responsibility for gambling continues to be held by the Department for Culture, Media and Sport. However, devolvement of responsibility for public health to LAs may mean that increasing health focus is given to local gambling policy. This is most likely to occur in relation to the third licensing objective of the Act, which states that vulnerable people should be protected from harm. Who 'vulnerable people' are or the ways in which they may be vulnerable is not defined, though the GC states that for regulatory purposes it is likely to include:

> *"people who gamble more than they want to, people who gamble beyond their means and people who may not be able to make informed or balanced decisions about gambling due to, for example, mental health, a learning disability or substance misuse relating to alcohol or drugs*." (GC, 2012)

There is clear overlap with people of interest to public health policy makers and practitioners, namely those with mental health problems, other health issues and substance misuse problems. As the public health function within LAs matures, it is likely that gambling issues and protection of the vulnerable may increasingly fall within their remit. However, this broader policy shift has not occurred to date and it is noticeable the GC's consultation on LAs' revised Statements of Licensing Policy did not include any reference to public health.

Contribution of our project to this policy environment

It is against this policy and regulatory background that this project has been commissioned (see Figure 1). Our research explores what area-based vulnerability to gambling-related harm looks like and how it can be visualised geographically, focusing on Westminster and Manchester. By conducting spatial analysis and producing maps that highlight areas where those who are more vulnerable to harm may be present, we provide Westminster, Manchester and the industry tools to help understand local area risks. We hope these tools can be used as the basis for developing strategies and partnerships to address risk to the third licensing objective – that is the protection of vulnerable people.

Structure of this report

In this report we outline our methodology for producing the local area risk indices and results for Westminster and Manchester respectively. Chapter 2 gives an overview of the theoretical basis of model development, which is discussed more fully in our first report (see Wardle, 2015a). Chapter 3 discusses the development of the models, including an overview of the spatial analysis methods used. Chapter 4 presents results for Manchester and Westminster whilst Chapter 5 summarises key themes from this research.

2 Developing the risk index models: theoretical basis

Overview

In order to develop indices of risk to gambling-related harm, it was first important to establish the theoretical and empirical basis of the models. This included a process of consultation and evidence assessment to understand who may be more vulnerable to gambling-related problems and why. The resulting information was used as the basis for our models, which included assessment of what local data were available. The factors present in the final indices are those that have a strong theoretical and/or empirical basis and good quality data available at the local level.

Methods

Consultation interviews

To develop the theoretical basis of our risk models, we first had to establish which types of people were viewed as vulnerable to, or at risk of, gambling-related harm. This was done by consulting with a range of different stakeholders, which included:

- academics,
- policy makers,
- treatment providers,
- the industry, and
- legal professionals.

These stakeholders are those who are responsible for either creating or responding to gambling policy in Great Britain, translating perceptions into practice. Therefore, understanding the perceptions of these stakeholders was important since their views are highly salient to how we understand concepts of harm, risk and vulnerability in policy terms more generally.

Semi-structured interviews were conducted either one to one or within a group setting. Each interview discussed the following:

- definitions of gambling-related harm, who is harmed, why and how, and;

- who might be vulnerable to gambling-related harm, how and whether this has changed.

In addition, standards of evidence used in gambling policy were also discussed.

Quick scoping reviews

For each person type identified as being at risk or characteristic of vulnerability mentioned by stakeholders, quick scoping reviews (QSR) were conducted to see whether research evidence supported these perceptions. QSRs are a methodology recommended by the Government Social Research Office.[2] They are used to quickly determine the range of studies that are available on a specific topic and produce a broad 'map' of the existing literature (see Wardle, 2015a for more details).

To help synthesise results, the research evidence was evaluated using the following criteria:

1) Is the relationship plausible; does it make sense?
2) Is the relationship coherent with existing knowledge?
3) Is the relationship consistent over space and time? If not, what are the contextual factors that explain why not?
4) How strong is the relationship?
5) What are the alternative explanations?
6) Is there analogous evidence from similar policy areas?[3]

Assessing the evidence base using this framework allowed us to make judgements about how strongly supported each characteristic of vulnerability/risk was. We then used this information to make informed decisions about which features should be included in our models.

[2] See http://www.civilservice.gov.uk/networks/gsr/resources-and-guidance/rapid-evidence-assessment/what-is

[3] This framework of assessment draws on the work of Austin Bradford-Hill and his method for assessing causal relationships in epidemiology. See Hill, B (1965).

Definitions

Before considering the evidence relating to who is vulnerable to, or at risk of, gambling-related harm, it is worth considering how we define these terms.

Gambling-related harm

Among policy makers in Great Britain, gambling-related harm is defined as:

> *"the adverse financial, personal and social consequences to players, their families and wider social networks that can be caused by uncontrolled gambling" (RGSB, 2009)*

Policy makers also focus on:

> *"the shorter-term harms brought about by short-term bouts of intensive gambling, which may require a different preventative approach" (RGSB, 2009)*

In keeping with this, the stakeholders interviewed generally viewed gambling-related harm as something that could be temporary and episodic or exist over a longer time frame. There was a broad consensus that gambling-related harm meant adverse consequences from gambling and that these harms could be experienced by the individual, their families, social networks and by communities.

In academic literature, gambling-related harm is often conflated with problem gambling, yet the stakeholders interviewed generally felt that the two were distinct. It was felt that you did not have to be a problem gambler to experience harm but that most problem gamblers would experience harms from their gambling. Finally, it was argued that the types of harms experienced were likely to exist on a spectrum, for example, ranging from arguments with spouses to relationship breakdown.

The term 'gambling-related harm' is relatively new in policy and academic circles and there is a limited evidence base assessing it. The term has not been adequately defined and research evidence tends to focus on problem and at-risk gambling as a proxy for this. As such, evidence identified in the scoping reviews related more to 'problem' gambling rather than broader harms or harm to others. This is an acknowledged constraint of this study and thus our models. However, given stakeholders' views that people experiencing problems with gambling would almost certainly be experiencing harm, we are confident that this literature is appropriate to understanding one aspect of harm. It does mean that our indices are likely to be conservative as they focus on risk of gambling problems rather than broader harms.

Vulnerable people/vulnerable to gambling-related harm

Vulnerable people have been singled out for special regulatory attention in gambling policy. This is because the Gambling Act's third licensing objective specifically states that vulnerable people should be protected from being harmed or exploited by gambling. The Gambling Commission has stated that whilst they did not want to explicitly define who vulnerable people are, this is likely to include people who gamble more than they want to (GC, 2012).

Prior to this, the Gambling Review Report (known as the Budd report) suggested a range of groups who they felt could be considered vulnerable to harm. This included young people, those under the influence of drugs/alcohol, those with co-existing mental health conditions, low income groups and those most disadvantaged and marginalised by economic change (DCMS, 2001).

In our previous report, we highlighted how many stakeholders felt that anyone could be vulnerable to gambling-related harm. The experience of harm was seen as subjective, whereby negative consequences depended on individual circumstances and experiences. It was argued that anyone, under certain circumstances, could become vulnerable to harm. However, it was also recognised that these personal circumstances would not necessarily be known to regulators and gambling operators and therefore one had to think more probabilistically about who might be vulnerable. This included thinking about the types of people who may be more likely to experience or be susceptible to gambling-related harm. This approach recognises that not everyone with a certain characteristic will experience harm if they gamble, but rather that they may have an elevated risk of harm because of their characteristics or circumstances. Our risk indices draw on these assumptions. It is a risk-based, probabilistic, approach to understanding vulnerability.

Evidence and risk

This project explicitly acknowledges that the experience of gambling-related harm and vulnerability to gambling-related harm are, at the individual level, inherently subjective. However, data and evidence have highlighted generalities and patterns that give us confidence that we can take a risk-based approach to exploring area-level vulnerability to gambling-related harm. The generalities observed mean that whilst we may not know the exact mechanisms or contexts which shape behaviour, we can identify characteristics of heightened risk (Carter & New, 2004). As these risk characteristics belong to people, there is likely to be local area variation in potential vulnerability to harm based on how the profile of people in different locations varies.

Taking a more probabilistic approach to assessing risk requires a changing way of thinking about evidence and what it means. When looking for generalities, we are observing patterns. These patterns are informative as they highlight the potential presence of a range of causal processes (Carter & New, 2004). The association itself should not be viewed deterministically, whereby x causes y, but rather more generatively where x may generate y outcome under a, b, or c circumstances (Pawson & Tilly, 1997; Wardle, 2015b). This approach reflects the uncertainty of subjective experiences whilst recognising there are general patterns and associations that we can observe and use in our models, without having full knowledge of the exact contexts and mechanisms that shape outcomes for each individual. In this way, our models are not saying that everyone in a certain area or with certain characteristics will be at risk, but rather they may have elevated levels of risk.

Because people and places vary, this potential risk varies, and our models seek to identify the spatial variation of risk and visualise this on a map.

Who is vulnerable? Findings from phase 1

Stakeholder perceptions

From stakeholder interviews, common themes around who stakeholders felt might be vulnerable to gambling-related harm were identified. These were:

1) those with constrained social and economic circumstances. This tended to include those living in deprived areas, those who were unemployed, those with low income but also those experiencing social isolation or more uncertain social circumstances, for example homeless populations, offenders and migrants;
2) those with certain demographic characteristics. This included the young but also other characteristics such as gender and ethnicity – though it was broadly accepted that these characteristics may serve as a proxy for other mechanisms. For example, older people were mentioned but the mechanisms articulated around age related to social isolation, or the experience of common life events, such as bereavement and/or having low fixed incomes;

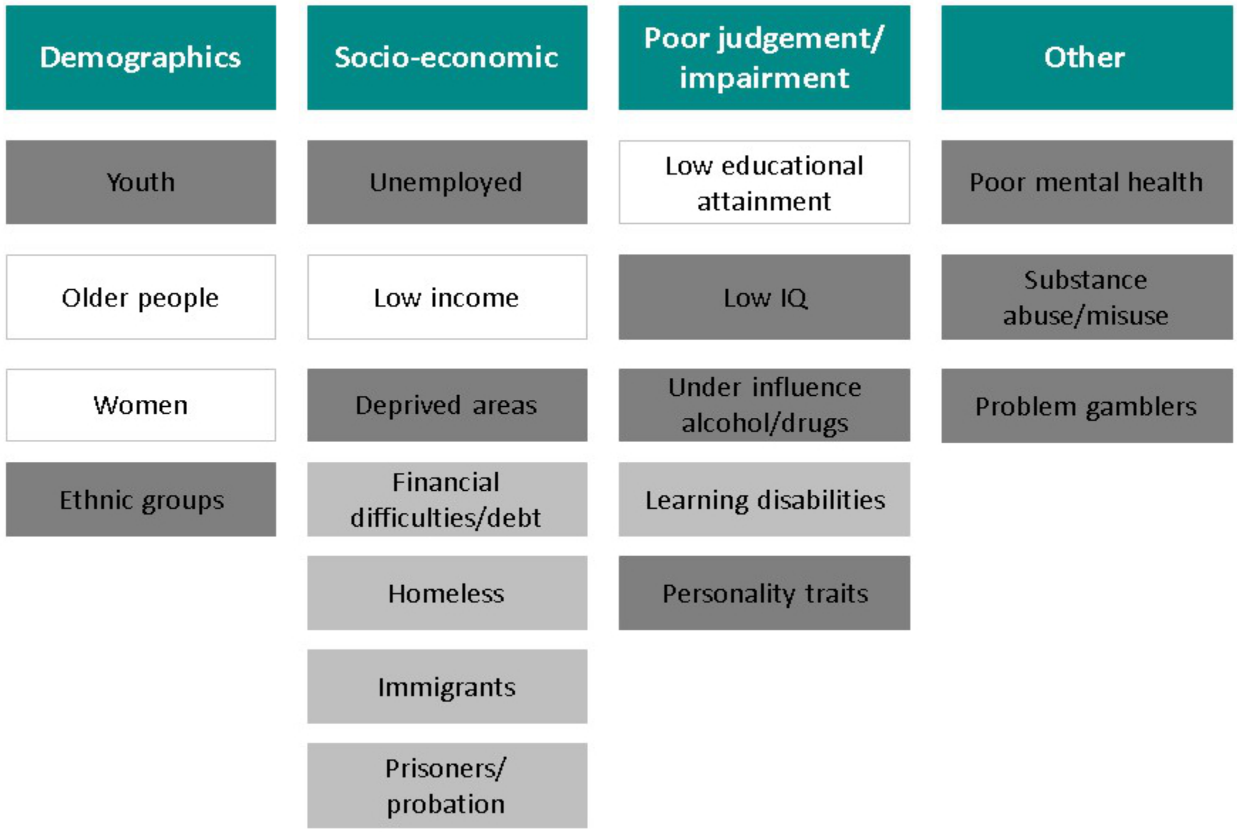
3) those who may have poorer judgement. This ranged from people with certain mental health conditions, those with learning disabilities or low educational attainment, to those with temporary impairment or longer term difficulties because of substance use/misuse, and;
4) other groups, such as problem gamblers seeking treatment or those with substance abuse/misuse issues.

For each characteristic or group mentioned, a scoping review assessed whether stakeholder perceptions were supported by empirical evidence or not. Those characteristics or groups found to be well supported by evidence or to have strong theoretical importance were then identified as candidates for inclusion in our risk indices. Our first report discusses the methods and findings in greater depth (see Wardle, 2015a). In the sections that follow, we outline key themes only.

Who is vulnerable? Findings from the scoping reviews

Figure 2 shows the full range of people/characteristics of people which stakeholders felt indicated increased vulnerability/risk to gambling-related harm. The characteristics which are shaded in dark grey show where the scoping reviews indicated that there was good evidence that these characteristics are associated with higher risk of harm. Those shaded in lighter grey are those where the scoping reviews showed emerging evidence of higher risk of harm. The remaining characteristics are those where either the evidence was mixed or there was no evidence (as yet) to support them (fuller details can be found in our first report, see Wardle, 2015a).

Figure 2: People vulnerable to gambling-related harm, by theme



As can be seen from Figure 2, there was good evidence to support young people, those who are unemployed, those from certain ethnic groups, such as Asian/Asian British, Black/Black British and Chinese/other ethnicity, those living in deprived areas, those with low IQs, those with substance abuse/misuse issues or under the influence of alcohol or drugs, existing problem gamblers (especially those seeking treatment), those with poor mental health and, finally, with certain personality traits (i.e., cognitive impairments, impulsivity) as being potentially more vulnerable to gambling-related harm. For those who are homeless or who are immigrants, there were some research studies highlighting these as potentially vulnerable groups. For example, for homelessness, there was only one British based study and for immigrants there were no British based studies, though some pertinent international literature. Therefore, these were classified as emerging areas. For learning disabilities, there was a small body of work highlighting this as a risk factor for boys but not girls[4], though none of this evidence was generated from Great Britain. Financial difficulties and debt had some emerging evidence from Britain to support these groups as potentially vulnerable. Finally, there was no or little evidence that older people or women should be considered especially vulnerable. However, we

[4] This literature only focuses on the experiences of young people.

recognise that these groups may experience social change and that themes of gambling to relieve social isolation may affect these groups more than others. The evidence relating to low educational attainment and low income was mixed, though we also acknowledged that these may be used as proxies for other related characteristics, such as low IQ or experience of financial difficulties. Finally, it is highly plausible that those on probation or parole may be considered vulnerable to gambling-related harm. There is some research which has demonstrated a link between gambling problems and incarceration. There is other research highlighting gambling cultures within prisons. However, the scoping reviews found that little research had been conducted among those on parole or probation in the community. Therefore, for the purposes of trying to identify vulnerable groups at a community level, this characteristic has no evidence base, as yet, supporting it.

Characteristics of vulnerability included in the risk models

The characteristics considered for inclusion in our local area models were those with either good evidence or strong emerging evidence to support each one. However, to be included in the final models we also needed to have good quality local level data representing each. This means that not all the characteristics shown in Figure 2 are included in our final models. In some cases, we have used what we consider to be reasonable proxies (for example, problem gambling treatment clinics to demonstrate that people with existing gambling problems will be present in a local area). Chapter 3 documents this process fully.

Finally, a key theme of the scoping reviews was the general paucity of evidence for many characteristics (like those on probation). Therefore, whilst the models documented in this report draws on existing evidence and theory, it should be considered open to change as the evidence base develops. In fact, we would encourage that the models are regularly reviewed and amended to take into account emerging research and insight.

3 Developing the risk index models: modelling and spatial analysis

Introduction to vulnerability/risk index models

Using spatial indices to display areas of greater vulnerability or risk to a certain outcome is a well recognised technique. This typically involves drawing together relevant sets of information to model area vulnerability based on a variety of characteristics. These models have been most commonly used to model risk to environmental hazards. A good example is work by Cutter et al (2003) who used data on housing stock and tenancy, income, ethnicity, housing density, personal wealth and infrastructure to create a social vulnerability model, highlighting areas in the USA of least resilience if faced with an environmental hazard. This model included aspects that might increase social vulnerability (like a higher proportion of mobile homes, which are very vulnerable to environmental hazards because they are not very sturdy) and those which may mitigate social vulnerability (for example, low debt to revenue income meaning that these areas could divert resources to dealing with an environmental hazard more easily). This work has been expanded upon and replicated in other countries.

More recently, social scientists have started to explore how similar methods could be used to investigate vulnerability to other social, health and wellbeing risks. For example, scholars have examined how vulnerability to childhood obesity varies across different parts of Texas. To do this, the researchers included measures of median income, proximity to fast food restaurants, ethnicity, proximity to grocery stores and parks in their models. Each characteristic was modelled separately and then combined to create an overall vulnerability index, showing the areas at greater risk of childhood obesity (MacBrayer, 2010). Other studies have looked at ecological risk factors for substance abuse treatment in Buffalo, New York (Mendoza et al, 2013). In this study, a range of risk factors associated with treatment outcomes for substance abuse were modelled at low level geographies. This included socio-economic risk factors, such as unemployment, relative poverty, age and female head of household status which are known to be associated with poorer treatment outcomes. It also included a physical environment domain, comprised of access to alcohol outlets and a mediating factor of presence of substance abuse clinics. This information was brought together into a single risk index to highlight areas with a greater risk of failed treatment outcomes. A key finding was that looking at individual risks alone masked broader patterns and inequalities. Mendoza et al (2013) recommended looking at multiple risk factors together. We drew similar conclusions in our previous report, where we highlighted the complexity range of risk factors to gambling harm and stated that a multiple risk factor approach may be useful (Wardle, 2015a).

Using risk or vulnerability indices to understand and explore environmental aspects of behaviour is an expanding area of research and policy interest. In Britain, this is likely to become even more important now that LAs have responsibility for planning and development, gambling premises licensing, safeguarding vulnerable people and protecting the health of the public.

The risk models presented in this report are not the first produced by gambling researchers. Studies from Canada and Australia have attempted to quantify local area vulnerability to gambling harms, though there are some methodological and theoretical differences between these studies and ours.

Robitaille and Herjean (2008) developed a 'vulnerability' index to assess the relationship between access to video lottery terminals (VLT) in Montreal, Canada and the vulnerability of the resident population within VLT venue catchments. Their methodology drew heavily on that used by Brent Council (London) when considering their application for a new 'super' casino license in Great Britain.[5] Brent Council developed a vulnerability index to characterise the population in the catchment area of the proposed new casino. According to Robitaille and Herjean (2008) this consisted of a range of characteristics, grouped within two domains: demographic and economic. The characteristics included in the models were: sex, age, educational attainment, marital status, household income, geography (i.e., proximity to proposed site), ethnicity and employment status. There are some overlaps with the characteristics we outlined in Chapter 2, for example age, ethnicity and employment status feature heavily in our models and the one used by Brent Council. However, our models extend beyond consideration of just demographic and economic factors, to include health and wellbeing and other vulnerable population groups (like the homeless, for example).

In Herjean and Robitaille's adapted model (2008), the variables used to create their vulnerability index were narrowed even further to the proportion of men aged 19-44, the proportion of single people, the proportion of people without a high school diploma and average income for each local area. These were chosen as they were well known correlates of problems with VLT gambling. Scores for each variable were standardised and added together to form an overall vulnerability index score that was then mapped and visualised for the Montreal area. When compared with accessibility to VLT venues, Robitaille and Herjean (2008) concluded

[5] The 'Super Casino' was an original feature of the Gambling Act, 2005. This special casino license was to create a new large, resort style casino with a customer footprint of up to 5,000 sq metres and housing up to 1,250 slot machines.

that there was a spatial link to areas where the resident population was most vulnerable to the experience of problems.

Herjean and Robitaille's (2008) work mirrors the process we have undertaken for this project. Like them, we have sought to theoretically identify characteristics of people who may be vulnerable or at greater risk of experiencing problems. Once identified, we combined this information together to create a single risk index and displayed these results spatially. Where our work differs is in the scope of the characteristics and variables included – we are not limiting ourselves to simply considering the profile of the resident community, but are also keen to explore how we can include more transient population groups in our models – for example by looking at the types of services available in specific places that may 'pull' vulnerable people into certain spaces at particular points in time. This is discussed further in the next section.

Further attempts to model the relationship between the catchments of gambling venues and area vulnerability have been undertaken in Australia. In 2010, Doran and Young used spatial analysis methods to explore gambling venue catchment areas and their relationship to area vulnerability. This analysis used the Australian equivalent of the British Index of Multiple Deprivation, the Socio-Economic Index for Areas (SEIA), which ranks areas in Australia based on relative socio-economic disadvantage. They combined this with information about gambling venue catchment areas and called this combined output their 'gambling vulnerability surface'. The results were mapped visually. They concluded that their combined vulnerability surface had a different spatial distribution than if they had just used socio-economic disadvantage alone. This too emphasises the importance of taking a multiple risk factor approach to modelling gambling vulnerability; in Doran & Young's (2010) case they included both demand (socio-economic disadvantage) and supply (predicted catchment areas of gambling venues) side variables in their models.

Rintoul et al (2012) expanded upon this work by adding gambling losses recorded at each venue into the model. However, socio-economic vulnerability continued to be represented by SEIA alone and the authors noted that this was a limitation of their model, highlighting how other social, cultural or geographic variables might influence machine gambling within communities. They recommended that future analysis build additional characteristics, such as the ethnic profile of areas, into their models.

Our study builds on the insight of these international studies by extending the range of characteristics which represent vulnerability to gambling-related harm beyond pre-existing measures of deprivation and disadvantage. Our study, however, varies from the Australian research in one major respect. These studies included catchments of existing gambling venues and gambling losses at venues to examine supply side vulnerability. Our work looks only at the profile and characteristics of people (or demand side variables). This is because this research is policy focused, aimed at providing useful tools for our clients. The research has been funded to help Westminster and Manchester City Councils when assessing licensing applications and the potential risk that an individual premise may pose to the three licensing objectives. **The Gambling Act is unequivocal; expected demand should not be taken into account or be a feature of decisions about premises applications.** By implication this means pre-existing supply is sidelined as a consideration. If expected demand is not a feature of decisions then whether there is already existing supply to service that demand is irrelevant to considerations. Because of this, we have not built pre-existing supply-side features (i.e., the location of existing gambling venues) into our models. Rather, we focus on modelling the potential risk to consumers in particular areas based on the profile of people in these places.

Our modelling approach

Overview

We have used spatial analysis techniques to examine local variation in vulnerability to gambling-related harm in both Westminster and Manchester. To do this we have:

- first, identified the main characteristics associated with gambling-related harm;
- second, identified data that best represents this at a local level, and finally;
- sought to combine this information into a single model for each region that shows areas of greater or lower potential risk.

There are many possible appropriate spatial models we could use in this analysis. The approach we have taken uses multiple layers of spatial data representing the relevant risk characteristics which are overlaid to build a bigger picture. This is known as an overlay model. Overlay models are a common approach to mapping risk or vulnerability; some examples have been discussed earlier. In the following sections we outline the main principles of our methodology. We start by providing an overview of which characteristics are in our final models and the data supporting them and then discuss our modelling and spatial analysis techniques.

Characteristics included in the models

As noted in Chapter 2, to be included in our final models, a proposed characteristic had to have either good or strong emerging evidence to support inclusion, and have good quality local data available. Table 1 summarises this information for each characteristic (a more detailed discussion of each dataset used is given later in the chapter).

The models attempt to capture vulnerable people by both their residence and the places they may be otherwise, often described as the 'daytime population'. This gives two different ways of spatially referencing people. Throughout our report we refer to these groups as either people 'at-home' and people 'away-from-home'. Our risk models include both and therefore represent information about local residents but also include places which will attract potentially vulnerable people to a specific area. In Table 1 we note the type of data available locally for each characteristic.

Table 1: Overview of potential variables to include in the models and available data

Characteristic	Supporting evidence	Local small area data available
Problem gamblers who are seeking treatment	Support for seeing those with problems or recovering from problems as vulnerable; evidence that problem gamblers 'relapse' when faced with gambling cues (like premises, adverts etc)	Away from home only
Substance abuse/misuse	Strong support for those with other substance issues as vulnerable	Away from home only
Poor mental health	Strong support for those with poor mental health as vulnerable	At home only
Unemployment	Strong support for unemployed as vulnerable	Away from home and at home
Under the influence of alcohol	Emerging evidence but strong theoretical inference	No suitable local level data available
Ethnic groups	Strong support for certain ethnic groups as vulnerable	At home only
Youth	Strong support for youth as vulnerable	Away from home and at home
Financial difficulties/debt	Emerging evidence that people with financial difficulties are vulnerable	Away from home only

Table 1: continued…		
Characteristic	Supporting evidence	Local small area data available
Homelessness	Emerging evidence that homeless population groups are vulnerable	At home only
Deprivation	Support for those living in the most deprived areas as vulnerable	Modelled by the above[6]
Low IQ	Support that those with low IQs are vulnerable	No local level data available
Personality traits	Strong evidence that those with certain personality traits or cognitions are vulnerable	No local level data available
Immigrants	Emerging evidence that immigrants are vulnerable	No local level data available
Learning disabilities	Some evidence of young males with learning disabilities being vulnerable	No local level data available
Low educational attainment	Evidence mixed, needs further investigation	Away from home and at home
Prisoners/probation	Need more evidence to examine this	No local level data available
Older people	Needs more evidence to examine this	At home only
Women	No evidence that they are vulnerable to gambling-related harm, though some may becoming more vulnerable than previously	At home only

As Table 1 shows, not all characteristics had good local level data available. Some characteristics, such as young people, have strong evidence to recommend inclusion and good local small area data. Others have strong or emerging evidence to recommend inclusion but no robust local level data to represent this and therefore have not been included in the final models. Some characteristics have limited evidence to support inclusion but have good quality local small area data. These too are omitted from the models. In addition, some characteristics

[6] Although deprivation data are available at low level geographies, this is not included in our final model as our models already include individual aspects which contribute to deprivation scores and we do not want to overstate our indices.

are only represented by the at-home population, others by the away-from-home population, and some by both depending on data availability.

To summarise, the following characteristics are included in our final models as there is sufficient evidence to support inclusion and there are small area data that we can use to represent them:

- Problem gamblers who are seeking treatment
- Substance abuse/misuse
- Poor mental health
- Unemployment
- Ethnic groups
- Youth
- Financial difficulties/debt
- Homelessness.

The following characteristics could have been included in the models but there was no local or appropriately specific small area data available to do so:

- Low IQ
- Personality traits and cognitions
- Immigrant population
- Under the influence of alcohol.

Further information about the exact data used in Westminster and Manchester respectively are now discussed.

Datasets

Selecting datasets

The datasets used in our models are based on the best available data to represent each risk factor. Some risk factors can be represented by multiple data and measures. There are also differences between Westminster and Manchester as the models depend on information collected by each Local Authority, which varies. Some data may be considered a 'proxy' measure where an ideal measure may not exist.

As the study aims to capture local variation, the model uses data at the smallest geographic scale or unit possible, including small-area census geographies and full postcodes. Where possible, we have used the most recent data available, though for some risk factors the age of the data varies. For example, data derived from the census uses information collected in 2011 though general neighbourhood demographic characteristics tend to stay fairly static within a several-year period. For other risk factors, like the location of facilities for treatment for addiction, which can be subject to change, we have used the most current data available to us.

Data sources can be roughly divided into that which is collected, standardised and available as a 'national' dataset (for example census data) and those specific to a local area, which are usually available for a LA or a group of LAs (for example, Westminster, Kensington and Chelsea and Hammersmith and Fulham for health data). For this study, data available via LAs have been sense-checked by reviewing the contents of the data and mapping them for any obvious spatial anomalies or missing information, and supplemented by web searches.

We have been mindful to not overstate or overestimate the model. Risk factors include a degree of correlation where the same individuals and communities have a tendency to exhibit multiple risk factors. Because of this possibility, we have omitted multiple deprivation as a measure because many aspects included in the multiple deprivation measure were already included separately in our models (like unemployment, for example). Also, some factors included in the multiple deprivation measure, like low educational attainment, were shown to have a varied relationship with problem gambling and we made the decision to exclude low educational attainment as a risk factor from our model.

All characteristics in the models are represented by different sets of data. Therefore, in our models risk factors are treated as silos although we acknowledge there may be correlation between them, both at the level of the individual and for local populations generally. There is currently no British evidence which examines multiple risk factors for gambling-related harm and our approach is based on existing knowledge about individual risk factors alone.

Datasets used

For each risk factor included in our models, we discuss the type of data used and its strengths and weaknesses. Full details are given in Tables 2 and 3.

Risk factor: problem gamblers seeking treatment

Dataset used: *Gamblers Anonymous meetings, and Gamcare counselling locations*

These locations are derived from lists provided by Gamcare and the Gamblers Anonymous website. These locations show the places where people with gambling problems will be visiting and hence ‘pull’ this potentially vulnerable group to this location. Whilst sense-checking is recommended (i.e., ensuring records are accurate), spatial accuracy to the full postcode will be dependable.

Risk factor: people with substance abuse or misuse problems

Dataset used: *Drug and alcohol treatment and recovery centres/clinics and clinics within GP surgeries, needle exchanges, accommodation for persons who require treatment for substance misuse*

As with problem gambling treatment centres, these clinics are likely to act as ‘pull’ for potentially vulnerable people to these locations. This dataset is an amalgamation of LA internal lists supplemented by web searches for any possible missing data on government websites (public health departments, LAs, NHS), together with data from the England Care Quality Commission (CQC) for accommodation locations. The analysis is dependent upon the LA and government sources being well informed, managed and current; further sense-checking of the input data using local knowledge is recommended. There are some sensitive locations which cannot be published in the public domain, but our combined results are non-disclosive. CQC data are a robust and complete national dataset.

There is variation in the 'types' of services offered in each treatment location, which have been modelled with the same importance. Further research could assess these treatment and support locations and attach different levels of importance to them should evidence show that some facilities are accessed by people who are more or less vulnerable to gambling-related harm.

Risk factor: people with poor mental health

Datasets used: *Number of resident outpatient attendances to acute hospitals relating to treatment function specialities 710 (adult mental illness), 722 (liaison psychiatry), 723 (psychiatric intensive care) – hospital episode statistics (HES)*

These data reflect residents who have sought treatment under the NHS and are being treated as hospital outpatients for mental illness. It does not capture those within the population who do not seek help. It is estimated that approximately 48% of those with common mental disorders had used a health care service for a mental or emotional problem (McManus et al, 2008). The HES data are therefore a very conservative measure of mental ill health among local resident populations. We have used the most detailed grouping of mental health types available within this dataset which covers a wide range of types of mental illness and psychiatry; it does not represent a detailed assessment of area-based mental health issues. Only an extremely small number of attendances are recorded as 'pathological gambling' cases as the primary/key treatment.

To protect the anonymity of individuals, the HES data are aggregated to Lower Super Output Areas (LSOA)[7] giving a broad neighbourhood accuracy of around 650 households. In those LSOAs with very small counts where it may be possible to identify individuals the data are not published (similar to UK Census data) although the overall trends remain the same since the counts in these LSOAs are so low. The data used are the latest provisional data released by the NHS Health and Social Care Information Centre at the time of the study. They constitute an authoritative and complete dataset of outpatients nationally.[8]

Capturing spatially accurate information about people with poor mental health is difficult and we acknowledge some limitations with this. First, data are aggregated to LSOA level meaning these data are, spatially, less precise than some of our other datasets which use postcode information. Therefore, these data represent a broader neighbourhood pattern than data referenced by postcode. Second, the mental health groups or diagnoses recorded in the data do not directly match the descriptors used in the empirical evidence (which considered things like common mental disorder, psychosis and so on). However, we believe there is sufficient overlap for these data to represent a measure of poor mental health in local areas, even if this

[7] LSOAs are geo-demographically engineered spaces which represent areas with a minimum of 1000 and a maximum of 3000 residents.

[8] Data in LSOAs can be mapped in two ways, either as a zone or as a single point reference. In our model we use the point reference but rather than simply identifying the geographic centre of LSOA, the point we used is weighted to reflect the underlying population distribution in the LSOA.

is a conservative measure represented at a broader geographic scale. These data have been supplemented with further insight from the GP register.

Number of patients recorded on the GP register with schizophrenia, bipolar affective disorder and other psychoses, and other patients on lithium therapy or with depression (18 or over) – NHS Quality Outcomes Framework (QOF)

These data reflect those residents who have sought primary care treatment under the NHS via their general practitioner. Again this excludes those residents who do not seek help. The types of mental health measured reflect those defined in the QOF database and do not represent a detailed assessment of area-based mental health issues.

Because these data are georeferenced to the unit postcode of the GP practice they reflect both a 'daytime' service location and a neighbourhood based residence statistic. GP practices tend to serve a catchment area of residents in the immediate geographical hinterland. These catchments, however, vary in size. They are not geo-demographically engineered to reflect similar population or household sizes, or geographic size around the GP location. As each GP catchment area varies in size, either by population, geographic area or both, they provide a less accurate way of measuring resident-based trends spatially.

Not all GP practices have their mental health statistics included in the QOF database. Nationally 13% of GPs have mental health information missing. In 2013/14, 16.5% of GPs in Westminster had missing mental health data and in Manchester it was 14.9%.[9] These GP locations have been included as there will be a level of treatment and care in each location, but not weighted by number of people recorded on the GP register.

Despite the limitations noted above, the QOF data does represent a broad approximation of residents in GP catchments areas who have sought primary care for a range of mental health conditions.

Risk factor: Unemployed people

[9] These estimates are for the full borough and the 1km surrounding area of each borough.

Datasets used: *Location of job centres*

Job centres will be accessed by members of the population who are likely to be unemployed and considered likely to have a combination of very low income and a large amount of personal disposable time.

These data are gathered from the Directgov website and should provide a complete and current list of job centre locations.

Number of economically active unemployed residents – Census 2011 table QS601

This dataset is used to represent unemployment among resident populations. Derived from the 2011 UK Census data, a potential limitation is the currency of the data, now being four years out of date although we recognise that the locations of higher unemployment in cities tend to persist through time. Despite this, Census data gives good spatial aggregation and accuracy of data at the output area level, representing around 300 people on average, and so represents unemployment among local residents.

Risk factor: Minority ethnic groups

Dataset used: *Number of residents from Asian/Asian British, Black/African/Caribbean/Black British ethnic groups, Arab or other ethnic groups – Census 2011 table KS201*

Census data were used to look at the ethnic profile of local residents. As with the unemployment data, currency may be an issue and we would recommend sense checking this information.

All relevant ethnic groups vulnerable to harm are considered equal within our modelling, commensurate with current research evidence. As new evidence emerges about the relative risk among different ethnic groups, the models could be updated to reflect this.

Risk factor: Youth

Datasets used: *Number of residents aged 10-24 years – Census 2011 table Q103*

The age range of 10-24 has been selected based on the interpretation of the evidence including ‘emerging adults’ as well as younger children in ‘transitional life stages’ as vulnerable. We recognise the reality of a ‘fuzzier’ boundary of age, where these developmental stages may occur at different times in different individuals. However, for the purposes of quantitative modelling, a distinctive age range has been used.

This dataset also exhibits the currency issue of the latest Census data.

Education institutions with students of 13-24 years– Edubase2

These data list all known educational institutions for people aged 13-24 and are derived from a complete and current government database, so can be considered a reliable source.

These locations have been included as they represent areas where younger people will be present in greater numbers at certain points of the day. Many educational institutions can have catchment areas much broader than their immediate locale and they reflect the daytime population. In the case of higher educational institutes, this will also reflect greater night-time populations too. We have chosen the slightly older age range of 13-24 to reflect the potential vulnerability of younger people gaining access venues under the legal age.

As with the resident based measures, the 'fuzzy' boundary of age also applies here. Only schools with pupils in this age range are included, but other aspects of the school including accessibility are not considered in our models. For example, individual policies surrounding whether school pupils are allowed to leave school grounds at break times may contribute to a greater or lesser risk of accessing local gambling facilities. This is unknown and therefore not included in our models.

Risk factor: those with financial difficulties and/or debt

Datasets used: *The location of payday loan shops*

These data represent locations where those with financial difficulties and debt problems are more likely to be present, visiting places where credit is accessed through less secured means. Although pay day loan shops may be accessed by many members of the population, these locations may serve to pull vulnerable populations with financial and debt problems into an area by providing them with access to unsecured and easy-access finance.

Completeness and currency is a key data quality issue. National business datasets commonly use classifications which cannot accurately pin-point this type of business. These data are therefore derived from local web searches.

<u>The location of food banks</u>

This dataset aims to model financial difficulties and debt problems, through places where people are so severely financially constrained they cannot afford to buy food. This aims to capture risky locations by those with the biggest financial strains.

Again completeness and currency are key data quality issues. Food banks are opening at a fast rate and there appears to be no central database managing these locations as they are usually not council-led services or officially part of government policy or welfare state provision. Web searches have been used to add extra locations where they were missing from LA lists.

Risk factor: Homelessness/housing instability

Dataset used: *<u>The location of homeless accommodation from Local Authority lists/Homeless UK</u>*

Although considered emerging evidence in our review, it was felt that the evidence was strong enough to consider it appropriate for inclusion in the model. There are a variety of accommodation provision types for the homeless, ranging from emergency shelters to more mid to long-term support representing broader 'housing instability'. Data on the location of accommodation for homeless were provided by Westminster and corroborated through online checks. Locations for Manchester City Council were not available, so these have been derived from online lists available at Homeless UK which give key locations. However, this database may not include sensitive locations not fit for publishing in the public domain (for example, women’s refuges), as well as smaller accommodation provision.

All homeless accommodation types included in the models have been given the same importance. Further analysis might consider these different types to determine if some accommodation types may be accessed by people at greater or lesser risk of gambling-related harm.

Table 2: metadata details for datasets used in the Manchester model

Characteristic	Indicator/measure	Dataset name	Reference date	Geographic scale/ aggregation	Dataset owner and copyright	Geographic availability	KDE band-width	Weighted by	Missing boroughs
Problem gamblers who are seeking treatment	Gamblers Anonymous meetings and Gamcare locations	Gamcare and web searches	06/2015	Unit postcode of the treatment centre location	Gamcare. Provided for the purpose of this project.	England	400m	None	None
Substance abuse/ misuse	Drug and alcohol treatment and recovery centres/clinics and clinics within GP surgeries, needle exchanges, accommodation for persons who require treatment for substance misuse	Lists provided by Local Authorities, CQC care directory (for accommodation) and web searches	05/2015	Unit postcode of the treatment centre location	Manchester City Council and surrounding districts. Provided for the purpose of this project. Care Quality Commission (CQC) open data.	Local Authority	400m	None	Needle exchanges – Cheshire East, Tameside, Bury, drug clinics within GP surgeries – all surrounding boroughs

Poor mental health	Number of patients recorded on the GP register with schizophrenia, bipolar affective disorder and other psychoses, and other patients on lithium therapy or with depression (18 or over)	Quality Outcomes Framework (QOF) GP statistics	2013/2014	Unit postcode of the GP practice	Health and Social Care Information Centre (HSCIC). Open data.	England	400m	Number of patients	None
Unemploy-ment	Jobcentre Plus Offices	Directgov http://los.direct.gov.uk/	06/2015	Unit postcode of the job centre location	Directgov. Data in the public domain.	Local Authority	400m	None	None
	Number of economically active unemployed residents	Census 2011 table QS601	03/2011	2011 Output Areas (OA)	Office for National Statistics (ONS). Available under Open Government Licence (OGL).	UK	750m	Number of residents	None
Ethnic groups	Number of residents from Asian/Asian British, Black/African/Caribbean/Black British ethnic groups, Arab or other ethnic groups	Census 2011 table KS201	03/2011	2011 Output Areas (OA)	Office for National Statistics (ONS). Available under Open Government Licence (OGL)	UK	750m	Number of residents	None

Youth	Education institutions with students of 13-24 years	Edubase2	08/2015	Address coordinates of the school location	Department for Education (DoE). Available under Open Government Licence (OGL)	UK	400m	None	None
	Emerging adults and younger children - number of residents aged 10-24 years	Census 2011 table QS103	03/2011	2011 Output Areas (OA)	Office for National Statistics (ONS). Available under Open Government Licence (OGL)	UK	750m	Number of residents	None
Financial difficulties/ debt	Payday loan shops	Web searches	05/2015	Unit postcode of the shop location	n/a	Local Authority	400m	None	None
	Food banks	Local Authority lists supplemented by web searches	04/2015	Unit postcode of the food bank location	Manchester City Council and surrounding districts. Provided for the purpose of this project.	Local Authority	400m	None	None
Homeless-ness	Emergency, second stage and specialist homeless accommodation	Homeless UK	02/2015	Unit postcode of the residence	n/a	Local Authority	400m	None	None

Table 3: metadata details for the datasets used in the Westminster model									
Criteria	**Indicator/measure**	**Dataset name**	**Reference date**	**Geographic scale/ aggregation**	**Dataset owner and copyright**	**Geographic availability**	**KDE band-width**	**Weighted by**	**Missing boroughs**
Problem gamblers who are seeking treatment	Gamblers Anonymous meetings, and Gamcare locations	Gamcare and web searches	06/2015	Unit postcode of the treatment centre location	Gamcare. Provided for the purpose of this project.	England	400m	None	None
Substance abuse/ misuse	Drug and alcohol treatment and recovery centres/clinics, needle exchanges, accommodation for persons who require treatment for substance misuse	Lists provided by Local Authorities, CQC care directory (for accommodation) and web searches	05/2015	Unit postcode of the treatment centre location	Westminster City Council. Provided for the purpose of this project. Care Quality Commission (CQC) open data.	Local Authority	400m	None	Needle exchanges - Brent
Poor mental health	Number of patients recorded on the GP register with schizophrenia, bipolar affective disorder and other psychoses, and other patients on lithium therapy or with depression (18 or over)	Quality Outcomes Framework (QOF) GP statistics	2013/ 2014	Unit postcode of the GP practice	Health and Social Care Information Centre (HSCIC). Open data.	England	400m	Number of patients	None

	Number of resident outpatient attendances to acute hospitals relating to treatment function specialities 710 (adult mental illness), 722 (liaison psychiatry), 723 (psychiatric intensive care)	HSCIC hospital episodes statistics	2013/ 2014	Lower Super Output Area (LSOA)	Health and Social Care Information Centre (HSCIC). Provided under restricted licence for the purposes of this project.	Local Authority	750m	Number of residents	Brent, Camden, City of London, Lambeth, Wandsworth
Unemploy ment	Jobcentre Plus Offices	Directgov http://los.direc t.gov.uk/	06/2015	Unit postcode of the job centre location	Directgov. Data in the public domain.	Local Authority	400m	None	None
	Number of economically active unemployed residents	Census 2011 table QS601	03/2011	2011 Output Areas (OA)	Office for National Statistics (ONS). Available under Open Government Licence (OGL).	UK	750m	Number of residents	None
Ethnic groups	Number of residents from Asian/Asian British, Black/African/Caribbea n/Black British ethnic groups, Arab or other ethnic groups	Census 2011 table KS201	03/2011	2011 Output Areas (OA)	Office for National Statistics (ONS). Available under Open Government Licence (OGL)	UK	750m	Number of residents	None

Youth	Education institutions with students of 13-24 years	Edubase2	08/2015	Address coordinates of the school location.	Department for Education (DoE). Available under Open Government Licence (OGL)	UK	400m	None	None
	Emerging adults and younger children - number of residents aged 10-24 years	Census 2011 table QS103	03/2011	2011 Output Areas (OA)	Office for National Statistics (ONS). Available under Open Government Licence (OGL)	UK	750m	Number of residents	None
Financial difficulties/ debt	Payday loan shops	Web searches	05/2015	Unit postcode of the shop location	n/a	Local Authority	400m	None	None
	Food banks	Local Authority lists supplemented by web searches	04/2015	Unit postcode of the food bank location	Westminster City Council and surrounding districts. Provided for the purpose of this project.	Local Authority	400m	None	None

Homeless-ness	Westminster supported housing projects, including 'offenders or people at risk of offending' , 'people with alcohol/ drug problems', 'people with mental health problems', 'rough sleeper hostel services', 'rough sleeper supported housing services', 'single homeless hostel services', 'young people at risk or leaving care'	Local Authority lists	03/2014	Unit postcode of the residence	Westminster City Council	Local Authority	400m	None	Kensington and Chelsea, Brent, Camden, Lambeth, Wandsworth

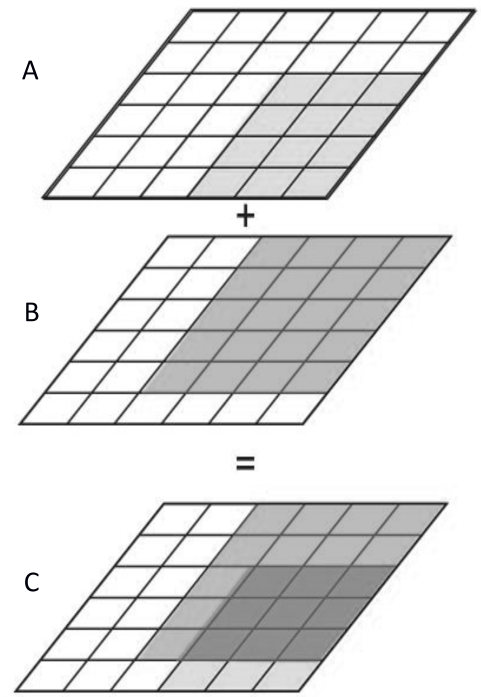
Spatial analysis techniques

Raster overlay analysis and tree-based models

Having identified the risk factors to use in our models, our next step was to build the localised spatial risk indices for Westminster and Manchester respectively. We did this using an overlay analysis based on a tree-based model. Overlay analysis is a methodology that has been used in planning and policy for many years (McHarg, 1969). It is simply the placement of map layer A (representing a set of features) on top of map layer B, to create a new map layer, C, which is some combination of A and B (see Figure 3 – after Smith, Longley, Goodchild, 2015).

For this study, each map layer represents a different risk factor for gambling vulnerability, which are added together to calculate a cumulative value or vulnerability score at any one location. It is possible to overlay many different types of data. We have chosen to model continuous surfaces called raster-based data. Raster data divides the study area into a continuous surface of square cells, and it is these cells that become overlaid and added together for each cell location.[10]

Figure 3: visual representation of overlay



[10] This type of spatial model has been used to underpin planning and initiatives for some time. A recent model was developed for the Department of Communities and Local Government to identify the extent of town centres in order to track the efficacy of central government's retail planning policy. Key to this approach was the aggregation of a number of different indicators within a tree-based data structure (Thurstain-Goodwin and Unwin, 2000).

A tree-based approach is the conceptual model showing how all indicators are structured within our models. This structure then guides the method and order in which the final indices are calculated. For example, the tree-based structure is used to define which layers of data represent certain risk factors and these data are then grouped together. The tree-based structure also defines how these data should be added together as a weight is applied to reflect the importance of each characteristic. Essentially, common groups of risk factors become branches in the model and funnel into the final composite model. Our tree structures for Manchester and Westminster respectively are shown in Figures 4 and 5.

Looking at Figure 4, at the top level are the 'leaves' of the tree representing a range of different types of data for each risk factor. These feed into conceptual 'branches' of the model and the 'branch nodes' which represent each risk factor group. In some cases, there is more than one source of data for each risk factor. For example, the location of pay day loan shops and food banks feed into the conceptual branch of the model called 'financial problems'. The 'base' of the tree is the final composite index of risk.

The benefit of the tree-based approach is that it is flexible. The model can be repeatedly applied to other study areas (given the same data availability), and the structure of the tree can also be changed to reflect the local study area data availability (i.e., extra branches can be added, if appropriate). The tree-based model can also incorporate new, updated or better quality data when it is available and where the evidence base develops and changes. Ideally, the tree structure will be standardised so that it is comparable between study areas. However, the data available for modelling between LAs will vary and may be different in structure meaning that each LA will likely have a slightly different model. The tree-based model offers a simple way of identifying those small differences. This is the case for Westminster and Manchester and the tree models for each area are shown in Figures 4 and 5.

Figures 4 and 5 also show two main branch nodes in our models: 'people away from home' and 'people at home'. Populations by their inherent nature are not static in space or time. To identify the locations of vulnerable people, the models incorporates locations where these people may be when they are at home (i.e. local residents) or away from home (visiting certain services in a local area). The tree-based model has been conceptually separated into these two indices. Separate indices illustrate areas of risk pertaining to the 'at home' populations compared with the 'away from home' population. These indices are then added together to give an overall composite index for each area (see Appendix 1 for illustrations of these characteristics). Having these separate indices gives a better understanding of the local area and the elements that form the overall model. It also helps to understand what is driving risk in a particular location: the resident 'at home' population, the 'away from home' population, or both.

Figure 4: tree-based model for the Manchester gambling-related harm risk index

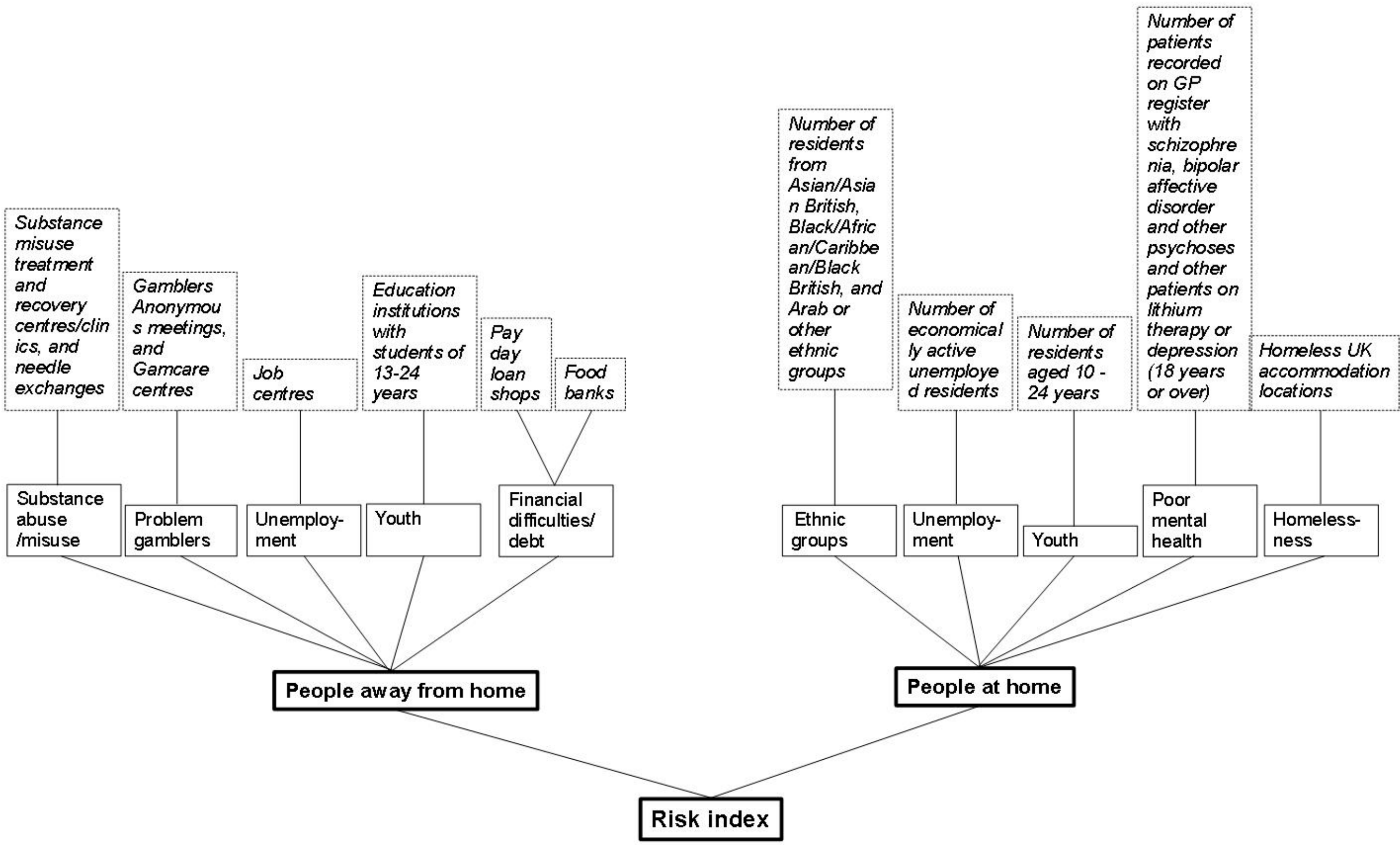
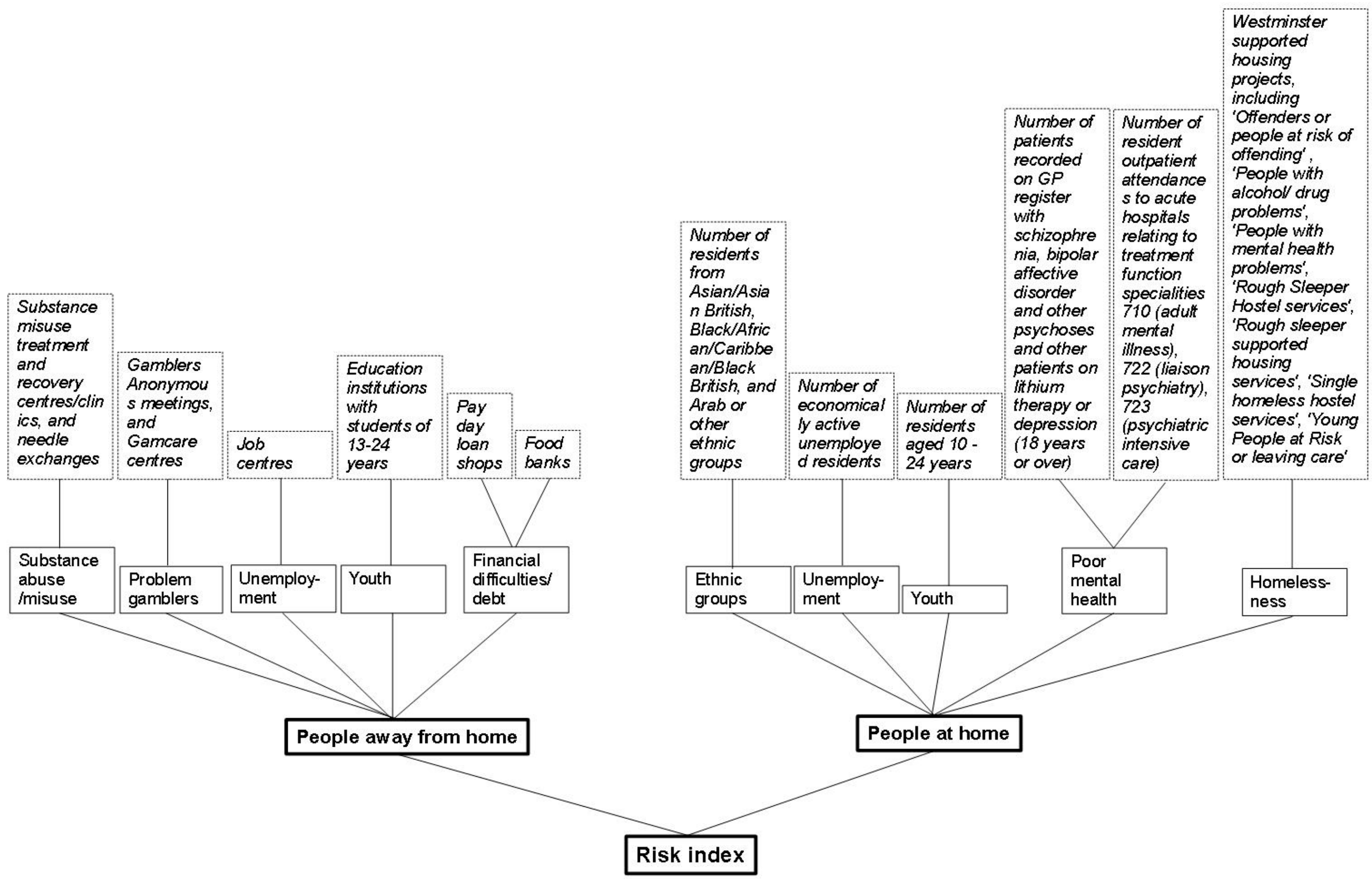


Figure 5: tree-based model for the Westminster gambling-related harm risk index



Modelling factors and equations used

Each raster data layer in the tree is added together with arithmetic addition according to the order of the tree structure. The calculation is represented with the following formula:

$$ghvi = \sum_{i}^{n} a_i s_i$$

where

ghvi = gambling-related harm risk index

n = number of indicators

i = each indicator

a = weighting for each indicator

s = transformed z score normalization of each indicator

The gambling-related harm risk index is a probabilistic measure of the likelihood of the risk to gambling-related harm at any one location.

Within the tree-based model, there are variations in the types of data included. This includes variations in the spatial scale by which measures are aggregated (e.g., larger and smaller census areas) and the units of measurement (e.g., residents or facility locations). Where the data types are the same, a simple arithmetic addition of the input surfaces is calculated. Where data types are different we first normalise each input raster surface before adding them together using a z score function. This normalisation maintains the spatial variation and overall relative pattern in the raster surface by expressing the values as standard deviations of the input frequency distributions. This creates a standardised metric that makes the cell values comparable between raster datasets, and allows them to be integrated.

By ‘normalising’ the values of cells we also standardise the mathematical impact of ‘branch nodes’ or risk factors being measured so that no single risk factor dominates.

The calculation for normalised z scores is represented with the following formula:

$$(\mathrm{a} - \mathrm{b})/\mathrm{c}$$

a = data point or cell value

b = mean of data points or cell values

c = standard deviation of data points or cell values

Weighting

Why weight?

When developing risk indices, it is standard to apply weights to the different component parts of the model. This recognises that the relative importance of each risk factor is not the same and seeks to represent this in the model. This principle is the same for our models. Whilst we have a range of different risk factors, they are not all equal in terms of the relative risk attached to each. Therefore, we have developed a weighting scheme and applied it to our final models.

Weighting scheme used in the models

The weighting scheme developed for this project draws on two different domains to assign a relative risk weight to each factor. These are:

- the strength of the empirical evidence and,
- the relative level of gambling harm/problems exhibited by each group.

Looking at the strength of evidence domain first, throughout this project we have reviewed and assessed the empirical evidence relating to each risk factor. This assessment included review of both the quantity and quality of the evidence. Whilst we recognise this is subjective, we believe our judgements reflect well the existing evidence and were judged to be sound by independent peer reviewers.[11] We have translated this assessment of strength of evidence into a scale ranging from 0 to 1, where 0 equals no evidence and 1 equals excellent evidence. The values given to each risk factor on this first domain are shown in Table 4 below, along with a brief justification of the value assigned.

Table 4: Strength of evidence weighting domain

Risk factor	Value	Explanation

[11] Our first phase report was independently peer reviewed by two leading gambling academics who were asked to specifically comment on our assessment of the evidence, which they judged to be sound.

Problem gamblers who are seeking treatment	0.25	The existing evidence shows strong logical inference that those seeking treatment are liable to both relapse into gambling harm and being influenced by gambling-related cues. However, no study examining this in Britain was identified and the existing evidence did not offer much quantification of the issue. For this reason, we have allocated a lower rating for strength of evidence.
Substance abuse/misuse	1	The evidence base demonstrating the strength of the association between substance misuse/abuse is strong. There is both British based and international data from studies using gold-standard methodologies.
Poor mental health	1	As above, there is both British based and international evidence supporting this, with studies using gold-standard methodologies.
Unemployment	1	As above, there is both British based and international evidence supporting this, with studies using gold-standard methodologies.
Ethnic groups	1	As above, there is both British based and international evidence supporting this, with studies using gold-standard methodologies.
Youth	1	As above, with the addition that youth are singled out for additional regulatory protection in the Gambling Act, 2005.
Financial difficulties/debt	0.5	There is emerging evidence of the relationship between financial difficulties and debt and gambling harm. The few British based studies use gold-standard methodologies but this remains to be further explored.
Homelessness	0.25	There is only one British based study examining this and this focuses on one area in London only. There are similar findings from the USA, including a recent study which reports similar prevalence estimates to the British study. However, this is an emerging area and therefore we have assigned a lower strength of evidence value.

Our second domain focuses on the relative levels of risk of problem gambling among each group. This ranking has been produced by examining rates of problem gambling among each group and calculating the extent to which these rates are higher than that of the general population. This is calculated by dividing the estimate for each risk factor by the population average. A score of 0 means that the rate of problem gambling among this group is the same as the national average, anything above 0 means that problem gambling among this group is x times higher than the national average. One exception is the score given to problem gamblers seeking treatment. All of this group are already known to be problem gamblers so have been allocated a score of 100, representing that all of them (i.e., 100%) are known to be problem gamblers (making comparisons to the general population prevalence defunct).[12] Results are shown in Table 5.

Table 5: Relative risk of gambling problems weighting domain

Risk factor	Value	Explanation
Problem gamblers who are seeking treatment	100	All people seeking treatment for problem gambling are problem gamblers
Substance abuse/misuse	4.3	This uses the median estimate of problem gambling among those with various substance abuse/misuse disorders from the Adult Psychiatric Morbidity Survey, 2007 (see Appendix Table A1, Wardle, 2015a) (3%) divided by 0.7%, the population average recorded in the same dataset.
Poor mental health	4.2	This uses the median estimate of problem gambling among those with various substance abuse/misuse disorders from the Adult Psychiatric Morbidity Survey, 2007 (see Appendix Table A1, Wardle, 2015a) (2.95%) divided by 0.7%, the population average recorded in the same dataset.
Unemployment	2.0	This uses the problem gambling prevalence estimate among unemployed people reported in the combined Health Survey for England and Scotland report (1.2%) divided by the equivalent population average in that report (0.6%). See Wardle et al, 2014. The problem gambling rates among unemployed people in this report are lower than the BGPS series, which means this may be a conservative estimate.

Table 5: Continued…

Risk factor	Value	Explanation

[12] We tried a range of different weighting criteria for problem gambling which did not materially alter the results observed.

Ethnic groups	4.0	This uses the median problem gambling prevalence estimate among minority ethnic groups reported in the combined Health Survey for England and Scotland report (2.4%) divided by the equivalent population average in that report (0.6%). See Wardle et al, 2014. The problem gambling rates among minority ethnic groups in this report are lower than the BGPS series, which means this may be a conservative estimate.
Youth	2.3	This uses the problem gambling prevalence estimate among young people aged 16-24 reported in the combined Health Survey for England and Scotland report (1.4%) divided by the equivalent population average in that report (0.6%). See Wardle et al, 2014. Problem gambling rates among younger children internationally are believed to be higher than this, meaning that this may be a conservative estimate.
Financial difficulties/debt	2.3	This uses data from the APMS 2007 survey showing problem gambling prevalence rates among those experiencing debt/financial problems and divides this by the population average reported in that study. See Appendix A, Wardle 2015.
Homelessness	19.3	This uses problem gambling prevalence rates of 11.6% (as reported by Sharman et al) and divides this by the most recent population average (0.6%).

Having created two different domains in our weighting scheme, one representing strength of evidence and the other representing relative risk of gambling problems, these were multiplied together to give the final weights for each risk factor. See Table 6. These were the final weights used in our models.

Table 6: Weightings applied to the model characteristics			
Risk factor	Strength of evidence	Relative risk	**Final weight**
Problem gamblers who are seeking treatment	0.25	100	**25**
Substance abuse/misuse	1	4.3	**4.3**
Poor mental health	1	4.2	**4.2**
Unemployment	1	2.0	**2.0**
Ethnic groups	1	4.0	**4.0**
Youth	1	2.3	**2.3**
Financial difficulties/debt	0.5	2.3	**1.15**
Homelessness	0.25	19.3	**4.8**

Creating the final indices

Once all data were normalised, weighted and added together, the final combination of rasters were integrated into an index measure for each area. This represents a standard continuous index range from 0-100, which is easier to interpret than standard deviations. The 'at home' and 'away from home' index calculations were recalculated to derive a usable score from 0-50. This was achieved by applying an offset to the cell values to set the minimum value as 0 using the following calculation:

*(50/maximum cell value)*cell value*

For each area, the overall composite index is the arithmetic addition of the 'at home' and 'away from home' input indices, giving a theoretical range of 0-100, where higher scores equate to higher risk. Not all study areas will have local areas where a maximum score of 100 exists because it unlikely that all the risk indicators, both at home and away from home, will be located in the same place.

Study area comparisons

This study was funded and commissioned by Westminster and Manchester City Councils respectively. This means the models are organised and defined for each LA respectively.

Ideally, within the context of national policy like local area risk indices, we would create a standard model which allowed direct comparisons between geographic areas. To do this, the same input datasets must be available in each case. However, each LA actually has a different range of data available. Therefore, the models created are bespoke to each LA, despite having the same methodological approach and theoretical underpinning. This limits comparability between Westminster and Manchester.

The models give a measure of risk for each LA which is relative only to that individual study area. In this way the cell values in one study area are not directly comparable with those in another, although they are similar as the index for each has been created in the same way. We therefore caution readers not make direct comparisons between Westminster and Manchester but to view each area independently. **The risk values produced for each LA are not comparable between study areas.**

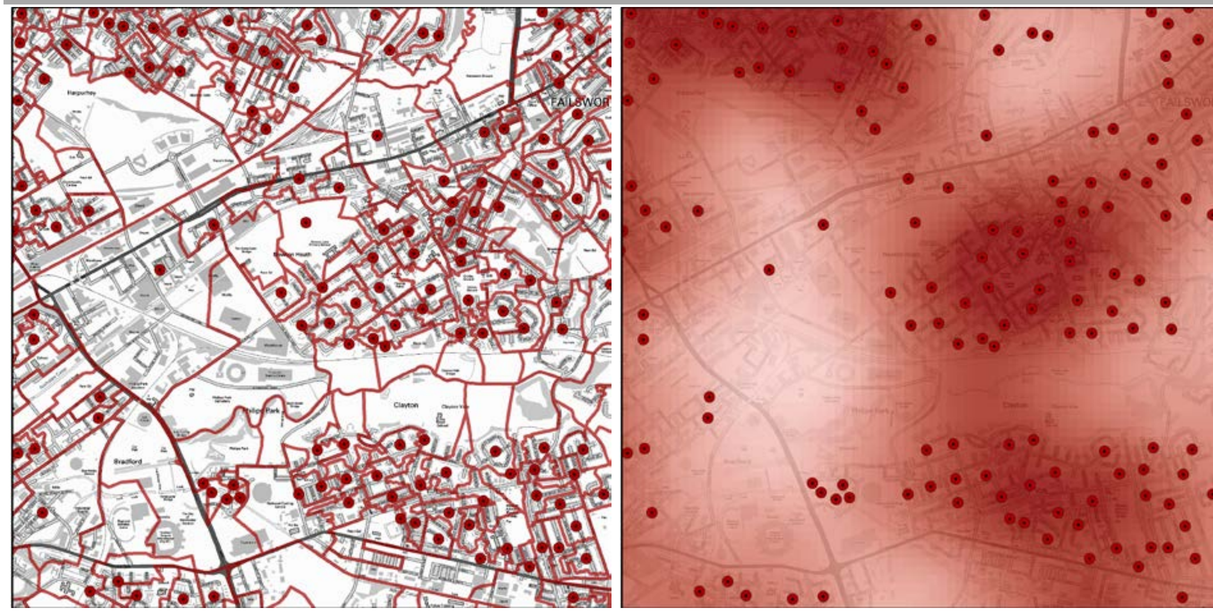
Input dataset modelling

Surface representations

We have chosen to model the input dataset as raster or 'surface' representations rather than distinct area units. Continuous data surfaces are often easier to perceive and understand by eye (see Figure 6 comparisons) and also have statistical analysis benefits. Output 'surfaces' or rasters are composed of cells, whose size can vary. Our modelling uses a 50x50m cell size, which is a similar and appropriate to the precision of unit postcode centroids data fed into the models.[13]

[13] A unit postcode centroid represents, on average, the centre around 15 geographically contiguous addresses

Figure 6: example spatial representations of small area census data: areal units vs kernel density estimations (KDE)



Kernel Density Estimations (KDE)

For this study, we are looking to estimate the concentration or density of multiple risk factors for gambling-related harm in local areas. This includes the density of residents with a certain risk factor or the density of facilities relating to the treatment of addiction for example. To do this, we have used Kernel Density Estimation (KDE), a technique which calculates and visualises the density of activity over a study area (Silverman, 1986).

In this project we are concerned with identifying facilities or residents regardless of their relative levels in the base population. It is important to identify where the people with each risk factor are situated regardless of whether the neighbourhood they live in is big or small, densely populated or sparsely populated. In line with the third licensing objective we are concerned with the location of potentially vulnerable people rather than the relative levels or ratio of vulnerable people to non-vulnerable people in an area. Because of this, the KDEs used in our models show the variation in risk across, and relative to, each LA area rather than showing rates of risk relative to population size at each area.

There are many functions which can be used to model slightly different KDEs. Our models use the Epanechnikov quadratic kernel, (Silverman, 1986, pg. 76, section 4.4). The selection of function to define the probability distribution is not as crucial to the model as the choice of kernel bandwidth or search radius (Bailey & Gatrell, 1995), which is discussed below.

KDE parameters

A KDE consists of several modelling parameters which can be changed for each KDE. Output cell size is one such parameter, which has been standardised for all calculations in this model. The other key parameter is the search radius, or the area around each data point in space that the estimation incorporates. Larger radii tend to return a more generalised pattern, and smaller radii reveal greater detail, and they are appropriately defined by the type and scale of the individual data being modelled.

For data relating to facilities and services we have used a 400m search radius which represents a logical walking distance to local services. There is no detailed advice available in government Planning Policy Guidance regarding accessibility to services. UK Government Planning Policy Statement 6 makes a brief mention to locations that are 'well connected and within easy walking distance' being up to 300 metres, although this is not qualified with any evidence or repeated elsewhere in literature. Some of our previous research used a 400m distance for service access, therefore continuing to use this measure is consistent with our previous work in this area (Wardle et al, 2014; Astbury and Thurstain, 2015). Facilities and services are geolocated by the centroid of a full unit postcode, which is accurate to approximately 15 contiguous addresses.

For residential data we have mostly used small-area Census geographies, including Output Areas (OAs) and Lower Super Output Areas (LSOAs) for England and Wales. OAs are the smallest area at which Census data are collected, with an average of 309 people in 2011 for England and Wales. LSOAs are slightly larger with an average of 1500 people. They are contiguous geographic areas covering the whole country which vary in physical size, but are geo-demographically engineered to be relatively homogenous in terms of their population count and demographic profile, and thus represent similar underlying base populations. We have used the population-weighted centroid of each area, which locates the optimal point where the majority of residents live within these areas.

Martin, Tate and Langford (2000) established that a search radius for kernel density estimates between 500m and 1,000m was optimal for use with these census areas, with anything over 1,000m tending to over-disperse isolated settlements into the surrounding area. We have examined different radii and 750m appears an optimal level to define neighbourhood-level variations in urban areas. This is the search radius we have used for these KDE estimates.

The parameters used for each input dataset are included in Tables 2 and 3, including which search radius was used for each dataset in the model.

Local Authority boundary edge effects

Whilst our study area is defined by the administrative boundaries of each Local Authority, real-life geography is continuous, so wherever possible we have gathered data from surrounding LAs and extended the modelling past the authority boundary. The data are modelled to include this extra data, with the raster or 'surface' representation shown at 1km past the boundary, to illustrate any significant areas in neighbouring jurisdictions which may impact on conditions within each LA.[14] Z scores are calculated on the LA extent plus the 1km surrounding area, so the normalised scores represent a 'study area' average of 1km past the LA boundary. Where extra data are not available from surrounding boroughs we have flagged this in Tables 2 and 3.

Known error margins and model limitations

As with all models, there are known error margins and potential limitations which should be considered when interpreting the results.

We acknowledge that where evidence does not currently exist or is weak, this does not necessarily equate to a potential risk factor having little or no importance. It could simply be a facet of a current evidence gap. The models presented are based on knowledge currently available at this time. We would strongly recommend that this report be read and considered in conjunction with the phase 1 report (see Wardle, 2015a).

The rationale for the choice of risk factors included in the models was based on research from phase 1 of this study. Whilst the first phase of the study was designed to reduce limitations as far as possible, there were some acknowledged caveats. They included the limited evidence base around broader gambling-related harm and associated focus of evidence on risk factors for problem gambling. The models presented inherit these limitations.

As far as possible we have used the most recent data available to model current conditions. However, census data are now four years old. If there has been significant neighbourhood

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[14] This additional 1km offers further context for the analysis of risk within a LA, but it too is potentially subject to edge effects by the absence of data beyond its outer limit. To counter this, we ensure that data are included beyond this 1km zone to a distance that is larger than the bandwidth of the largest kernel density surface used in the model.

developments and change, this will not be reflected in our models, although we considered this possibility to be fairly unlikely. We have identified none in either of our study areas.

We have also used the smallest area data available. Some data are only available at the LSOA level which gives a more general picture of local variation. However, we consider the majority of data to provide reasonable accuracy, scale and precision to reflect sub-neighbourhood level change and variation.

The models are reliant upon data quality. This includes data provided by each LA. Some data have been captured from web searches.

There are several datasets which would ideally be included in the models for which we have no available data source, including:

- Problem gamblers within the resident population – there exist no direct data on problem gamblers at the small scale with a large enough sample size.
- People with low IQ – these data do not exist at the small scale with a large enough sample size.
- Personality traits – these data do not exist at the small scale with a large enough sample size.
- Substance abuse/misuse within the resident population – these data were not available for this study at the small scale with a large enough sample size.
- Debt within the resident population – these data do not exist at the small scale with a large enough sample size.
- Levels of alcohol consumption within the resident population – these data do not exist at the small scale with a large enough sample size.
- Financial difficulties/debt - population – these data were not available for this study by resident locations.
- Immigrant groups – there is no standard data available at the small scale that is recent enough to be relevant.

Despite these missing data, we are confident that the data we have included in the models provides a robust base to model risk of gambling-related harm.

4 Results

Interpreting the results

The models show the risk of gambling-related harm at a given location. **They do not show where problem gambling is occurring**. They are a probabilistic measure of risk to gambling problems among the population. Each square cell (50m x 50m) for the Westminster and Manchester LA area has a value indicating the relative risk. These values are a measure of 'high' and 'low' risk relative to other places within Westminster and Manchester respectively. One must not fall into an 'ecological fallacy' when interpreting results. This would be to assume that every individual within an area with a high score will be at risk. Even though a certain place may, on average, be at higher risk, not all individuals in that space will be at risk.

For both Westminster and Manchester, there are three maps showing three different indices:

- the first shows the overall risk index for each area. This combines data from the 'at home' and 'away from home' indices. This is called the composite index.
- the second shows the index data based on the 'at home' or resident population, and
- the final index map shows the index data based on the 'away from home'.

The overall composite index has a total score of between 0-100. This is calculated by adding the 'at home' and 'away from home' indices together. On the maps shown, the higher the cell value, the higher the risk.

The models use 50mx50m square cells to measure points or specific locations across the study area: an appropriate scale at which to interpret the results. The results do not show building-level accuracy or variation but rather show sub-neighbourhood and in some cases sub-street level trends. It is recommended to consider a value or score within any one cell value within the context of the surrounding cells, so as not to assume a level of specificity and precision that is not appropriate. It is more useful to look at patterns across a neighbourhood.

Along with reviewing the three map indices for Westminster and Manchester respectively, it is also useful to view the spatial patterns of each individual input datasets. This gives insight into what is driving higher levels of risk in specific areas – for example, is it high levels of unemployment or high numbers of substance abuse treatment facilities? The individual maps for each study area are presented in Appendix 1.[15]

The results for Manchester and Westminster are now discussed in turn.

[15] Hospital episode statistics data have been omitted from the Appendix because of data confidentiality.

Manchester

Figure 7: map of composite risk index for Manchester

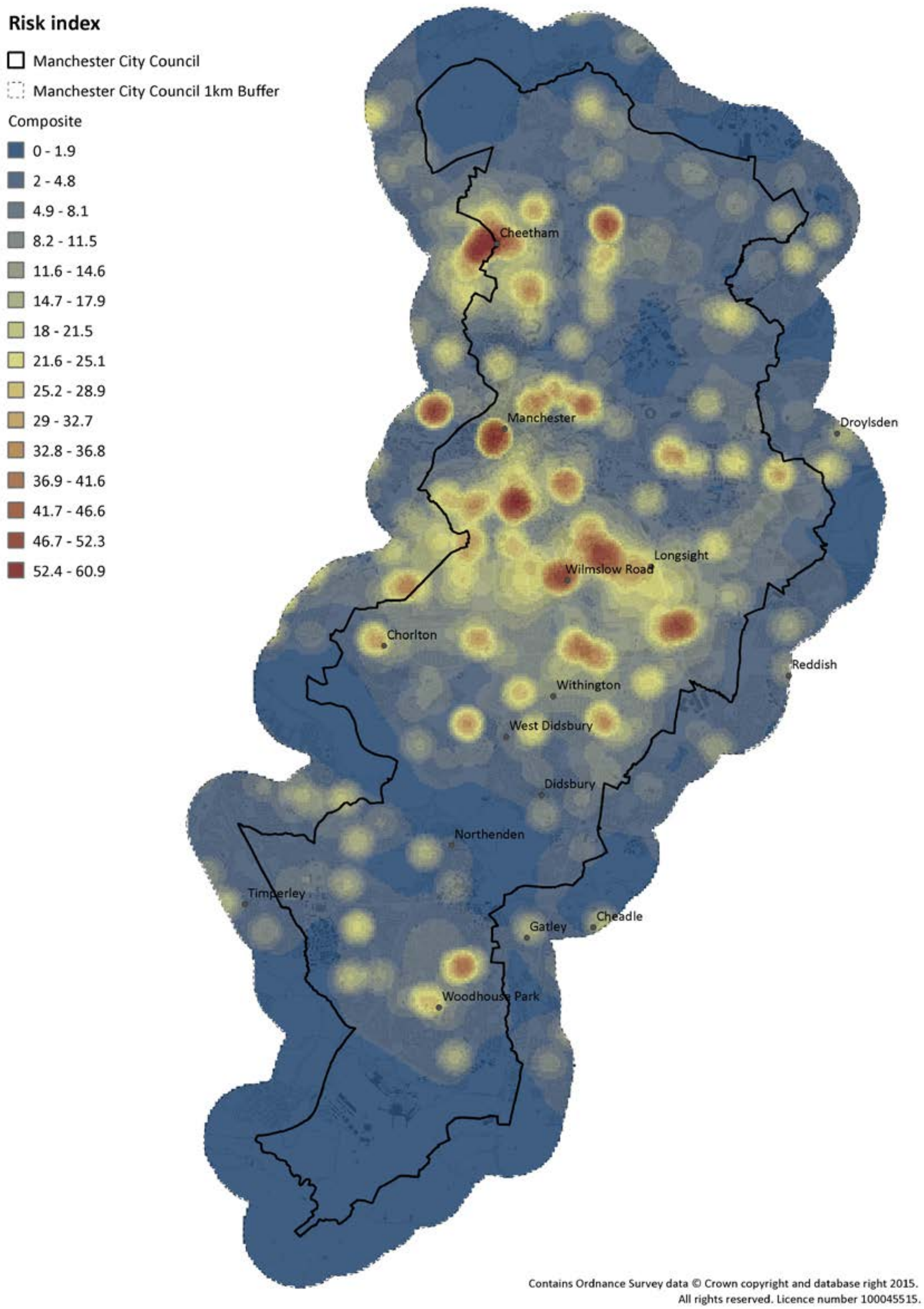


Figure 7 shows the overall composite risk index for Manchester. Risk scores vary between 0 and 60.9.[16]

There are a range of areas across the Manchester borough with higher risk to gambling-related harm. However, there are particular concentrations in three main areas. These are:

- The area to the north west of Levenshulme, between Rusholme and Longsight.
- The city centre and the area around the University of Manchester, around the Oxford Road.
- North Cheetham and Cheetham Hill.

Looking at Figures 8 and 9 we can see that there are different drivers of risk in each area. The area in the City Centre, for example, appears to have greater levels of risk on the 'away from home' index (Figure 9) whereas others have greater risk on the 'at home' index (Figure 8). Of course, overall risk is comprised of both aspects and we now discuss the prominent risk factors for each of the three case study areas.

[16] The bands of the scale vary as they are based on the underlying distribution of the data rather than being imposed by the authors (see Figure 7).

Figure 8: map of ‘at home’ risk index for Manchester

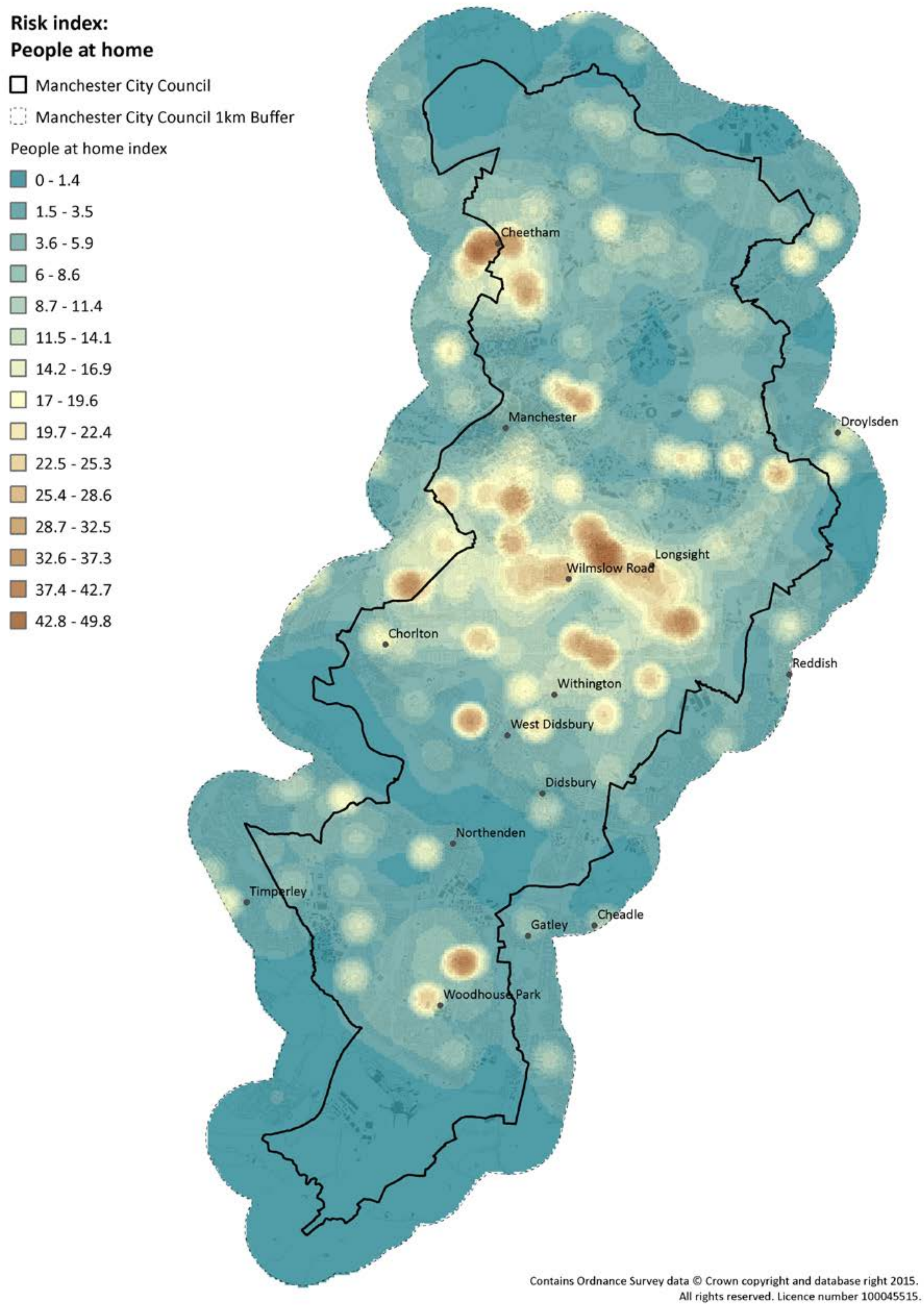
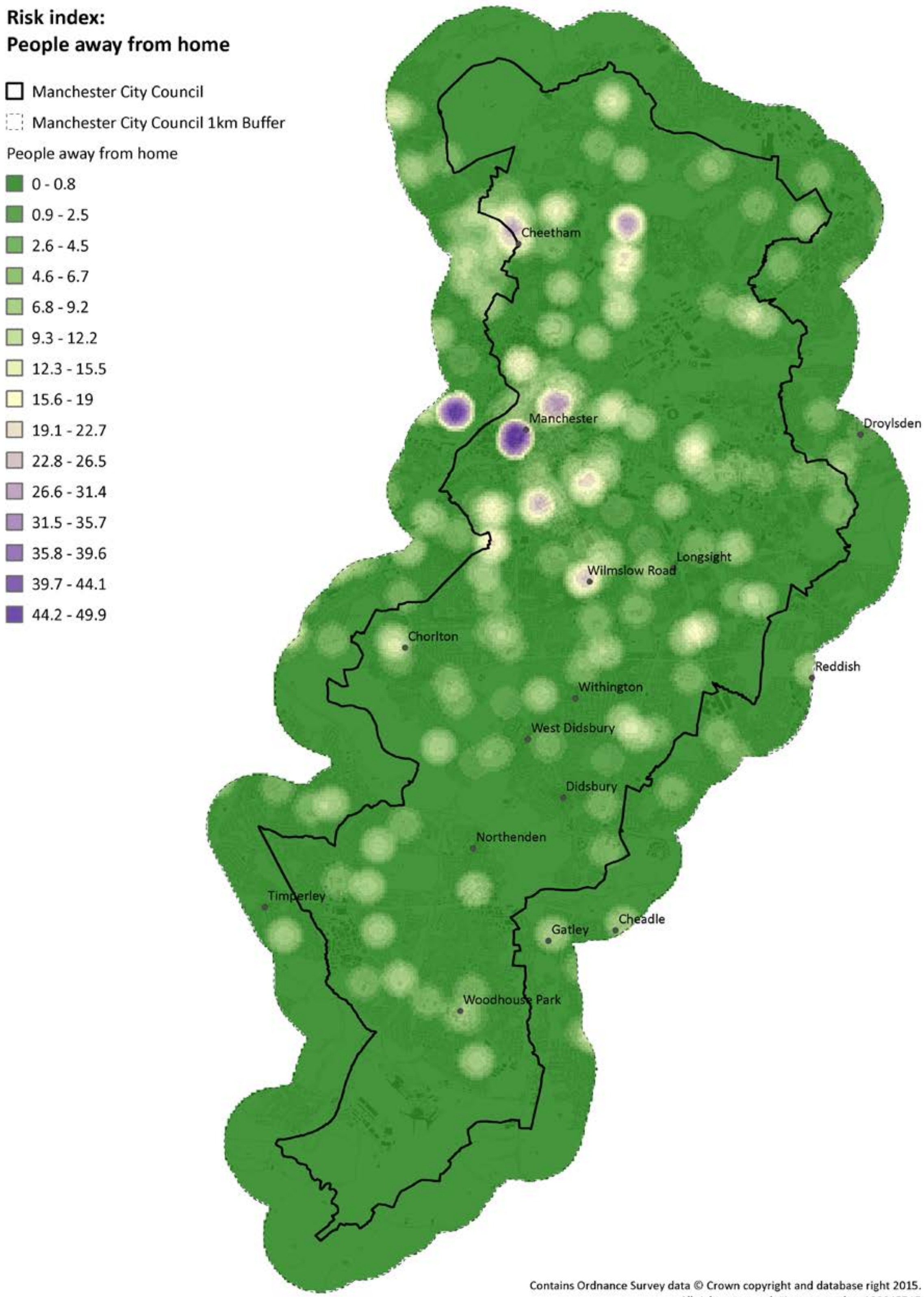


Figure 9: map of 'away from home' risk index for Manchester



Case study 1 - Rusholme and Longsight

The Rusholme/Longsight area is located in centrally within the borough of Manchester City and is south east of Manchester city itself. Looking at this area, it is clear that much of the risk in this region is derived from the characteristics of the resident population. As Figure 10 shows, there are high numbers of economically inactive people in this area, especially around Claremont and Longsight, where typically there were over 18 economically inactive people per output area[17] (see Figure 10). This area also has high ethnic diversity, with most output areas having over 100 people from minority ethnic groups (see Figure 11). The age profile of this area is also fairly young, with some output areas having over 300 residents aged 10-24 (see Figure 12). Mental health data did not show discernible patterns, though like all areas there were some local residents with mental health problems.

In addition to the risk profile of the resident population, there are also a number of services for vulnerable people in this area. For example, one of Manchester's eight foodbanks is located in the Rusholme/Longsight area, as are two clinics for the treatment of drug users. Three out of fifteen specialist homeless accommodation shelters are in this location. Finally, there are four educational institutions present.

Therefore, the risk profile of this region is driven by the profile of residents in relation to their youth, economic activity and ethnic make-up but also to some extent by the services for vulnerable people offered in this area.

[17] Output areas typically represent an average of 309 residents, though some can be larger or smaller than this.

Figure 10: Number of residents unemployed (per output area) in Rusholme/Longsight

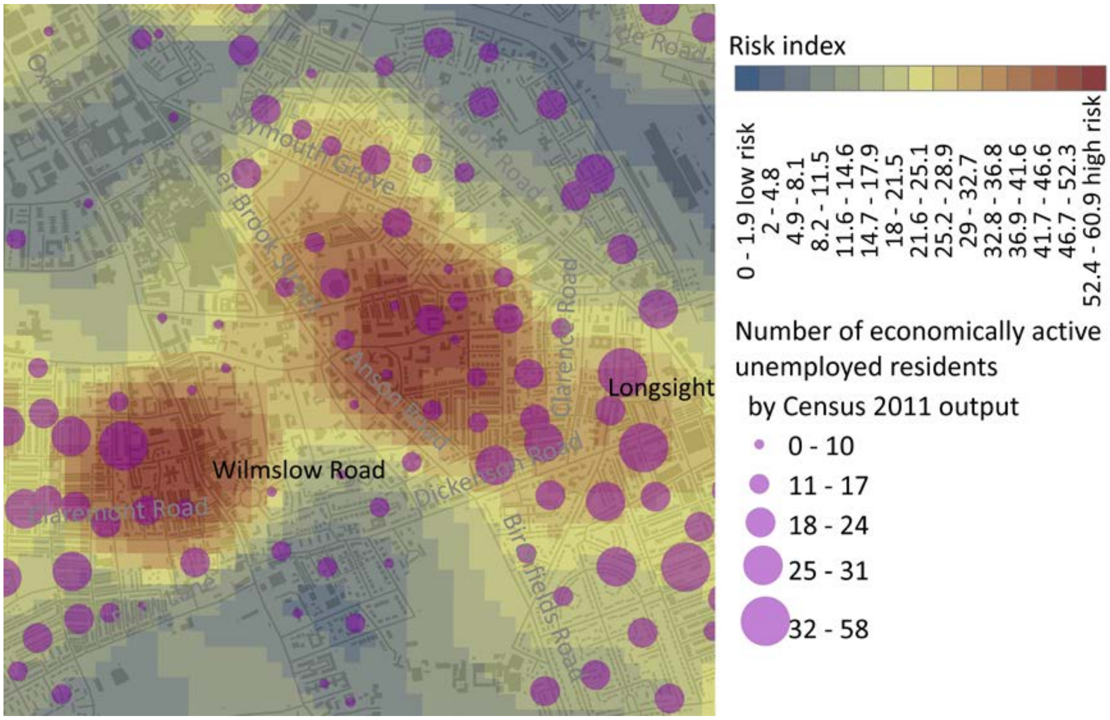


Figure 11: Number of residents from minority ethnic groups (per output area) in Rusholme/Longsight

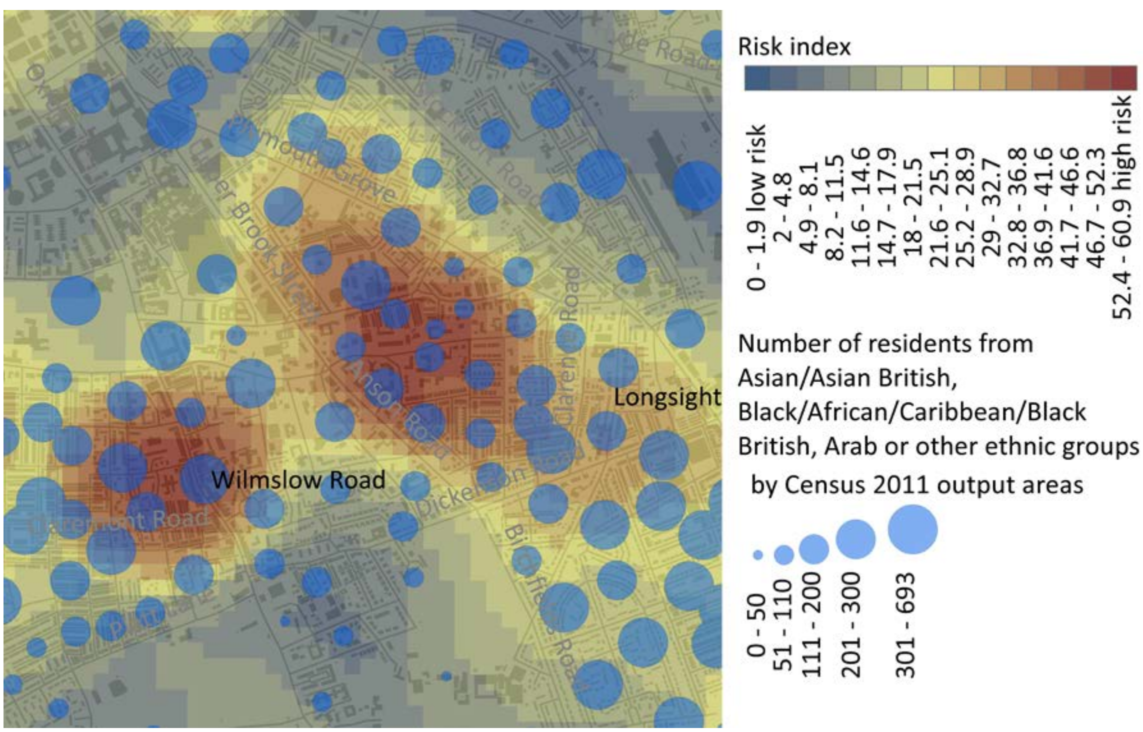
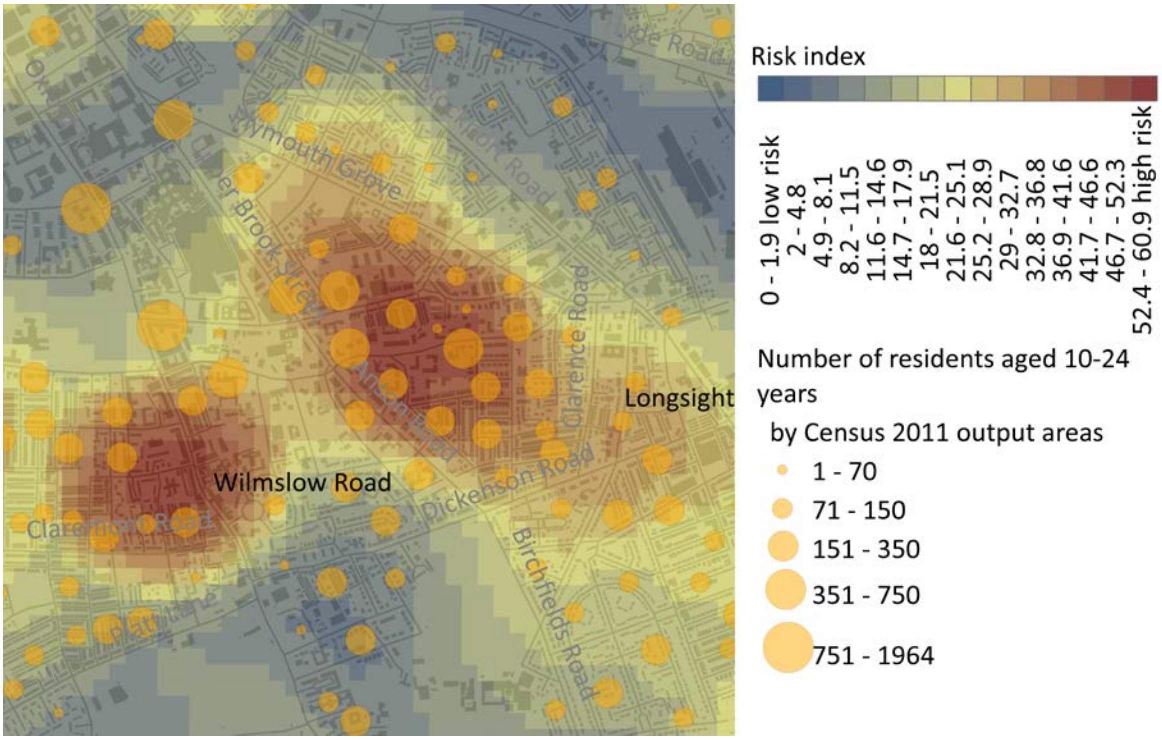


Figure 12: Number of residents economically inactive (per output area) in Rusholme/Longsight



Case Study 2: City centre and University area

This case study focuses on two areas around Manchester City of higher risk, that of the city centre and the area towards the south of the city, around the Oxford Road and the University of Manchester. As with case study 1, the risk profile in these areas is driven through a combination of the services offered in the locale and the resident population profile. This is especially the case with the area around the University.

Looking at the resident population first, the only notable characteristic of variation for the city centre area is the number of minority ethnic residents, where towards the south of the city centre and around Chinatown there are somewhat higher numbers of people per output area. The profile by age, unemployment and mental health does not seem to vary significantly across the central city centre area. However, this is not the case for the area around the University, which has a very ethnically diverse resident population, with some of the highest numbers of residents per output area living in this region (see Figure 13). The numbers of economically inactive people per output area are somewhat greater in the areas surrounding the University though not as numerous as in other areas (see Figure 14). Perhaps unsurprisingly, the

University has a distinctly younger age profile (see Figure 15) and, of course, has a number of educational institutes in this region.

There are some facilities in these areas which serve potentially vulnerable people. These include a homelessness shelter around the University area, two food banks around the perimeter of the University area and a needle exchange. To the north of the city centre there are three pay day loan facilities. Notably, the city centre is home to the only Gamblers Anonymous/GamCare treatment facility in Manchester.

Therefore, around the University area, the risk profile seems to be driven by the relatively young age profile of residents, its ethnic diversity and to some extent unemployment alongside some provision of services for vulnerable people. In the city centre, the risk profile is accounted for primarily by treatment services for problem gamblers.

Figure 13: Number of residents from minority ethnic groups (per output area) in Manchester city centre

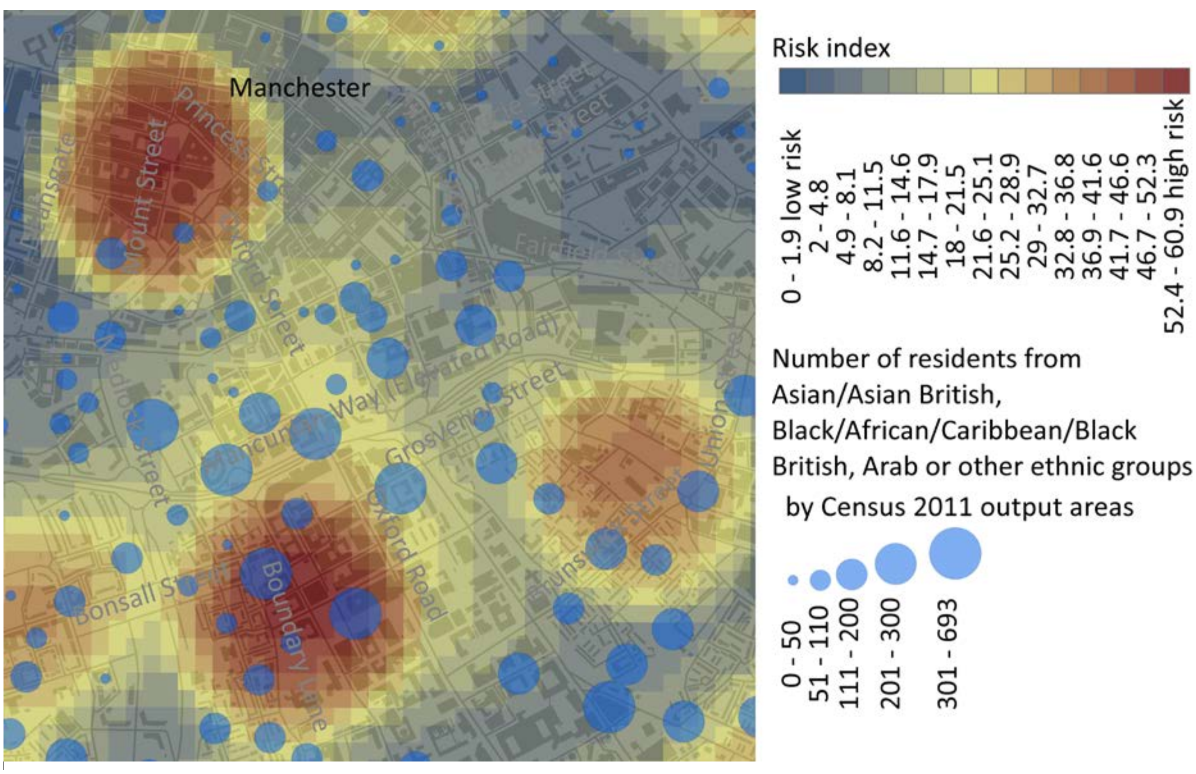


Figure 14: Number of residents unemployed (per output area) in Manchester city centre

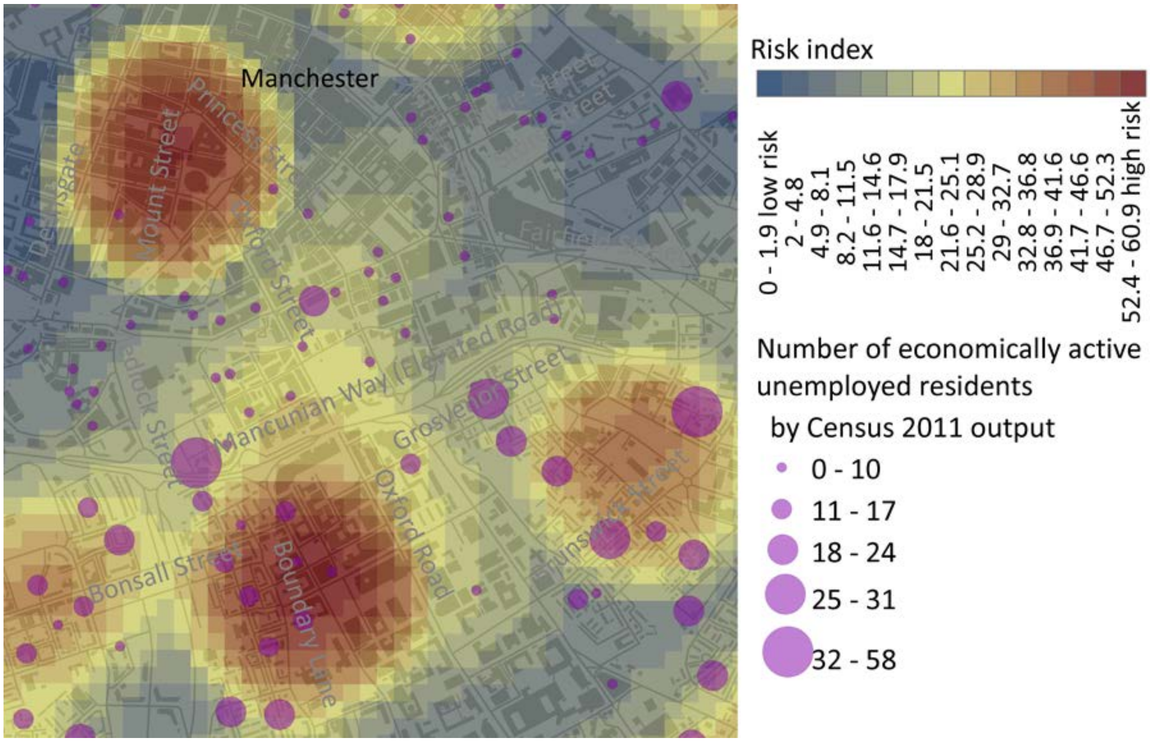
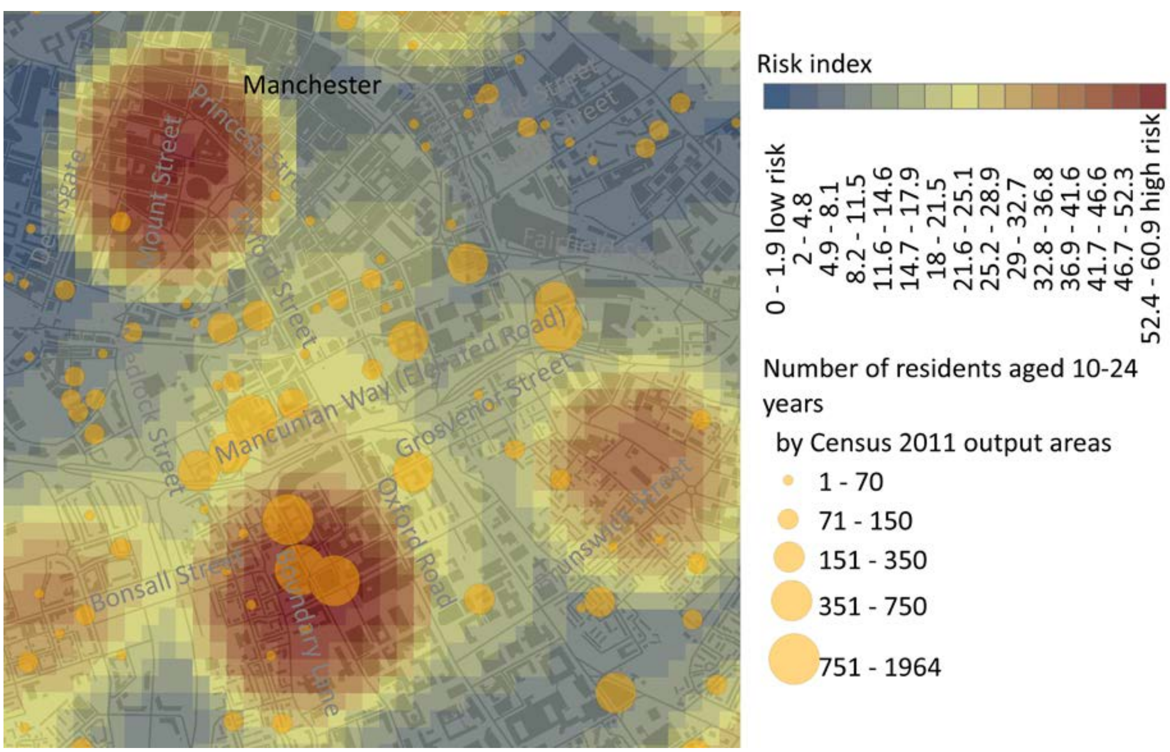


Figure 15: Number of residents aged 10-24 (per output area) in Manchester city centre



Case Study 3: Cheetham

The final case study area extends from Cheetham Hill northwards and across the Manchester City boundary towards Broughton. Like case study 1, there is a greater degree of risk attached to the resident population profile in these areas. Firstly, there are relatively high numbers of economically inactive people in the surrounding areas (see Figure 16). These areas are also ethnically diverse, especially around Cheetham Hill (see Figure 17). However, the age profile does not seem to be disproportionately youthful compared with others. The mental health data available for GPs in these areas, however, suggests a high number of residents with diagnoses for one of the relevant mental health conditions considered (see Figure 18). These appear to be the primary drivers of risk in these areas.

There are some facilities offering services to potentially vulnerable people in these areas also. For example, there are two facilities offering accommodation to people with substance abuse/misuse issues and two emergency homelessness shelters, a couple of pay day loan shops and one of Manchester's eight job centres is in this location. Therefore, there are some drivers of risk attached to the 'away from home' population in this area, but the main factors appear to be the characteristics of local residents.

Figure 16: Number of residents unemployed (per output area) in Cheetham area

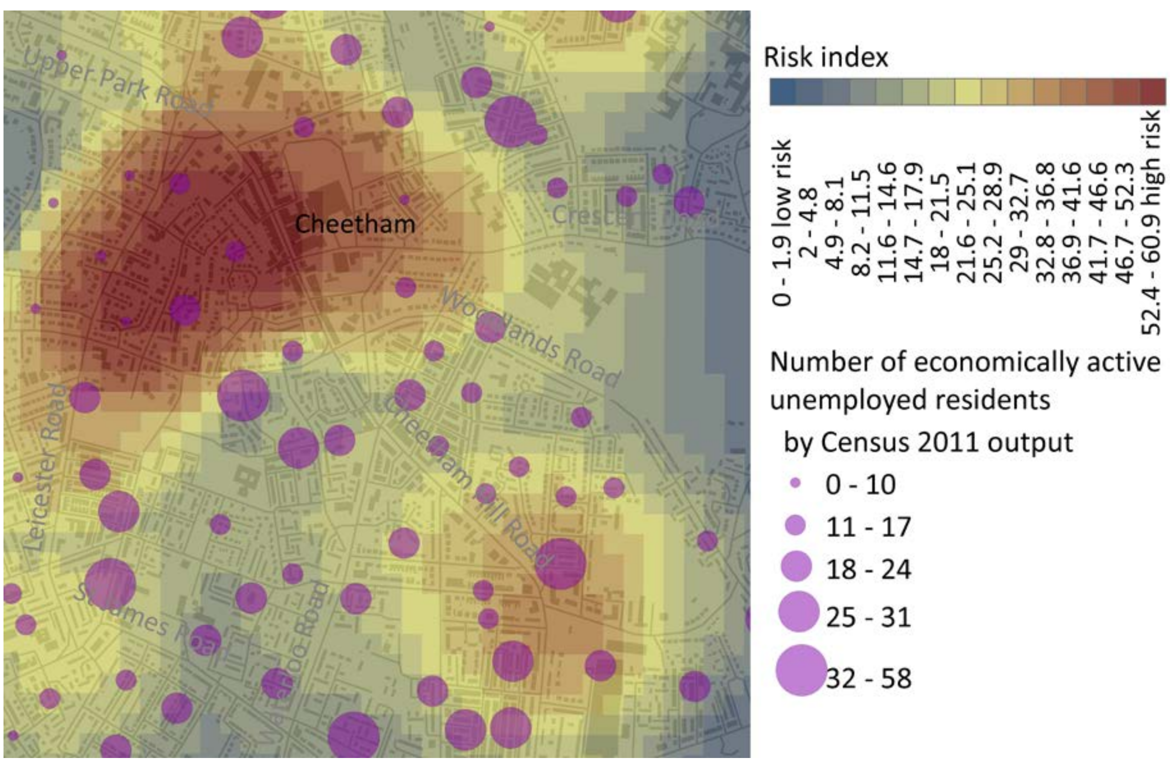


Figure 17: Number of residents from minority ethnic groups (per output area) in Cheetham area

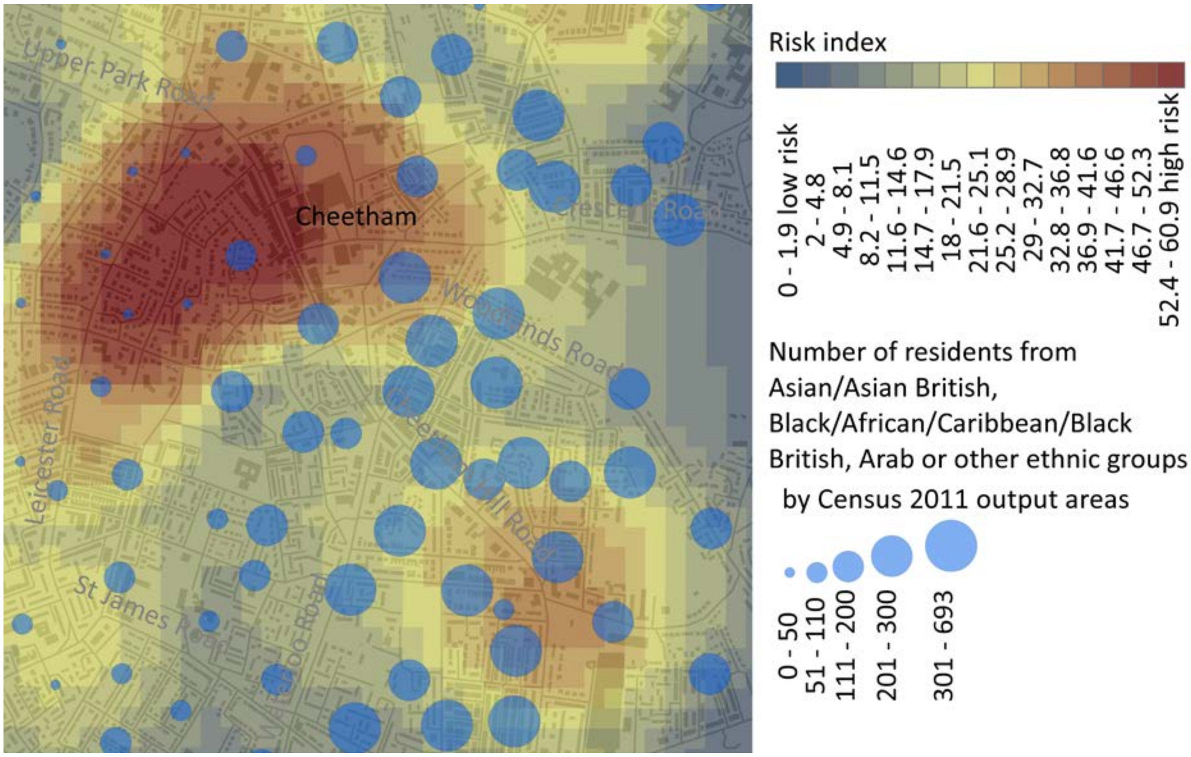
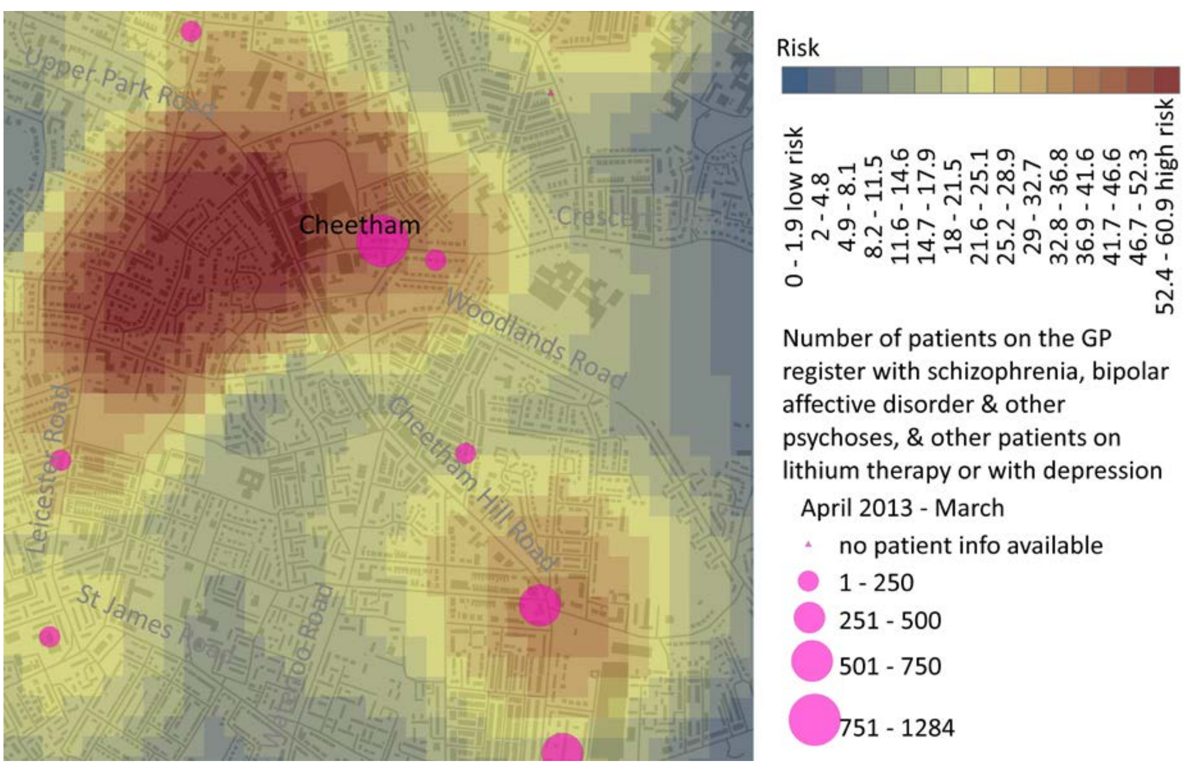


Figure 18: Number of GP patients with certain mental health conditions in Cheetham area



Westminster

Figure 19: map of composite risk index for Westminster

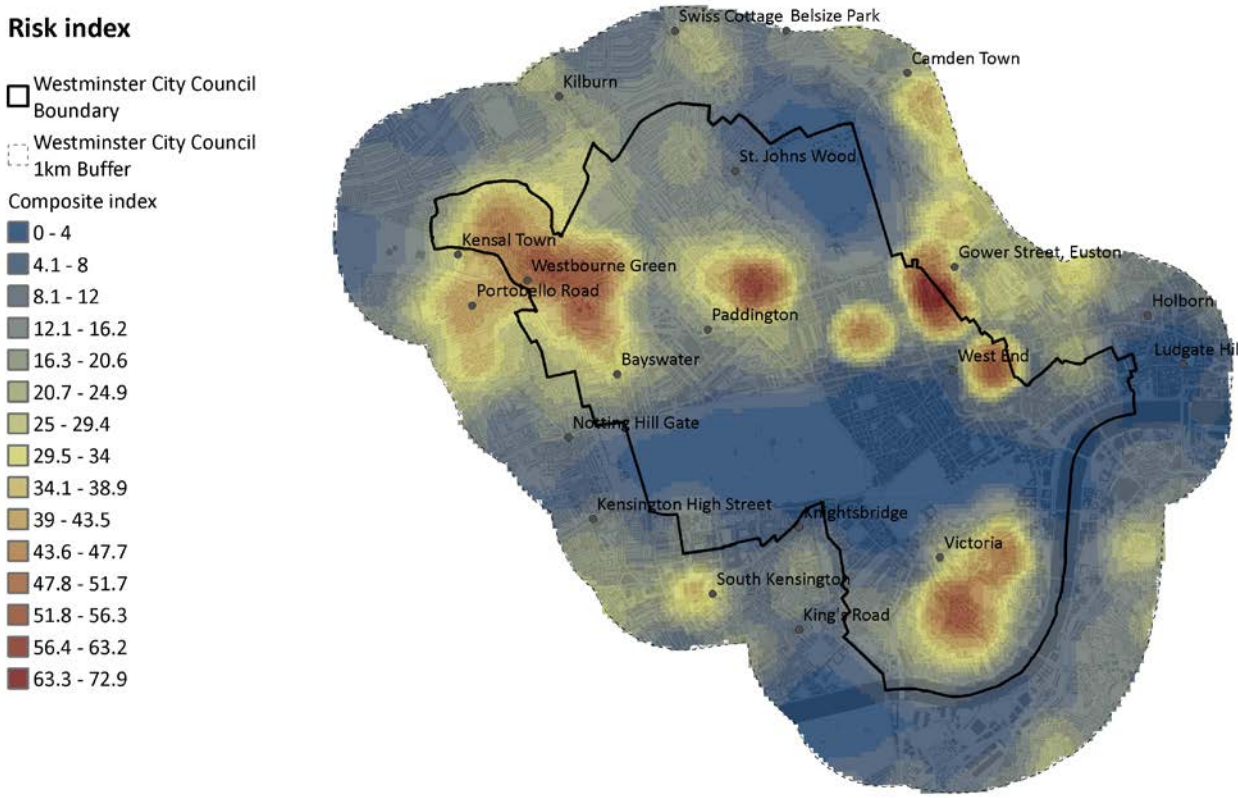


Figure 19 shows the composite risk index for Westminster. Risk scores vary between 0 and 72.9.[18] There are four main areas of greater risk to gambling-related harm identified. These are:

- the area around Westbourne Green towards Kensal Town in the north west of Westminster.
- the area around the Edgware Road in the north central part of Westminster,
- the area around Pimlico and Victoria to the south of Westminster, and
- the West End and Soho.

Looking at Figures 20 and 21, we can see that there are different drivers of risk in these areas. For three of these areas (the north west, Paddington and Edgware and Pimlico) the 'at home' risk index shows higher values, suggesting that the risk in these areas is driven more by the

[18] As previously, the breaks within the scales shown in Figure 20 are based on the breaks in the distribution of the index data.

local resident population. For the West End, risk is driven much more by the 'away from home' community. Of course, in each area there is some risk associated with both the 'at home' and 'away from home' populations. Each of these four areas are discussed in turn to explore the specific drivers of risk in each location.

Figure 20: map of 'at home' risk index for Westminster

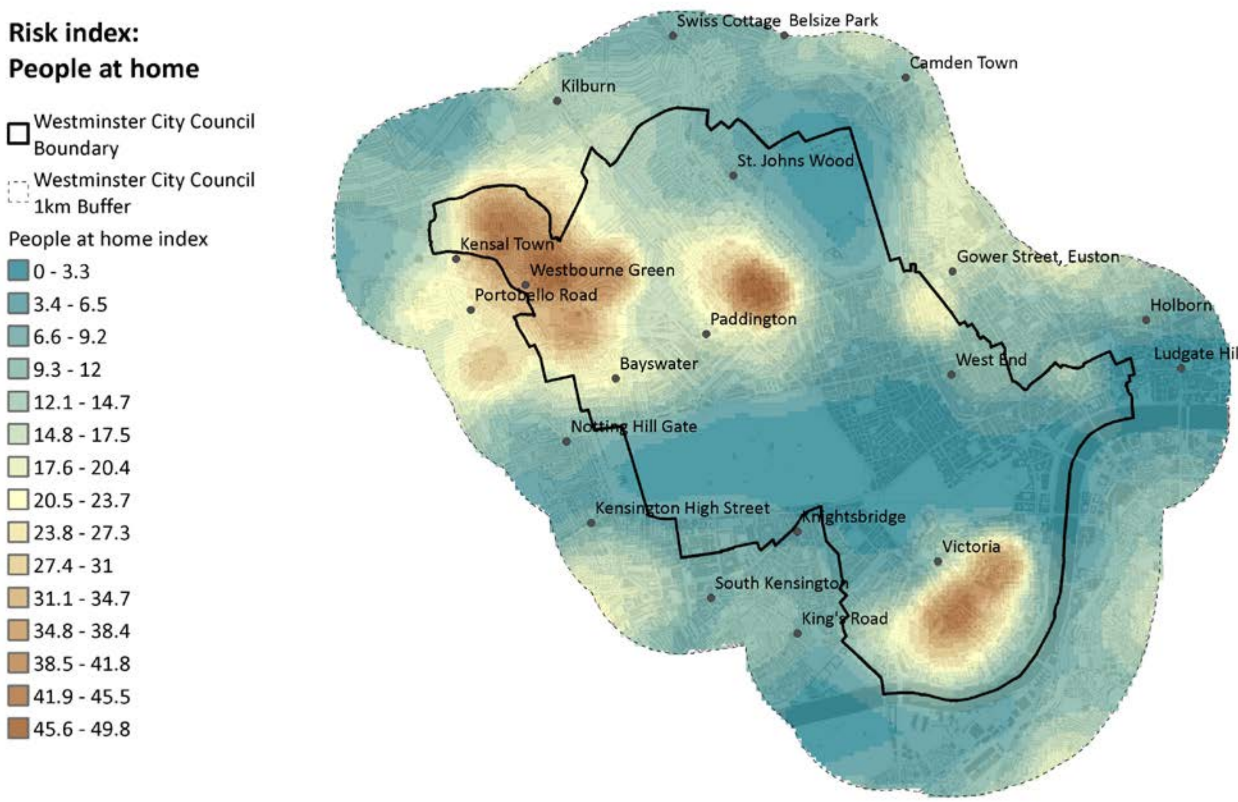
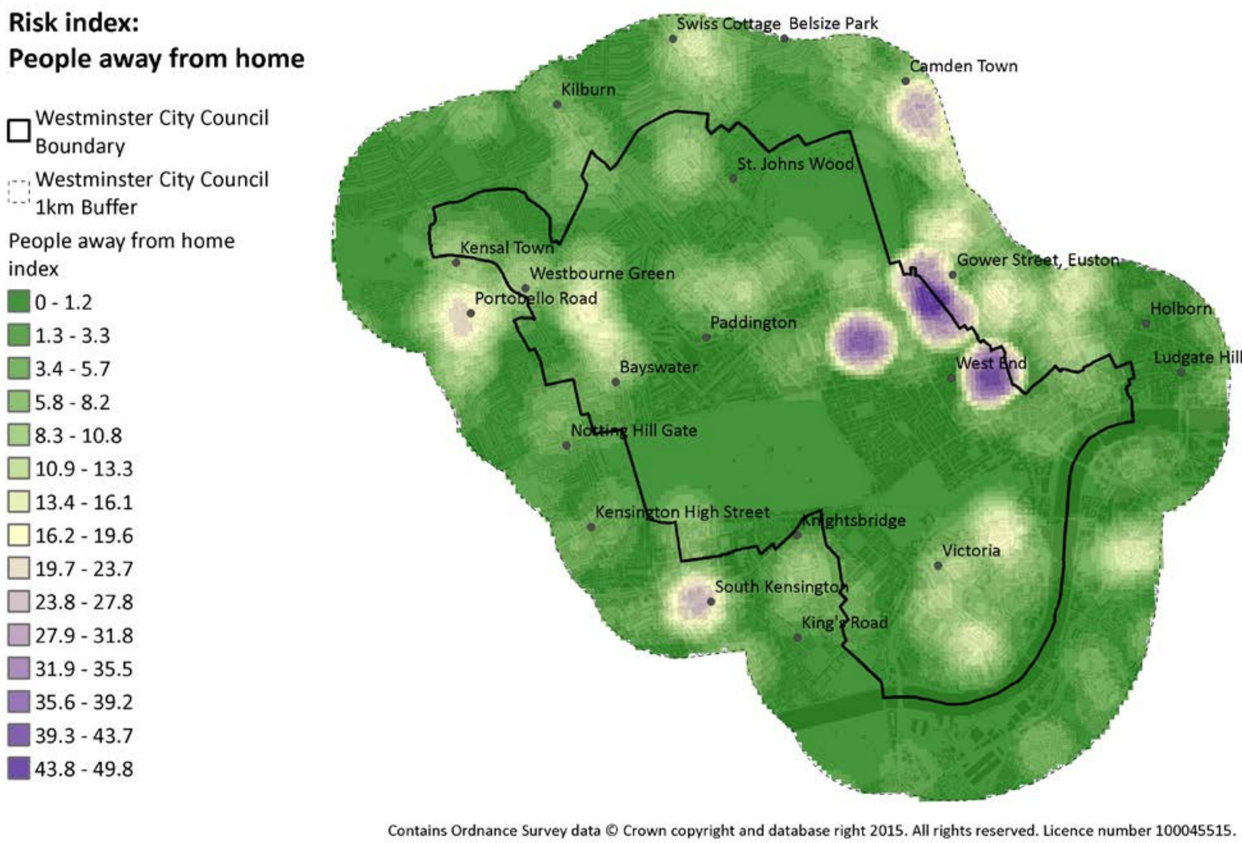


Figure 21: map of 'away from home' risk index for Westminster



Case study 1 – the north west/Harrow Road

This area extends north from Westbourne Green to West Kilburn to the north west boundary of Westminster. It therefore covers a broad area. Looking at this area, we can see that it has the one of the highest levels of risk associated with the 'at home' resident population. There are high numbers of unemployed people (see Figure 22) and high numbers of people from minority ethnic groups (see Figure 23). In fact, many output areas in this region have more than 100 residents from minority ethnic groups and more than 20 unemployed residents per output area. Relative to other areas in Westminster, the north west area has somewhat greater numbers of young people aged 10-24 (see Figure 25) though it does not have quite so many educational establishments as other parts of Westminster. Finally, for the resident population, there appear to be high numbers of people recorded on the GP register with schizophrenia, bipolar affective disorder and other psychoses, and other patients on lithium therapy or with depression. This is especially so around the Harrow Road area, where many of the GPs (where data was available) had over 190 patients with these diagnoses (see Figure 24). Taken together this builds a picture of multiple risk factors for gambling-related harm among the residents in this area.

Looking at the 'away from home' population, of the eight treatment and support services for substance abuse/misuse (not including needle exchanges) in Westminster, three are in the north west area, as is one of only two food banks in Westminster. There was also a high concentration of supported housing services in this area (12 facilities), showing higher potential risk among people who use these services in this area.

The risk profile in this area is therefore driven both by the characteristics of the resident population and by the facilities and services that exist in this area also.

Figure 22: Number of residents unemployed (per output area) in north west Westminster

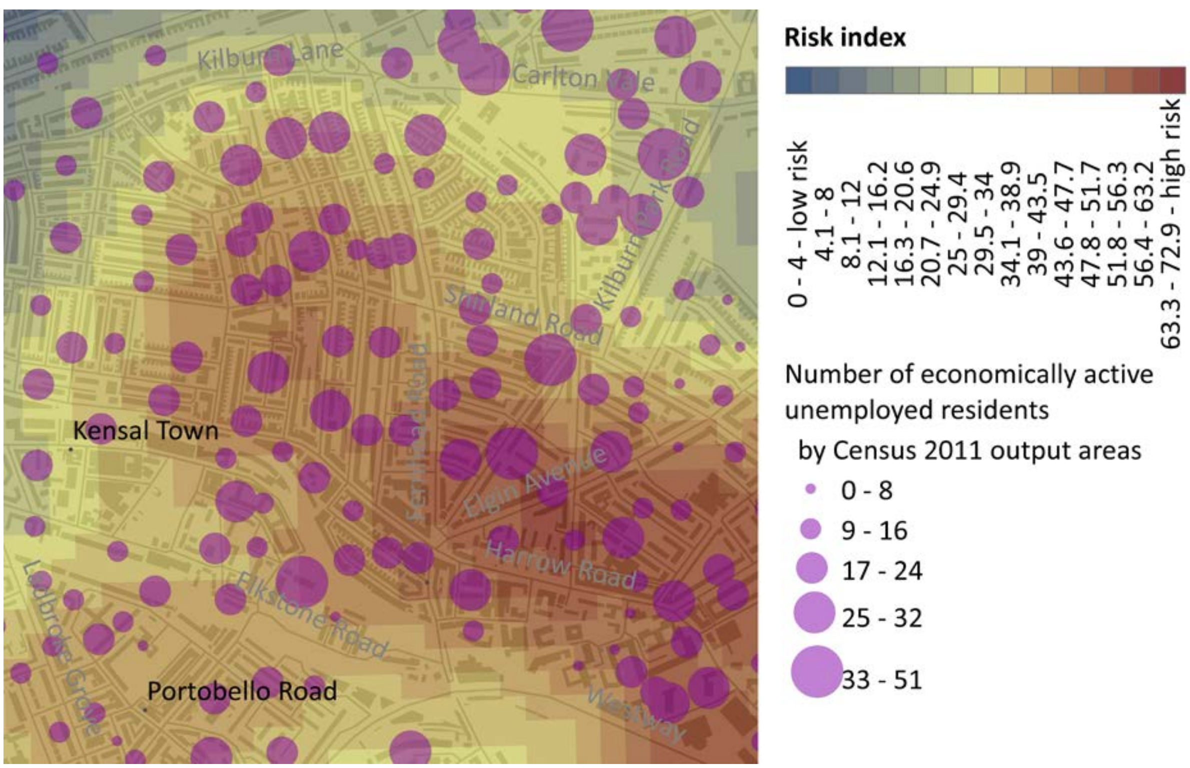


Figure 23: Number of residents from minority ethnic groups (per output area) in north west Westminster

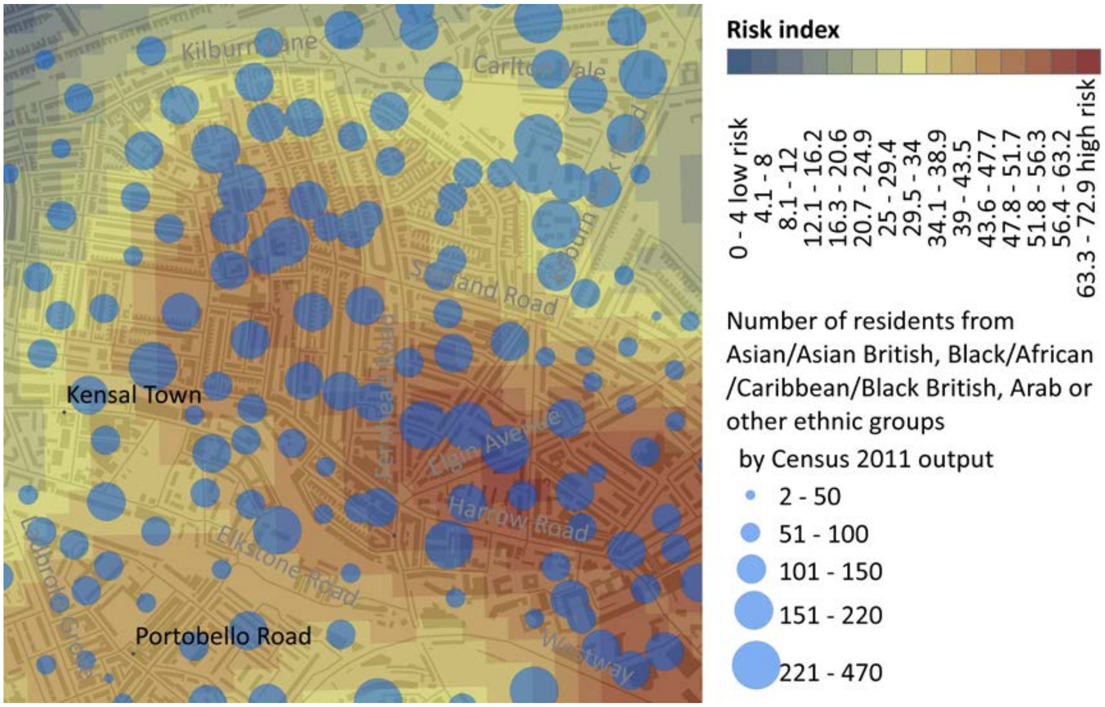


Figure 24: Number of GP patients with certain mental health conditions in north west Westminster

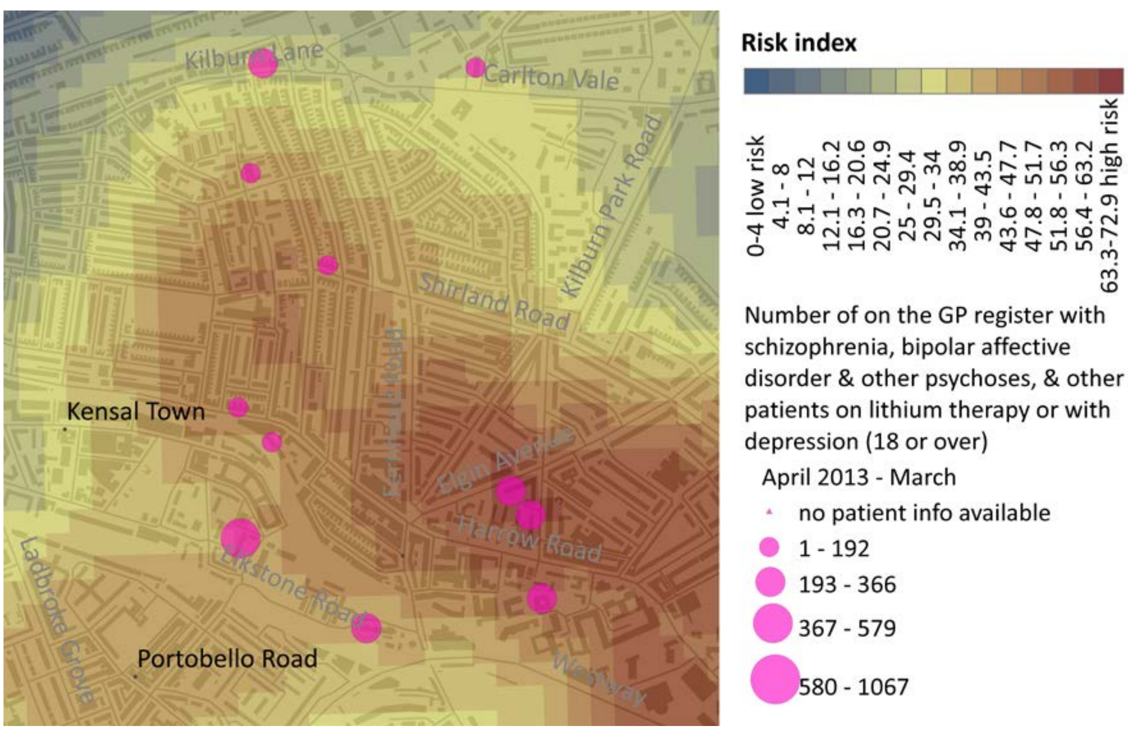
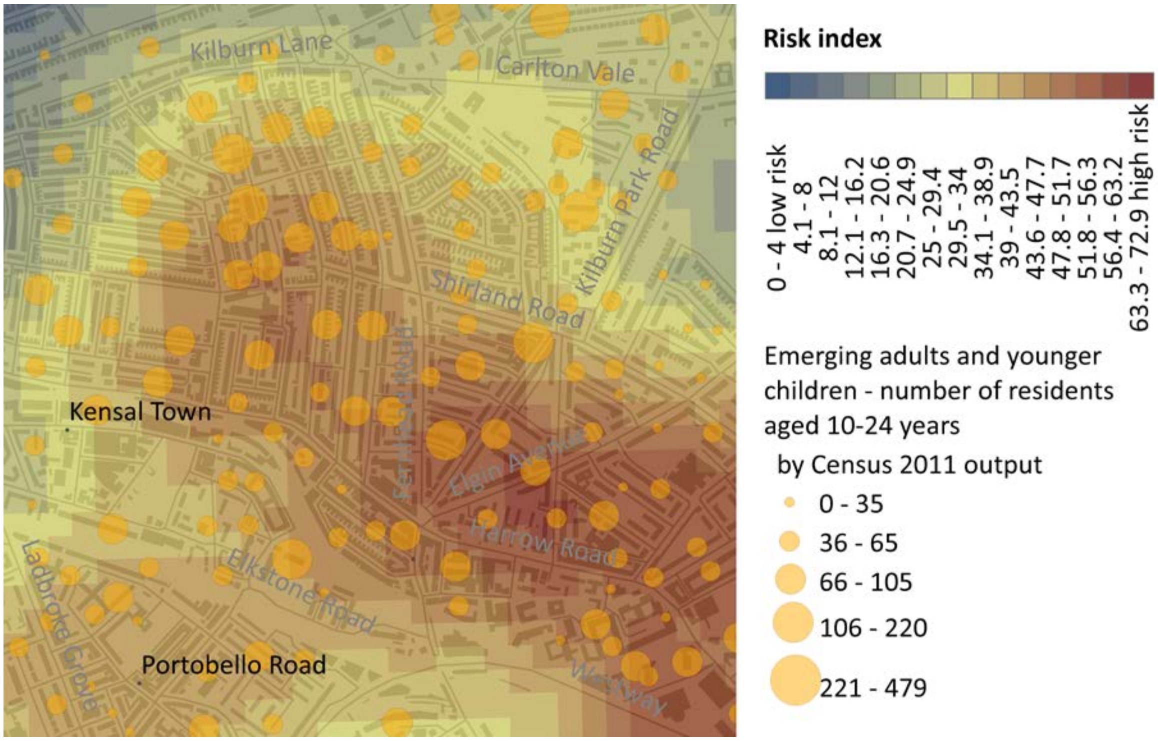


Figure 25: Number of residents aged 10-24 (per output area) in north west Westminster



Case study 2 – Paddington and the Edgware Road

Looking at the Paddington/Edgware Road area, the first pattern to note is that the area of risk is concentrated in a smaller geographical space. Highest risk is focused in the area that extends north between Edgware Road and Baker Street towards Lisson Grove.

Compared with the first case study, the risk in this area is driven primarily by four key factors: unemployment, ethnicity, youth and homelessness. Figure 26 shows that there are a high number of residents who are economically inactive in this area, typically more than 16 people per output area. This area also hosts only one of two job centres for Westminster. This is also an ethnically diverse area with more than 100 people per output area being from a minority ethnic groups (see Figure 27). Looking at youth, there are slightly higher numbers of young people (aged 10-24) resident in the area but there are five educational establishments within a small geographic space (see Figure 28). Five of the forty nine supported housing facilities are also in this small geographic area. Data for mental health diagnosis for GPs in this area is sparser, though the three GP surgeries mapped suggest higher numbers of diagnosis than other surgeries.

Unlike the north west, there are fewer facilities in this area which are likely to draw vulnerable people to these places. There are no treatment centres or drug facilities (with the exception of one pharmacy offering a needle exchange), there are no foodbanks and just one pay day loan shop on the edge of the area.

Therefore, it seems that the key factors driving risk in this area relate to unemployment, ethnic make-up, young people and homelessness.

Figure 26: Number of residents unemployed (per output area) in Paddington area

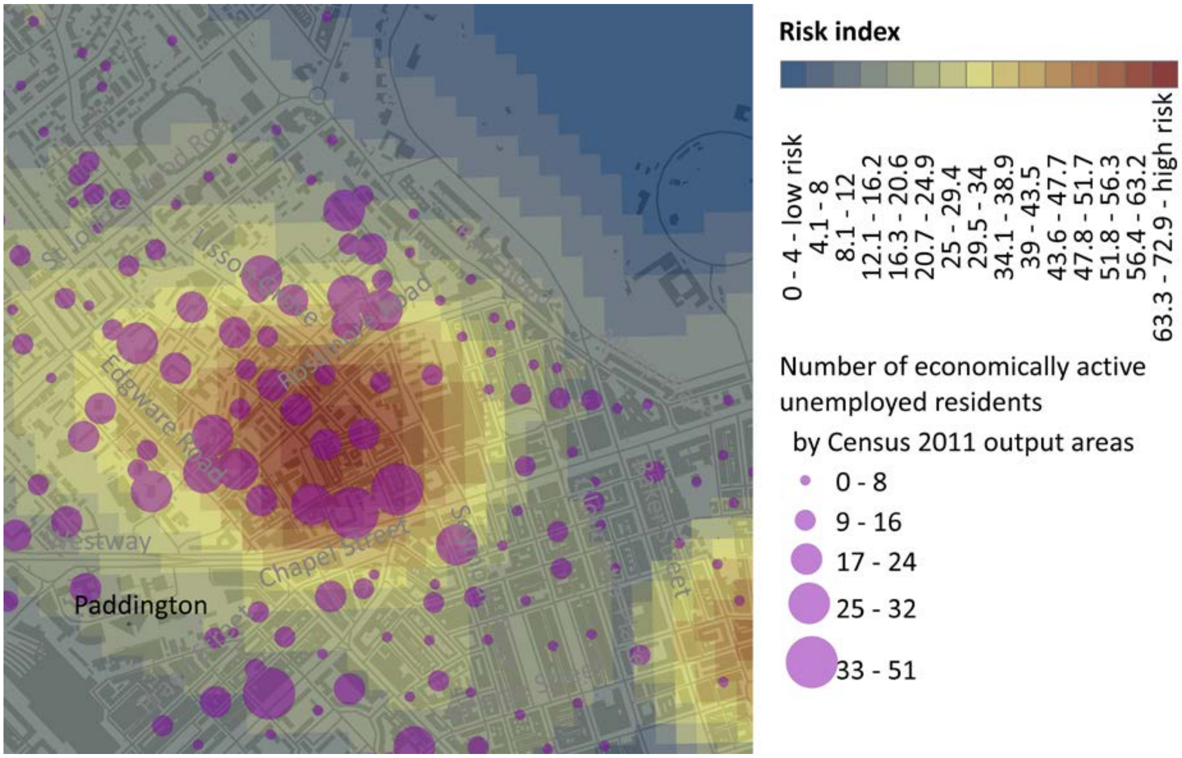


Figure 27: Number of residents from minority ethnic groups (per output area) in Paddington area

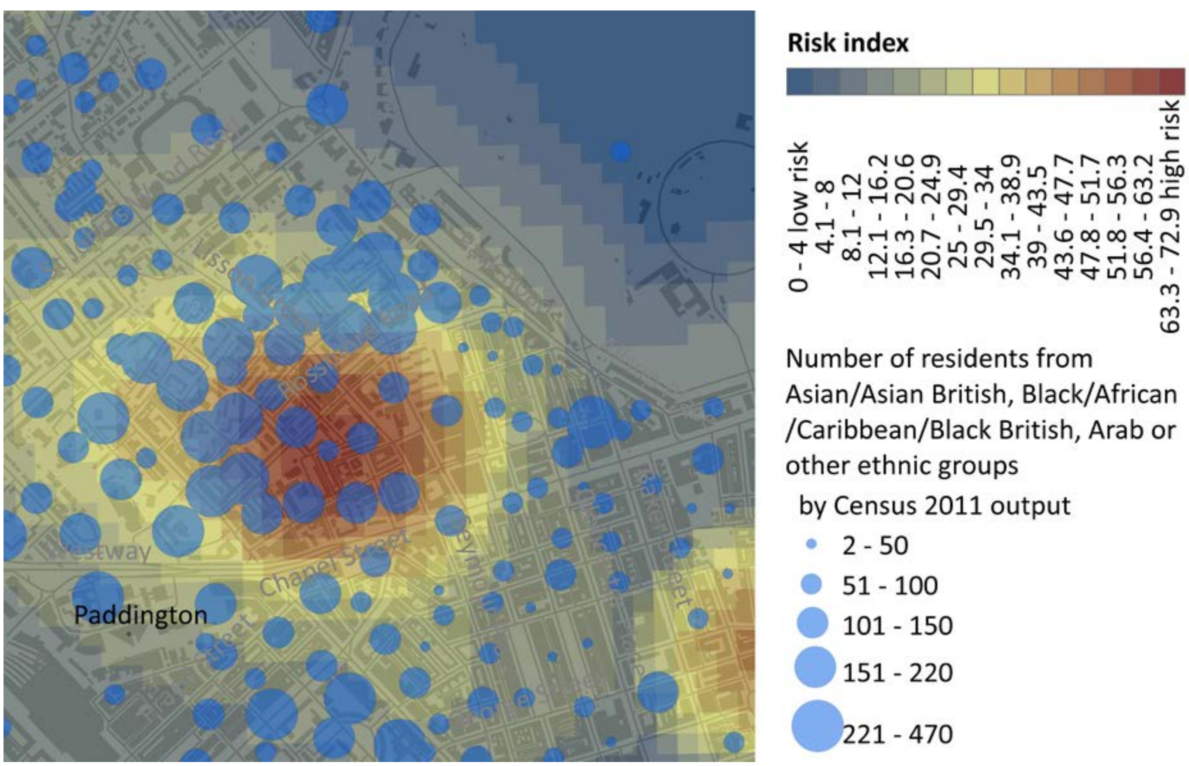
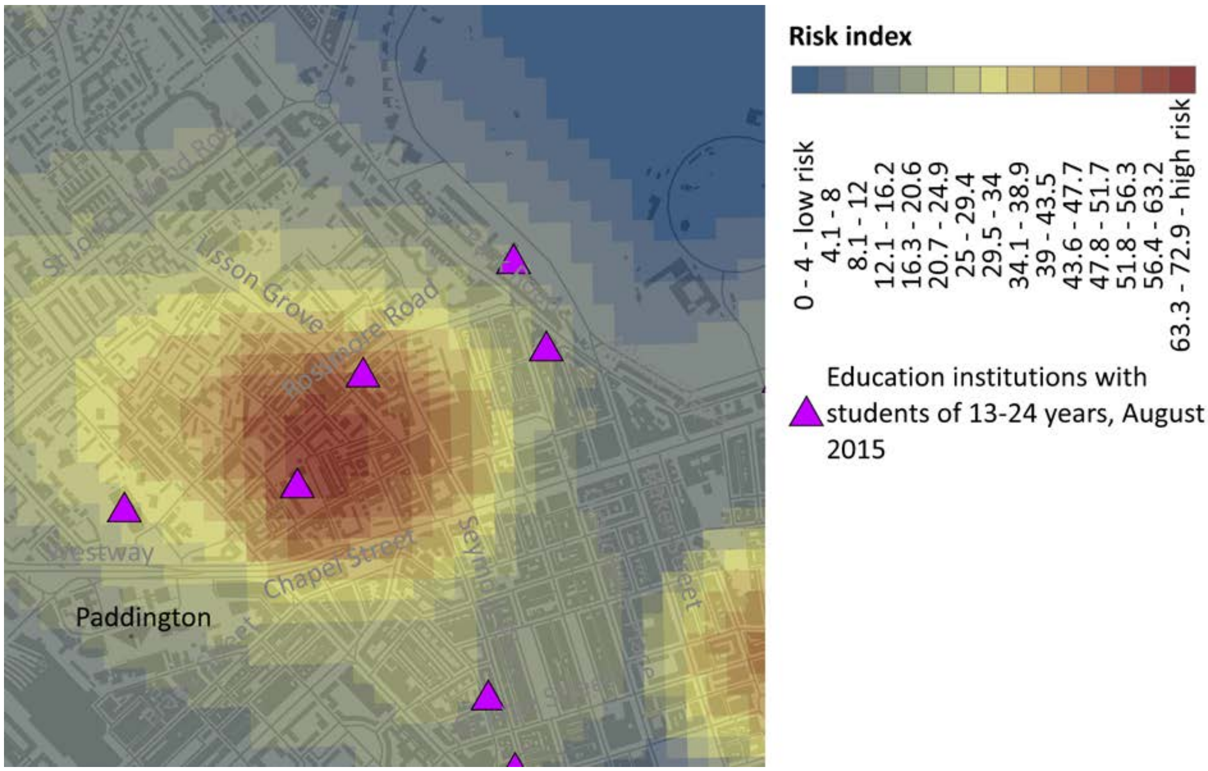


Figure 28: Location of educational institutions in Paddington area



Case study 3 – The West End

The risk areas in the West End focus on two distinct spaces, one around Soho and the other to the north of Oxford Street, between Goodge Street and Great Portland Street. Like the area around about Paddington/Edgware Road, both areas are smaller geographically than the area of risk in the north west.

The risk in both areas is broadly driven by the types of services offered in each area. For example, three of the four locations of Gamblers Anonymous/GamCare treatment services (see Figure 29) are in these areas. These areas are also home to five supported housing facilities; these are especially concentrated in the area north of Oxford Street. There are at least three payday loan shops around the Soho area. To the south of the Soho area, there is a treatment support service for those with drugs and alcohol problems.

There is less evidence that the risk profile is being driven by the profile of local residents, though the area to the north of Oxford St has some higher numbers of economically inactive people (with typically 15 people per output area) and those from a minority ethnic background (typically more than 150 people per output area) (see Figures 30 and 31).

Interestingly, Soho did not display noticeably higher numbers of residents from minority ethnic groups, despite this being the location of Chinatown. Whilst the residents will be represented, our models do not include facilities like Chinatown to which Chinese and other minority ethnic workers will gravitate. In this respect, the model around Soho is likely to be a conservative estimate of risk.

Figure 29: Location of GamCare treatment centres or GA meeting places in West End area

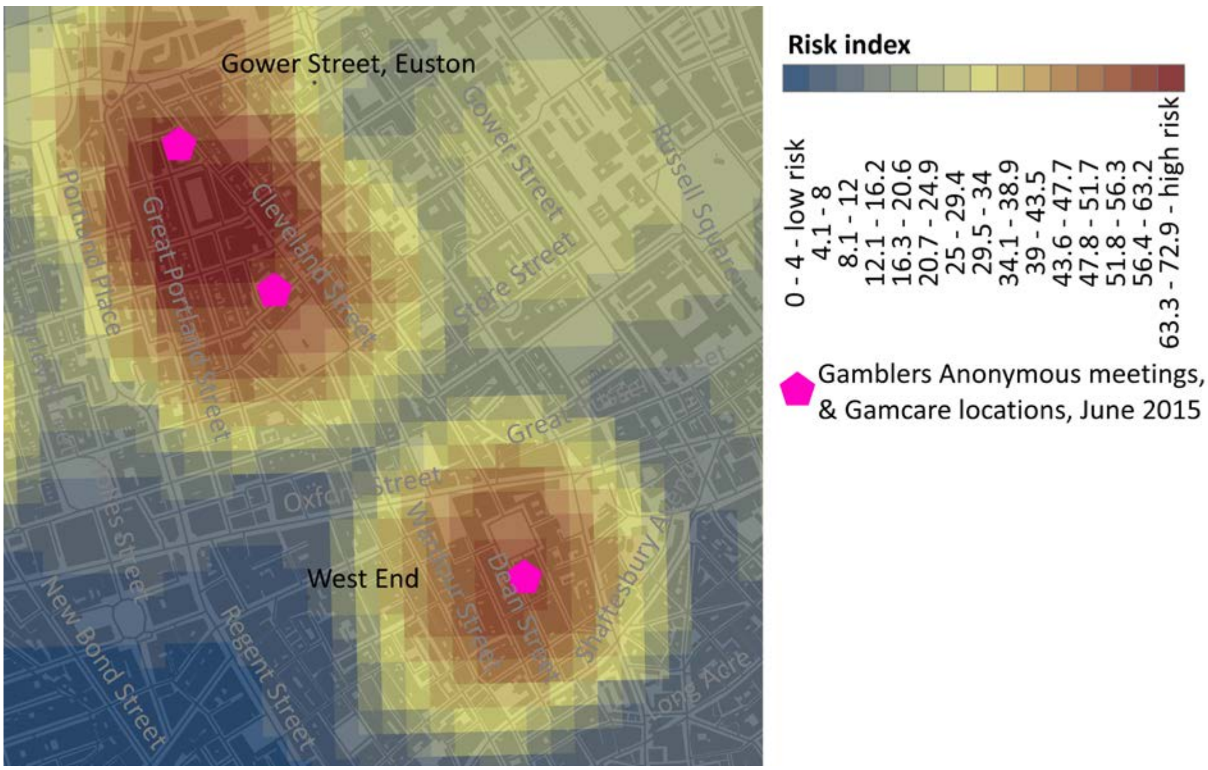


Figure 30: Number of residents unemployed (per output area) in West End area

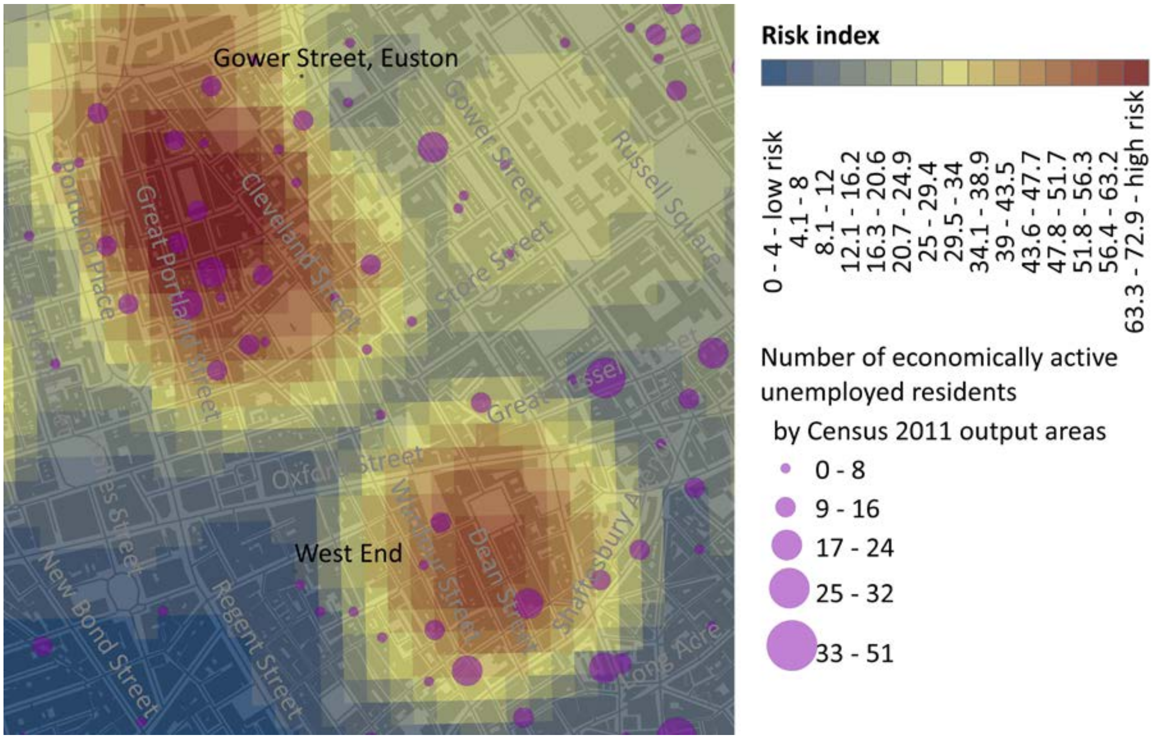
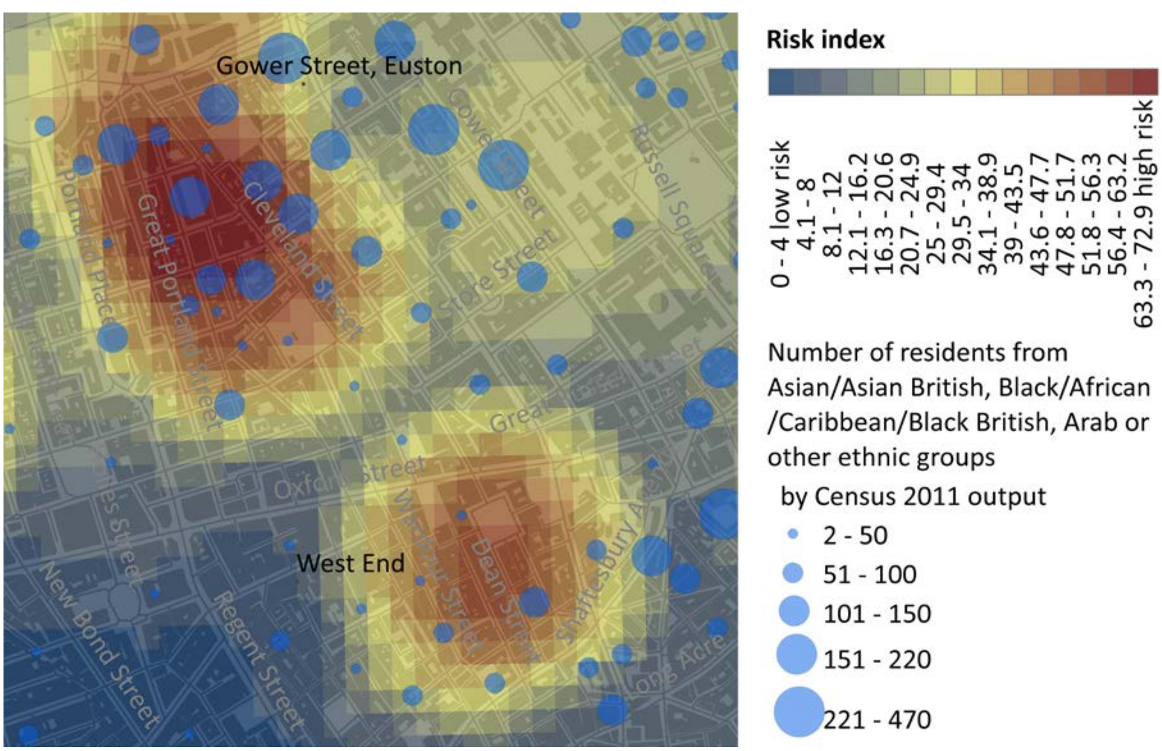


Figure 31: Number of residents from minority ethnic groups (per output area) in West End area



Case study 4 – Pimlico

The final case study area is the area to the south of Victoria and Victoria Road, around Pimlico. Risk in this area is driven by a mix of factors relating to the residential population and the ‘away from home’ population.

Looking at the resident population profile first, there are some areas in Pimlico which have greater numbers of unemployed people, though these numbers are not as high as those seen in the north west or Paddington (see Figure 32). Unlike the north west and Paddington, this area is less ethnically diverse with fewer residents from minority ethnic groups than the other case studies (see Figure 33). The number of young people in the area was also smaller than in the north west and Paddington regions. What was different, however, was that Pimlico had comparatively high numbers of residents with a mental health diagnosis on the GP register. For each of the GP surgeries with data shown, there were over 190 people with a relevant mental health diagnosis (see Figure 34).

In addition to the mental health of residents, other primary drivers of risk in the Pimlico region were the number of supported housing projects. Figure 35 shows that there were twelve such projects in this area, out of forty nine in total in Westminster. There were also two centres offering treatment for problems with alcohol, one pay day loan shop and Pimlico is the location of Westminster’s second food bank. In addition, ten educational institutes were located in this area.

Taking this together, risk in the Pimlico area seems to be related to the mental health of local residents and services for homelessness, substance abuse as well as educational facilities offered in the local area.

Figure 32: Number of residents unemployed (per output area) in Pimlico

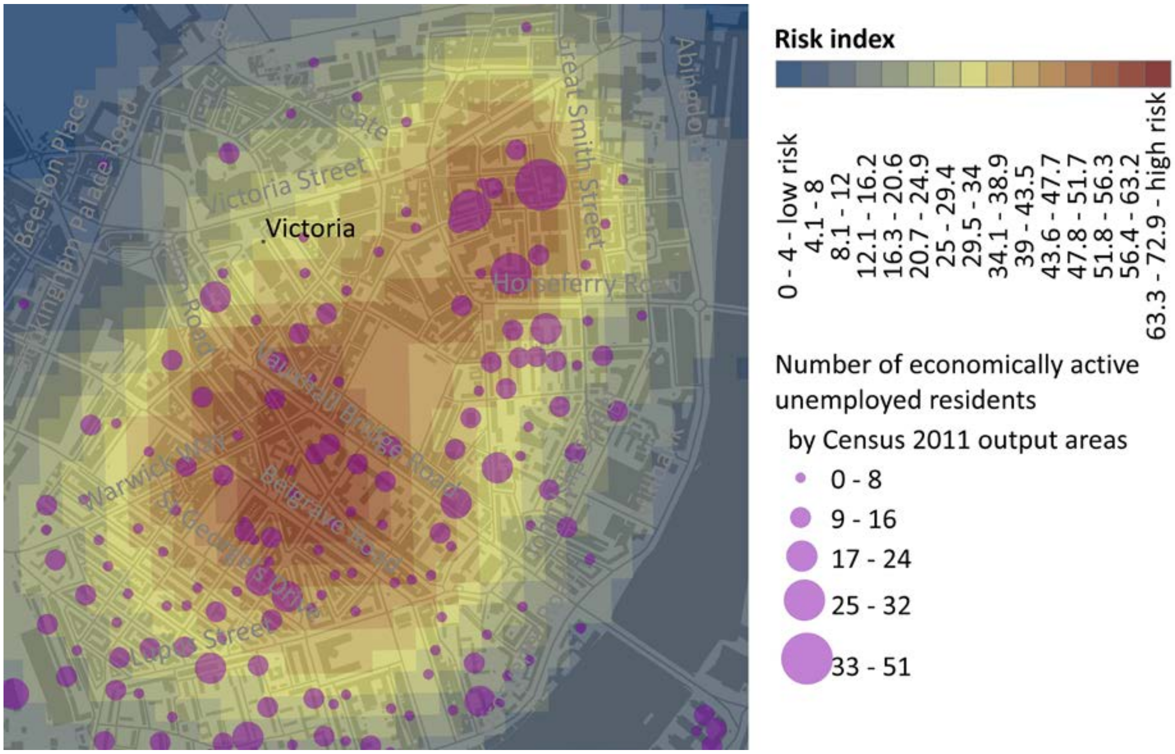


Figure 33: Number of residents from minority ethnic groups (per output area) in Pimlico

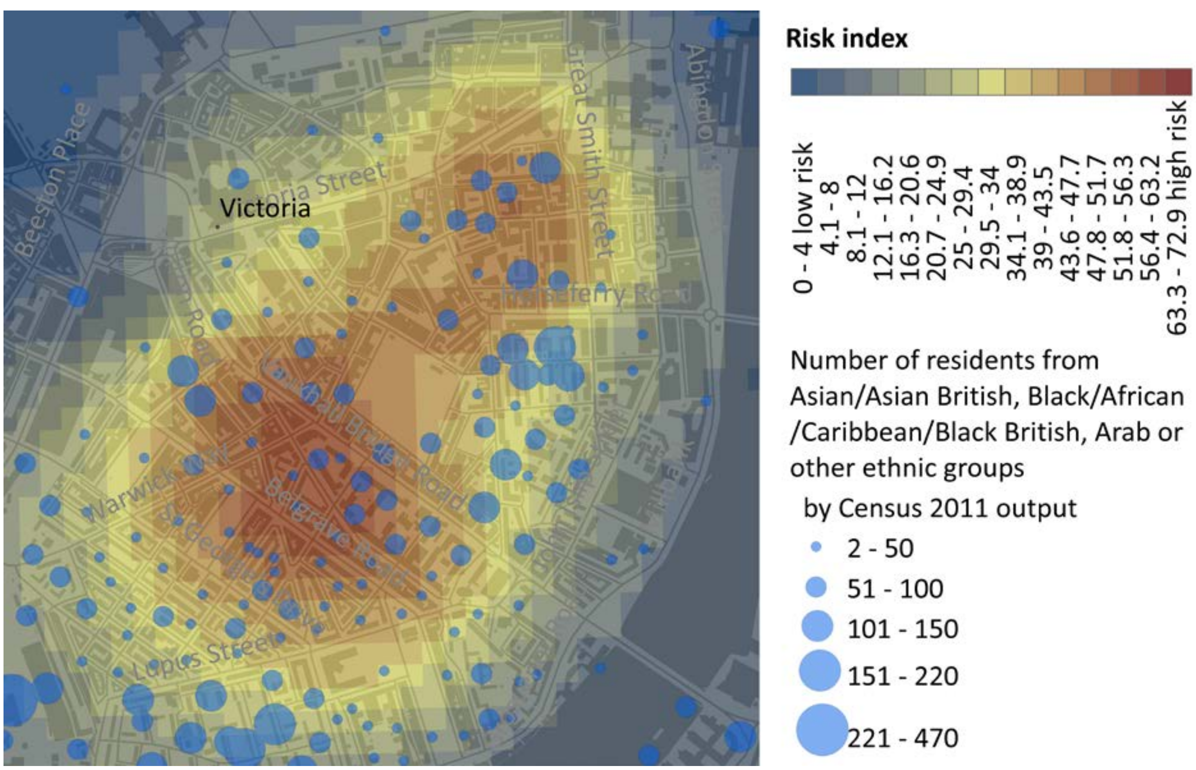


Figure 34: Number of GP patients with certain mental health conditions in Pimlico

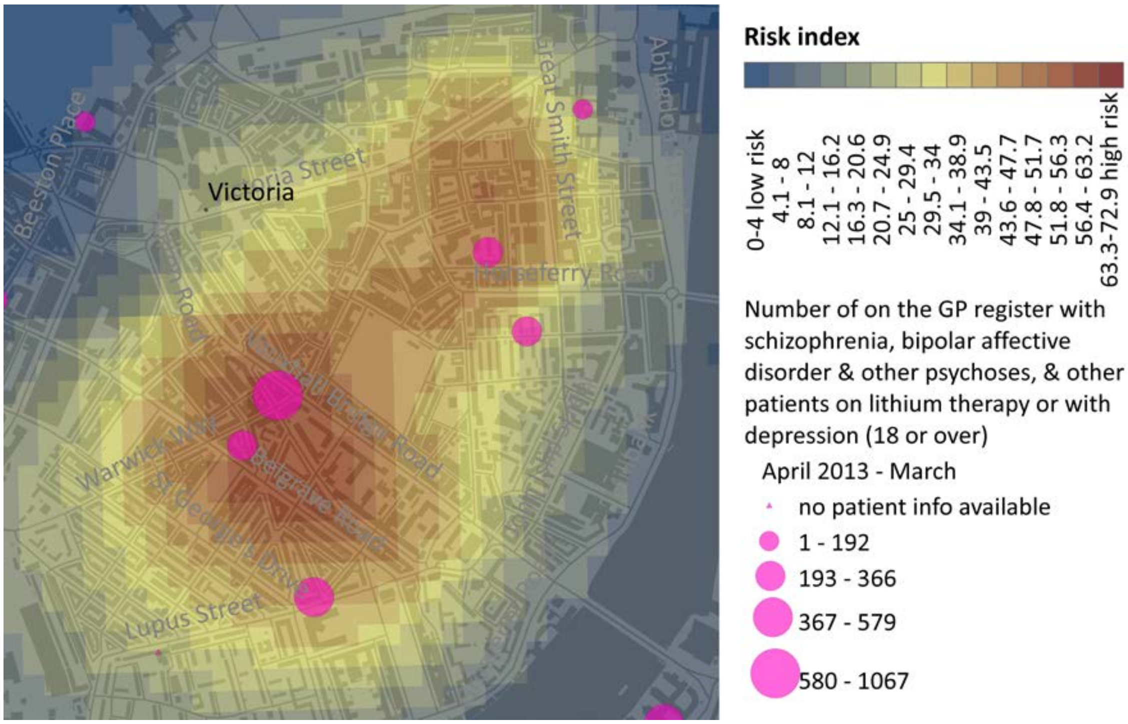
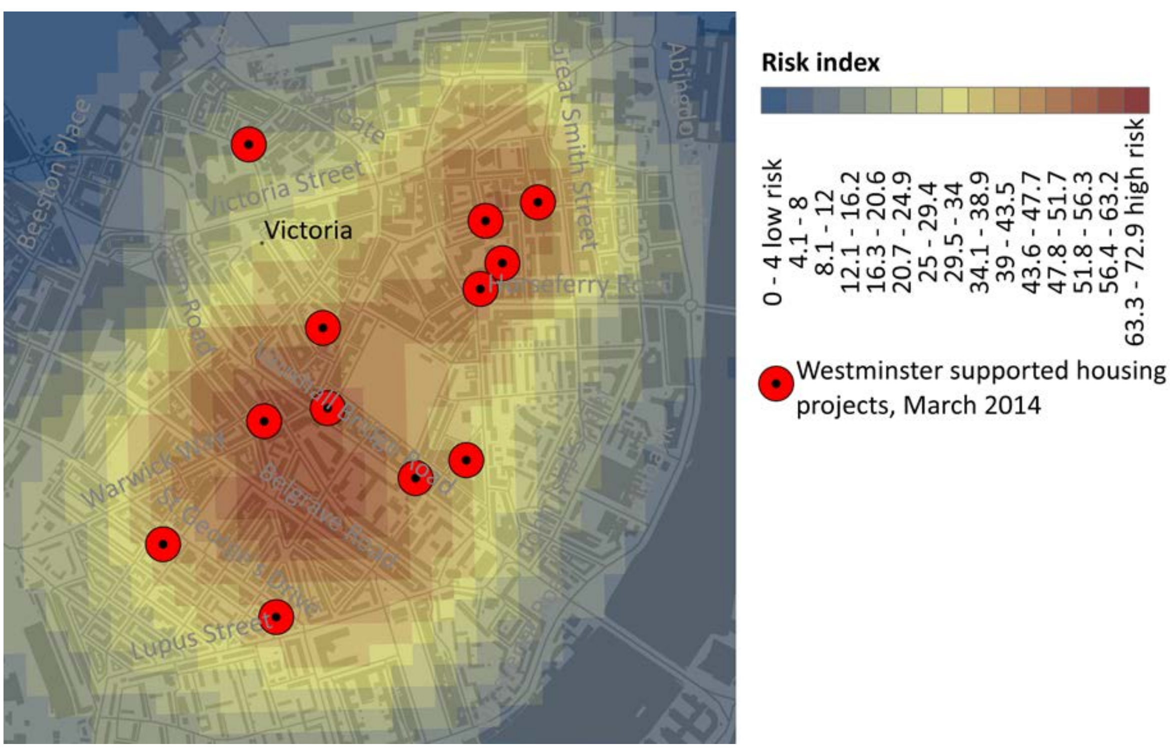


Figure 35: Location of Westminster Supported Housing Projects in Pimlico



5 Key themes

Policy context

- The Gambling Act 2005 singled out vulnerable people for special regulatory attention. To date, very little systematic consideration has been given to the protection of vulnerable people when making decisions about gambling premises licences. This is changing. New directives from the Gambling Commission now state that both gambling operators and Licensing Authorities (LAs) need to consider local area risks and take steps to militate against harm.

- This project is the first ever attempt in Britain to systematically consider who might be vulnerable to harm and, using this information, create a risk index so that areas of higher or lower potential risk can be easily identified.

- For both, Westminster and Manchester, we have highlighted the areas where risk of harm may be greatest. This is based on the types of people who live in each area (the 'at home' model) and the types of services offered which might attract vulnerable people to those locations (the "away from home" model).

- Our models significantly extend those that have been conducted internationally, since we have included a greater range of characteristics and have not relied on mapping indices of deprivation alone. Because specific policy directives state that demand or potential demand (and thus indirectly, pre-existing supply) for gambling venues should not be taken into account when making decisions about premises licences, our models do not include data on gambling venues.

Variation in risk by place

- Key findings show that risk of harm does vary from place to place. In Westminster, we identified four broad areas where there may be a greater risk of harm. These are those to the north west of Westminster, around the Harrow Road; to the south, around Victoria and Pimlico; north central areas around Paddington and the Edgware road and the West End. Careful review of the models shows that the heightened risk in each area is driven by different factors. For example, in Pimlico risk is higher because of a greater number of homelessness shelters and treatment providers in this area. In the north west area, risk is more driven by rates of unemployment, ethnic make-up and large numbers of resident young people.

- In Manchester, there are more areas of higher risk and we focused on three main zones – those around the city centre and the south of the city; around the Wilmslow Road and Longsight and an area around Cheetham. Risk is the city centre is driven primarily by the concentration of pay-day loan shops, education establishments and support centres for problem gamblers who are seeking treatment. Relatively high levels of unemployment, high concentrations of young people as well as ethnic mix are major driving factors in the other locations.

Benefits of approach

- The models produced for this research draw on empirical evidence about which groups of people are most likely to be vulnerable to harm from gambling. Using concepts like the 'harm paradox' we identified those who are more likely to experience problems from their gambling participation. Therefore, all characteristics included in our models are theoretically and empirically valid.

- Through careful consideration of how space is used, our models looked both at the characteristics of people who live in certain areas but also the characteristics of people who visit these areas at different points of the day. This allows us to represent dynamic movements in potential risk over time: people are not static and do move around locations at different points of the day. This is an important extension over previous international attempts to model vulnerability to harm.

- Our models are more nuanced than simply modelling deprivation alone. Area level socio-economic deprivation has been used as a proxy to represent local area risk by other scholars internationally and suggested as an approach to mapping local area risks by some LAs. Our research shows that deprivation is not necessarily an appropriate proxy for risk of gambling-related harm. First, the Index of Multiple Deprivation (IMD) has several domains, yet the evidence about who may be vulnerable to gambling-related harm shows that some of these domains (such as level of educational qualifications) do not have a strong relationship to harm. Using IMD as a proxy for risk of harm means some areas may be erroneously highlighted as having an at-risk resident population because of this unsound empirical basis. Second, IMD only looks at the profile of the resident population and not more transient people who move in and out of areas at different points of the day. We believe this is important. Finally, our results show that whilst there is some overlap between areas of greatest deprivation and those we have identified as high risk, there are some differences also. For example, the specific areas identified in our models as higher risk within Pimlico were actually areas with comparatively lower deprivations scores (relative to other neighbouring areas). A range of services offered to vulnerable, non-resident people drives the risk in Pimlico. Focus on IMD alone misses this detail.

Caveats

- Our models are probabilistic. Just because we have highlighted an area as being at greater risk does not mean that all people in those areas will experience harm. Our models suggest that there may be greater propensity for harm and therefore greater consideration should be given to attempts to militate this.

- Our models are based on current knowledge and available evidence and data. There were a number of groups which were plausible to consider vulnerable (such as immigrants or those on probation) but there was very little empirical evidence and/or a lack of local level data, leading us to exclude them from the final models. Our models are therefore skewed towards those areas where more research has been conducted (reflecting the priorities of those conducting and commissioning research) and where there were good quality local level data available.

- Our previous research highlighted that there may be people or areas with multiple risk factors for gambling-related harm. Our final models support this as there is a large degree of overlap of each component risk factor, giving higher risk scores to areas.

- Finally, reflecting the focus of researchers on understanding problem gambling, the evidence base used to develop the models tends to show those vulnerable to gambling problems rather than gambling-related harm. The models therefore may be a somewhat conservative profile of risk as it is generally recognised that gambling-related harm is broader than problem gambling, affecting more people and having a broader range of impacts.

Recommendations

- The Gambling Commission's introduction of local area risk profiles into practice and procedure represents a new opportunity for LAs and industry alike to think more deeply about the protection of vulnerable people from gambling-related harm. We would encourage all stakeholders to consider what this means and develop a more comprehensive understanding of who might be vulnerable and why. We believe this means extending understanding of local area risk beyond mapping areas of greater deprivation and considering a more nuanced range of factors, as presented in this research.

- LAs interested in pursuing this approach should start to consider the different types of data they have available and how these can be used in local area profiles.

- They could also start to consider what data and/or evidence is missing and how they could fill these gaps. For example, data collection exercises could be specifically designed to generate better data for the models. Westminster has already started this process, liaising with youth offender teams to collect information about gambling harm among this group. This will provide much needed evidence about vulnerability to harm which could then be included in the model at a later date.

- As with any modelling process, there are a number of refinements and recommendations we can make, especially as we see these models developing in an iterative way. These recommendations include:
    - The inclusion of specific datasets that are currently unavailable as and when they become available.
    - The inclusion of data available at a better scale as and when they become available.
    - Consideration of multiple-risk factors for harm to understand which groups are the most vulnerable and where they may be. This is a big challenge due to the lack of specific small area data and would possibly require primary data collection to achieve this.
    - An incorporation of future evidence as and when the wider research body expands.
    - To compare study areas exactly, the standardisation of data collection between LAs could be recommended, though this risks losing some local nuances.

- The models we have presented are based on the best information currently available. However, an acknowledged limitation of gambling research generally is the paucity of evidence available. We therefore recommend that the models developed for this project are periodically reviewed and updated to take into account growing knowledge, better data and changes in local areas.

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Appendix 1

Figure A1: Map showing characteristic data of treatment & support centres for problem gamblers in Manchester

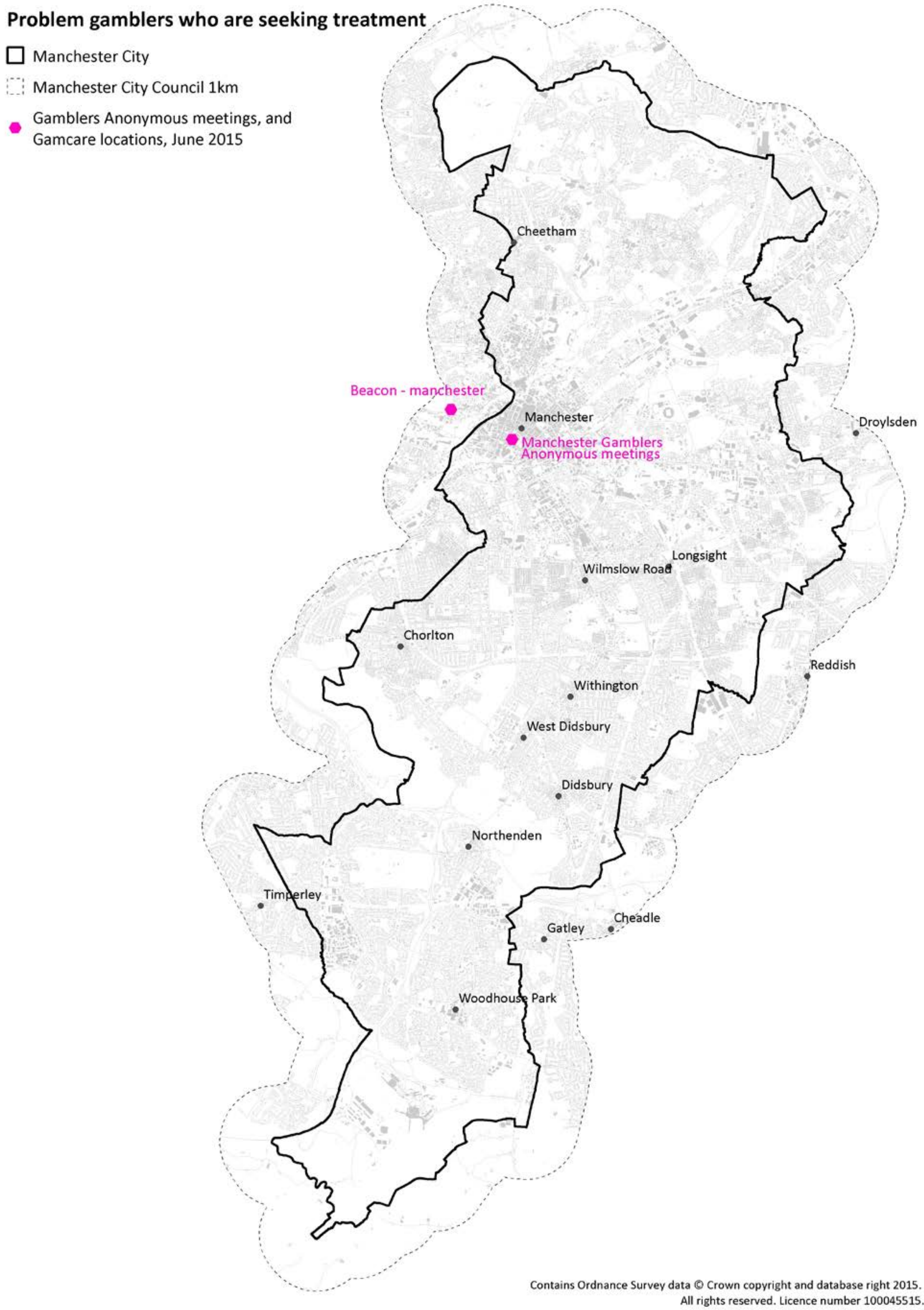


Figure A2: Map showing characteristic data of substance abuse/misuse in Manchester

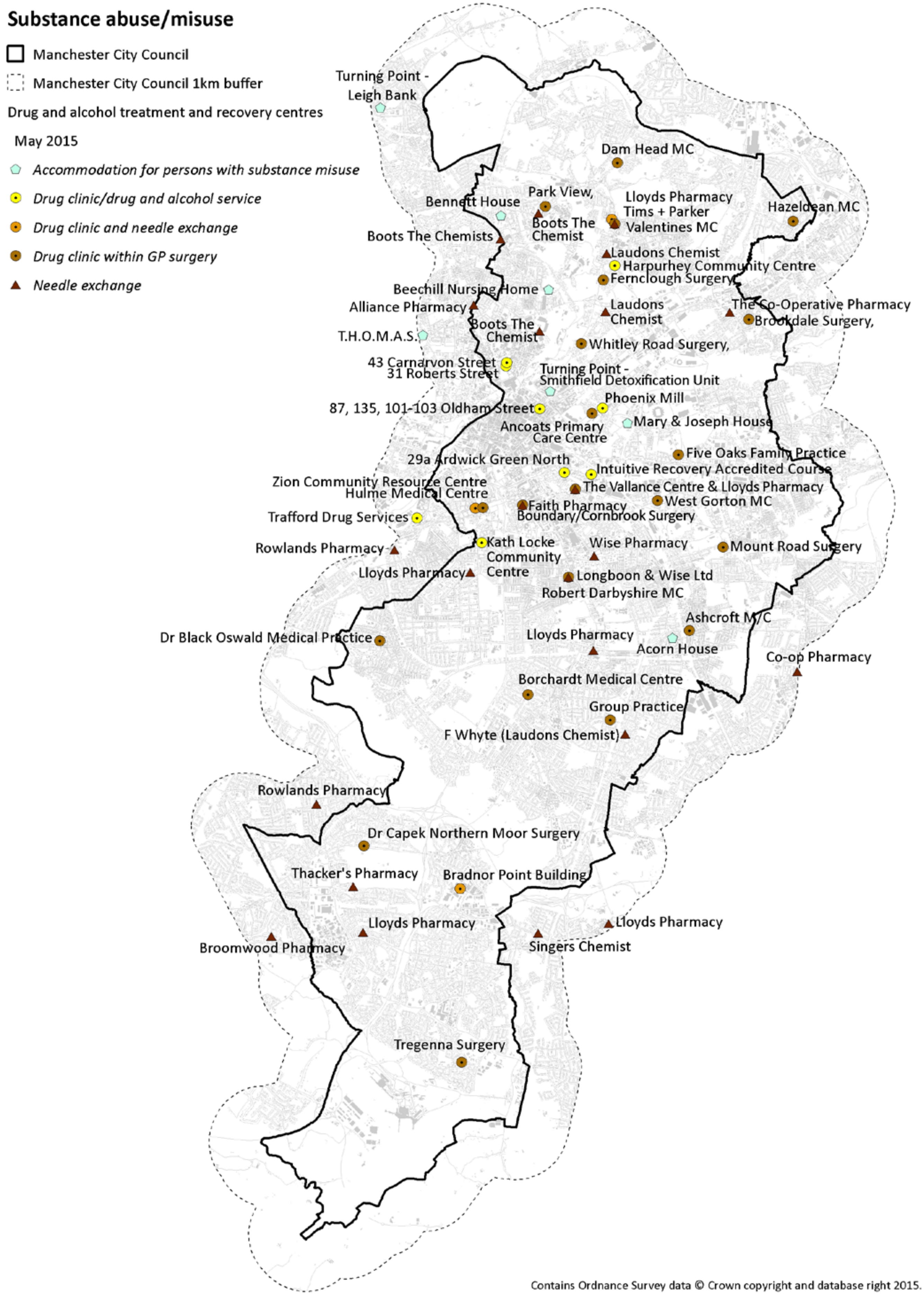


Figure A3: Map showing characteristic data of poor mental health in Manchester

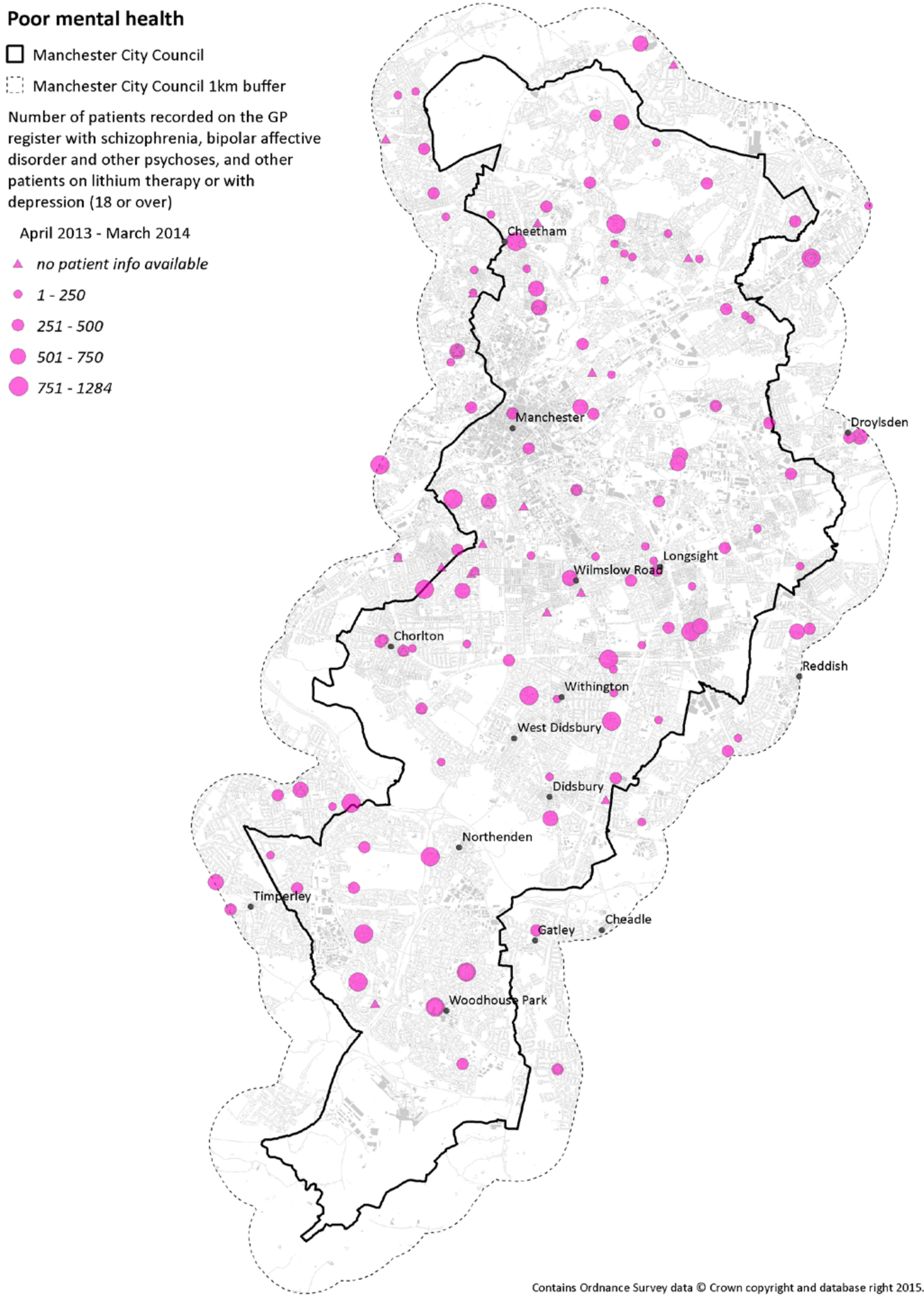


Figure A4: Map showing characteristic data of unemployment in Manchester

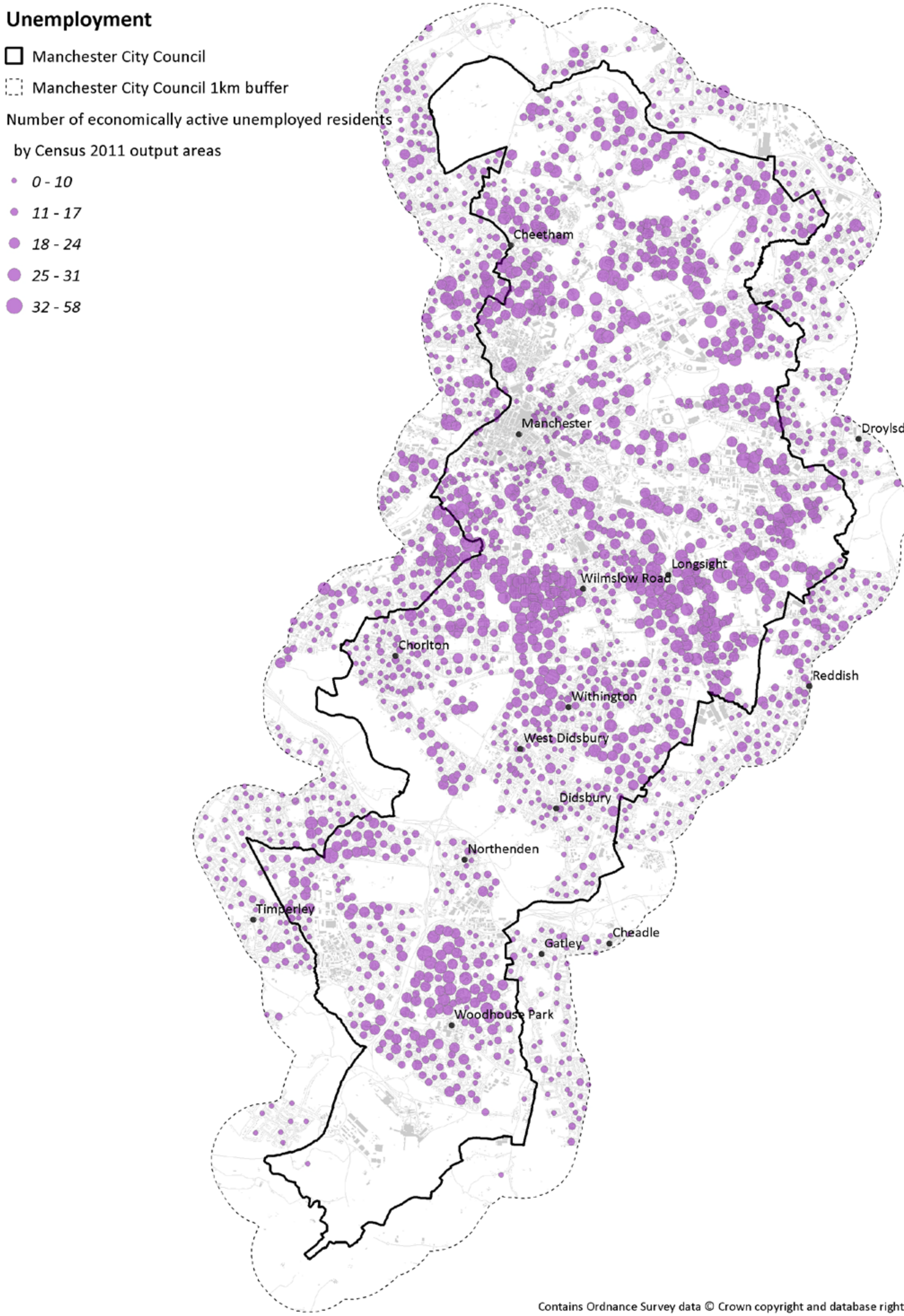


Figure A5: Map showing characteristic data of unemployment in Manchester

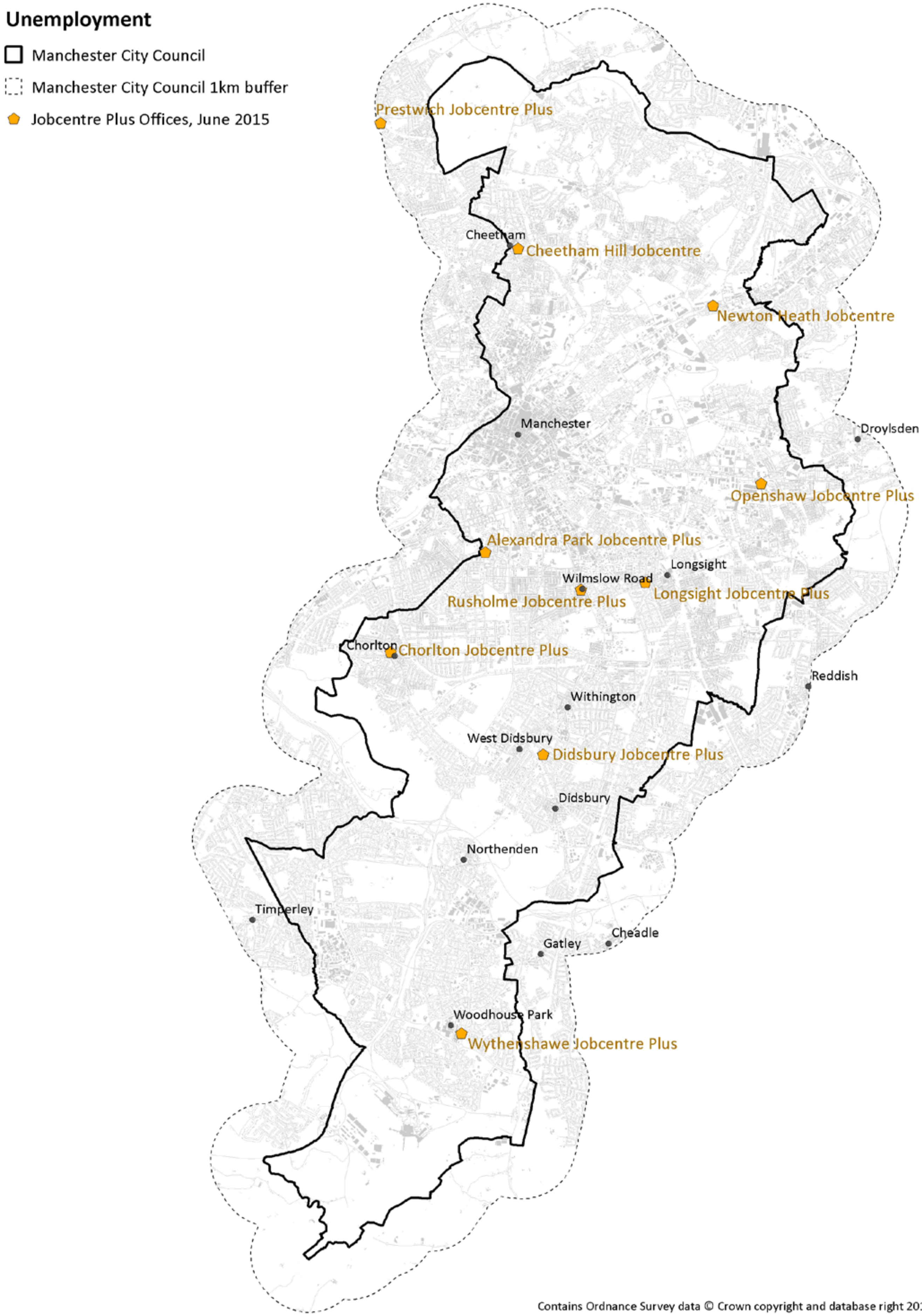


Figure A6: Map showing characteristic data of ethnic groups in Manchester

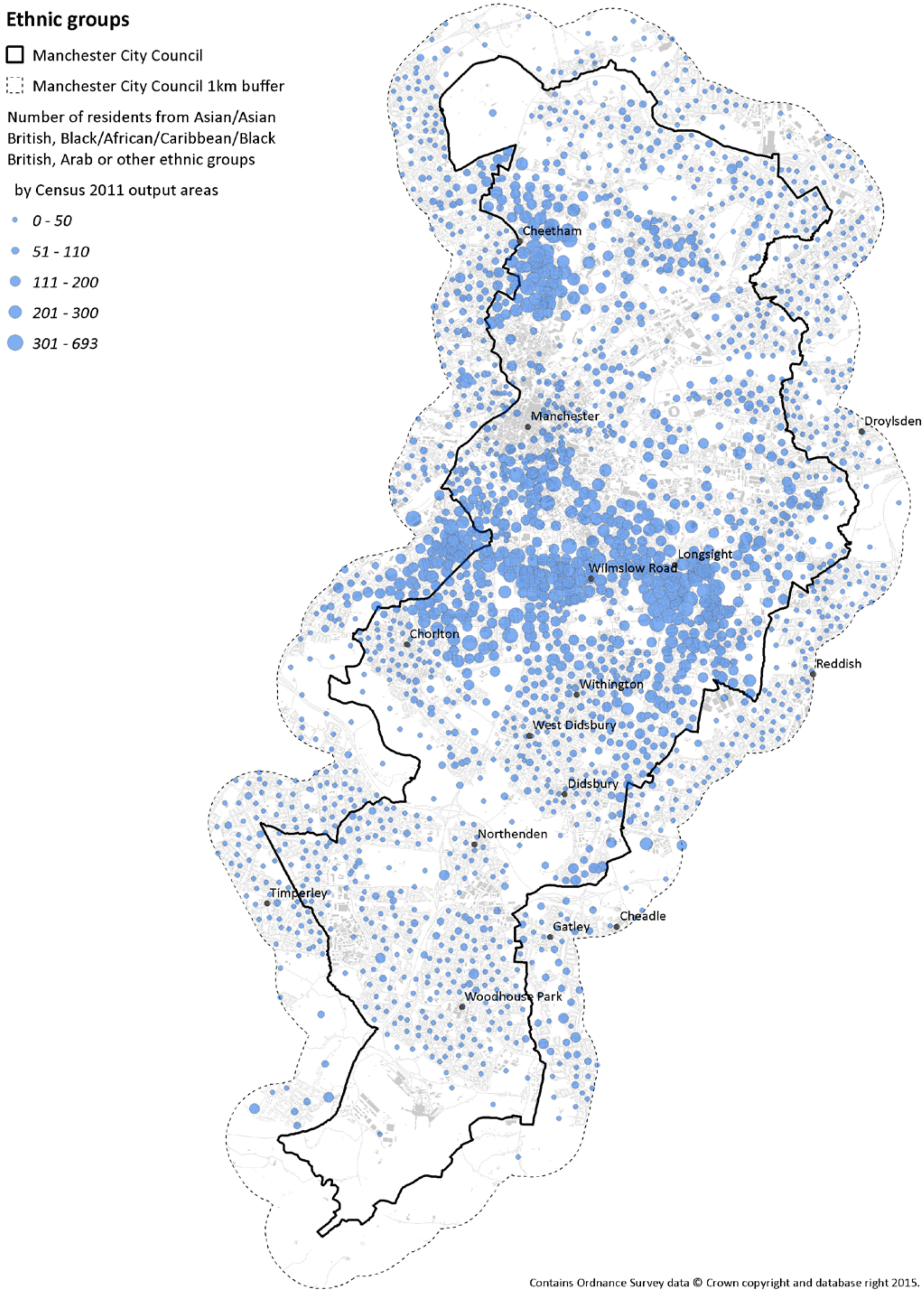


Figure A7: Map showing characteristic data of youth in Manchester

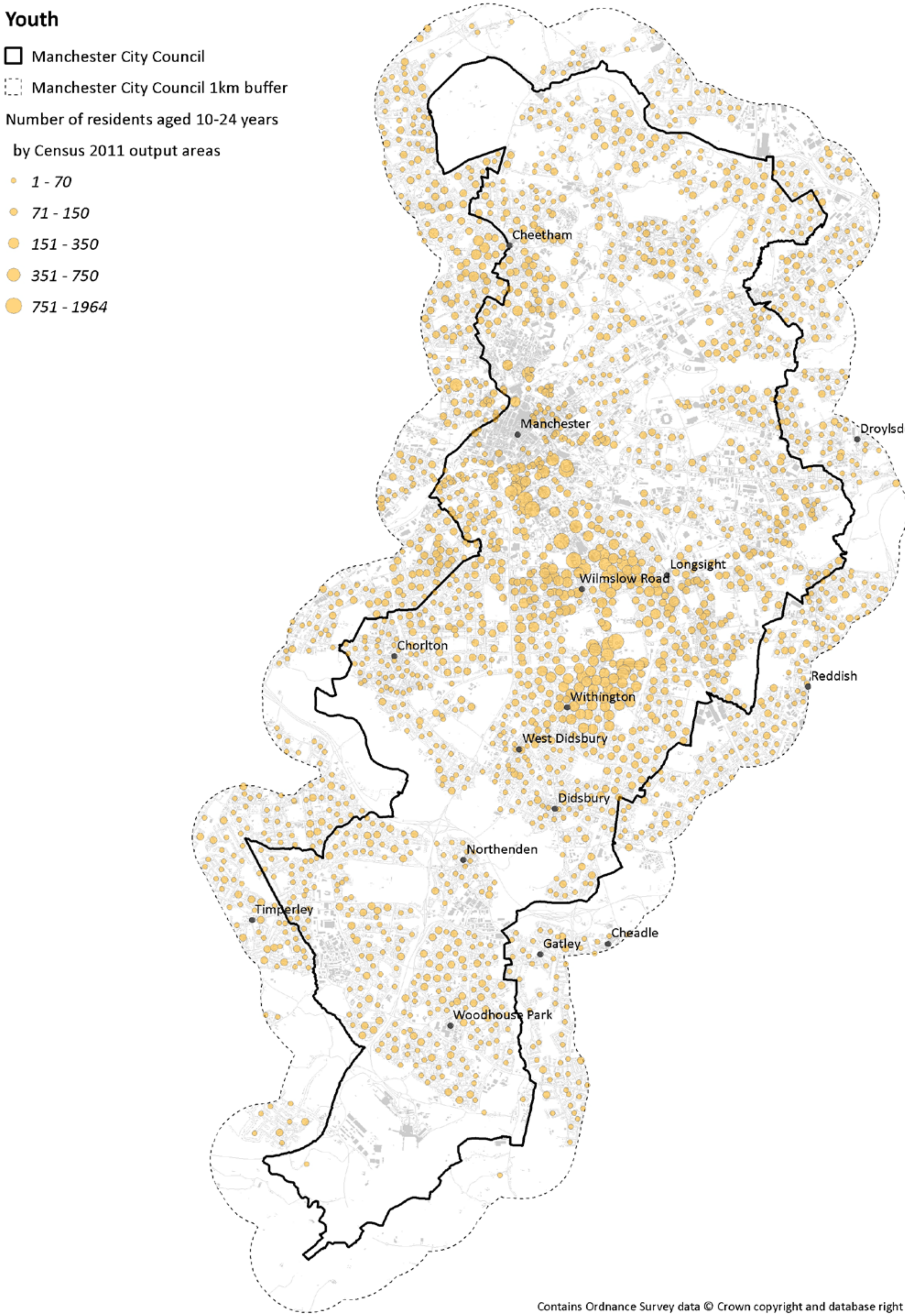


Figure A8: Map showing characteristic data of educational institutions in Manchester

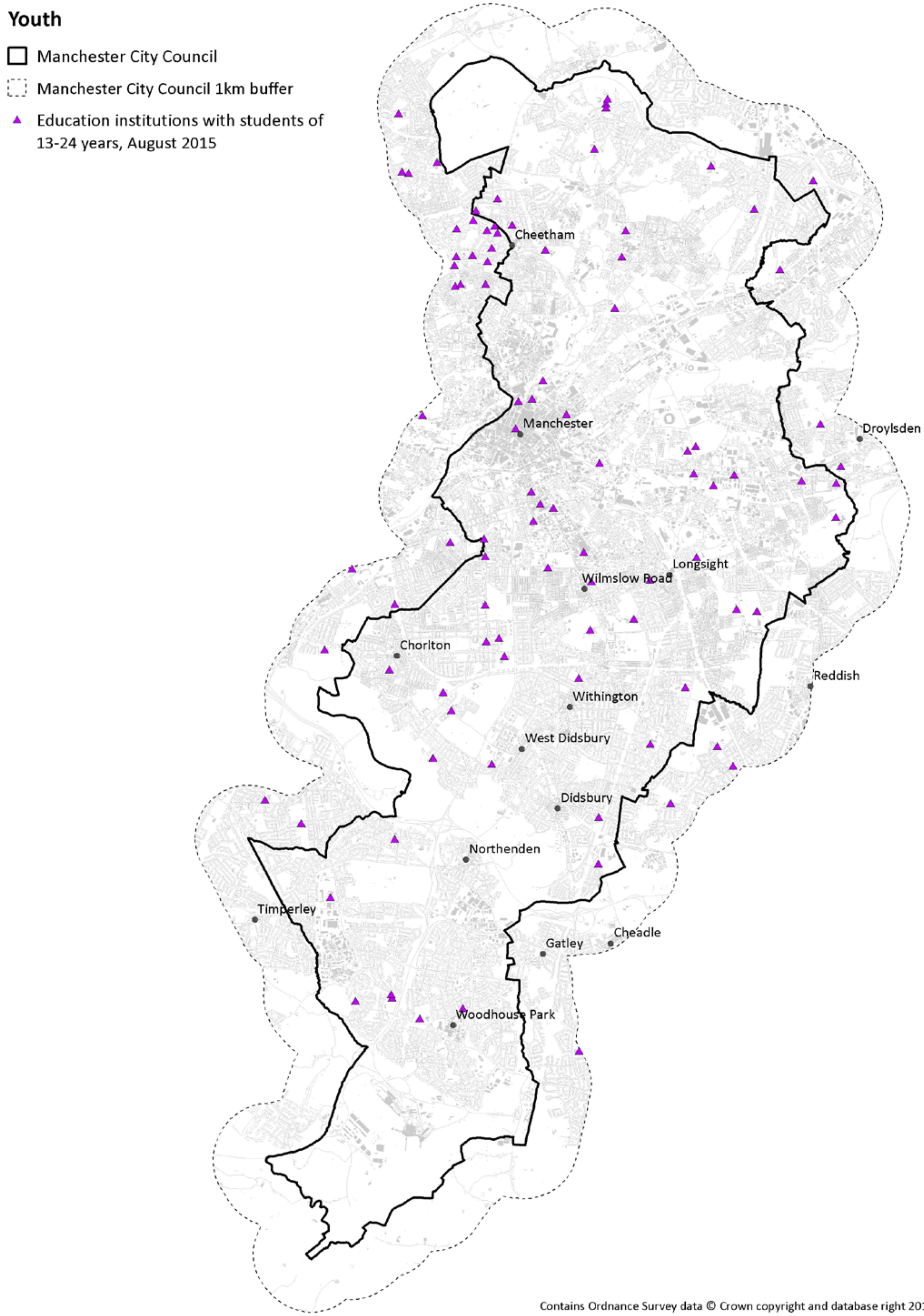


Figure A9: Map showing characteristic data of financial difficulties/debt in Manchester

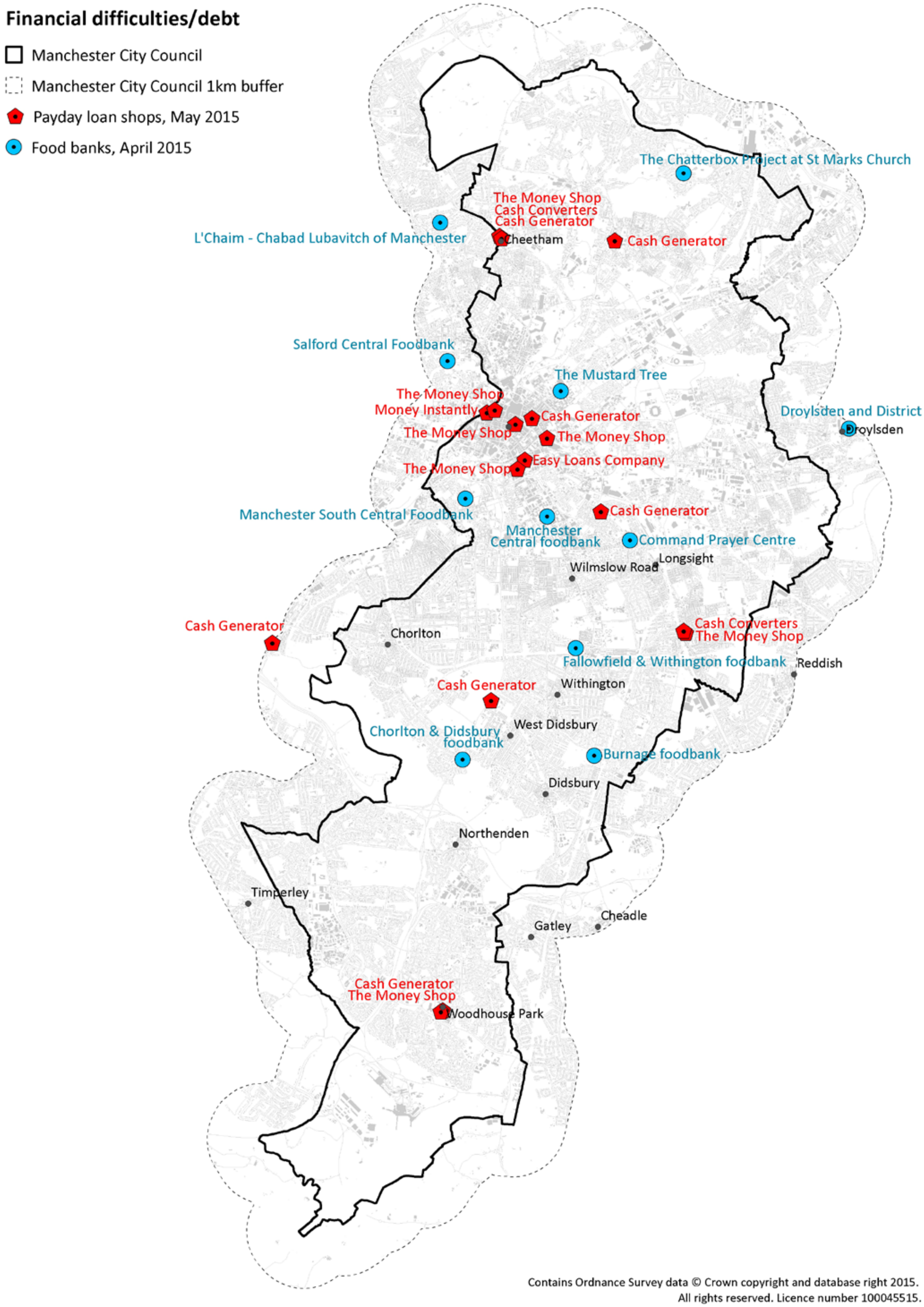


Figure A10: Map showing characteristic data of homelessness in Manchester

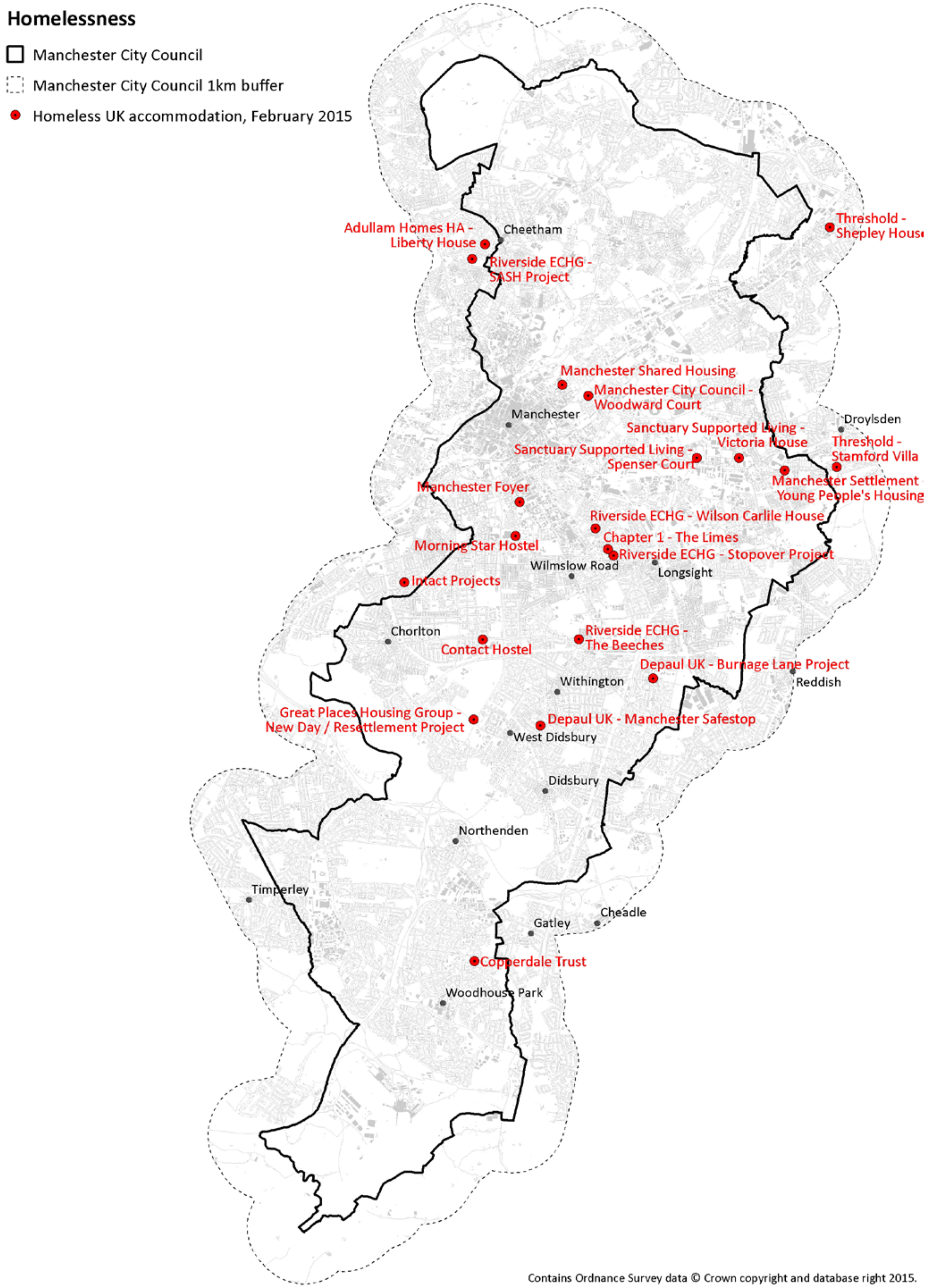


Figure A11: Map showing characteristic data of treatment & support centes for problem gamblers in Westminster

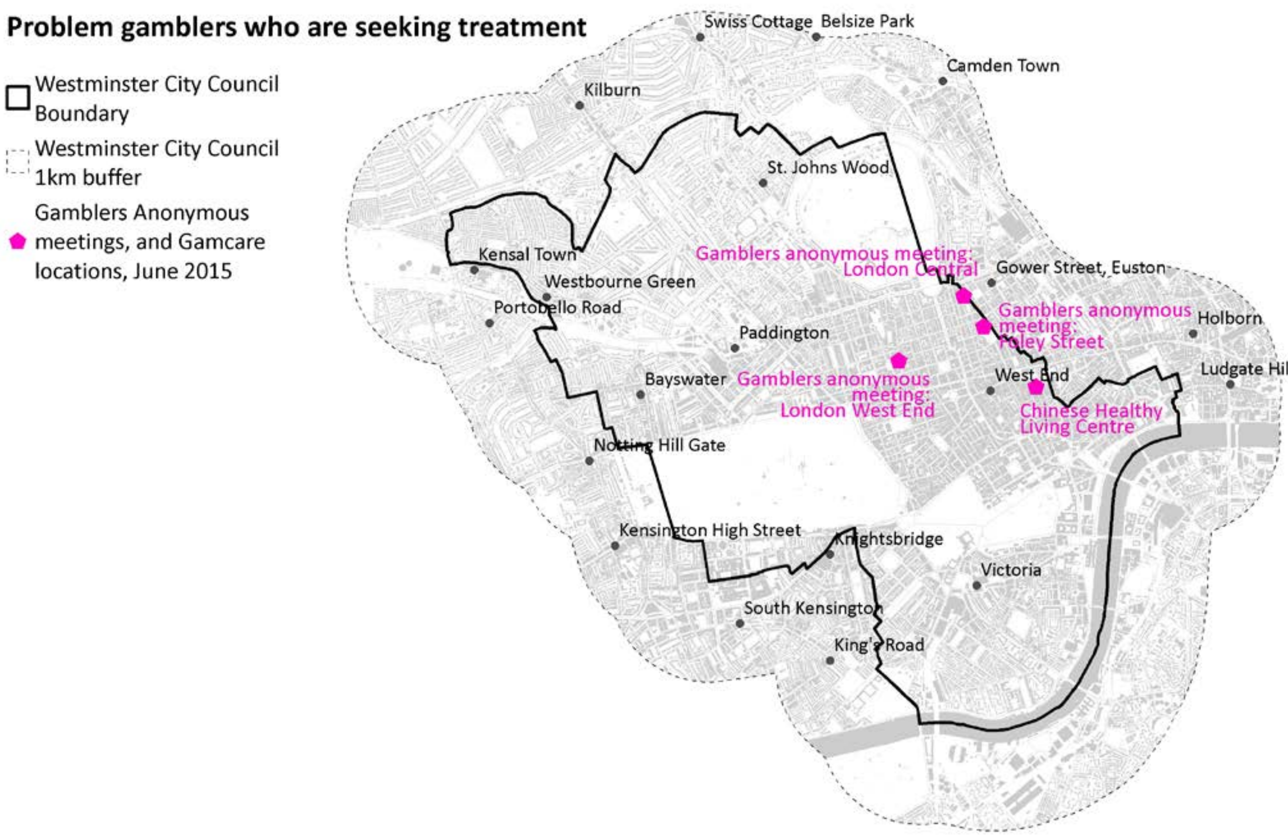


Figure A12: Map showing characteristic data of substance abuse/misuse in Westminster

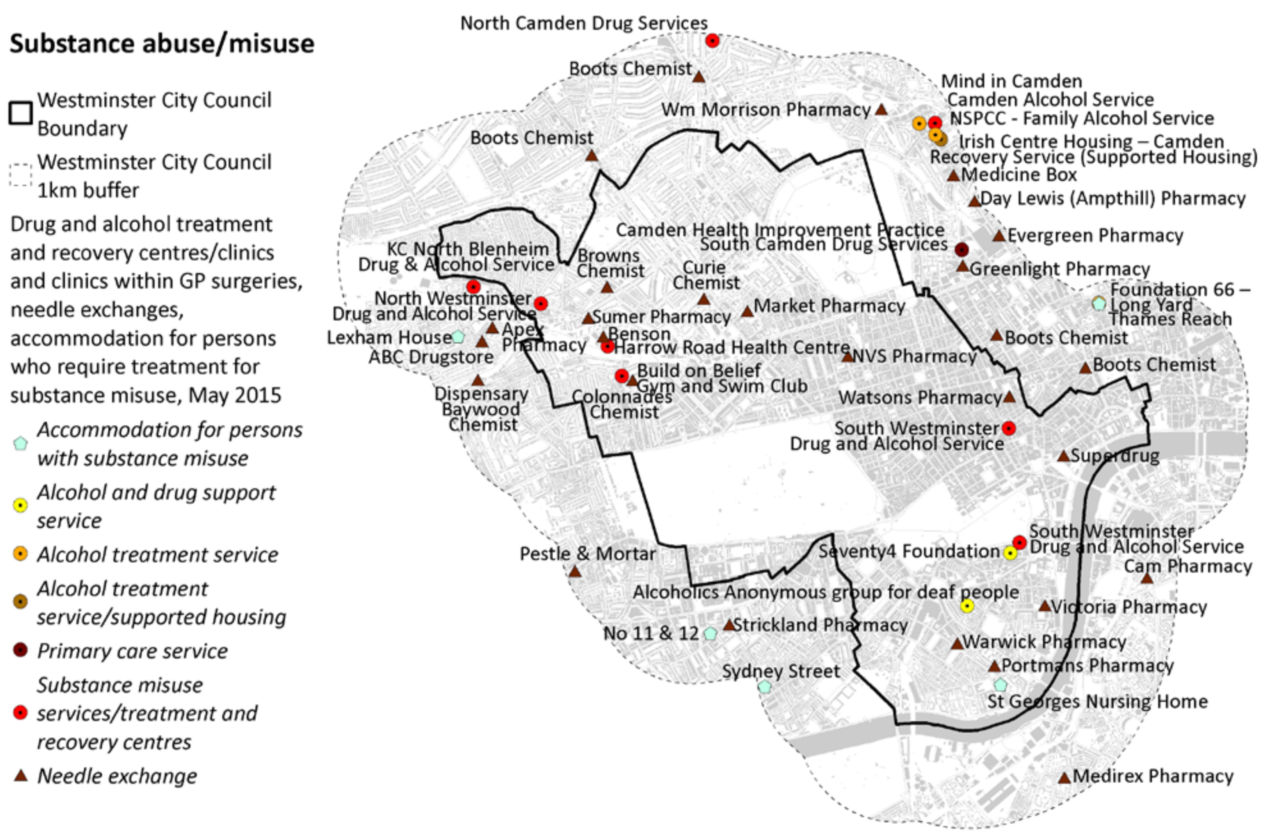


Figure A13: Map showing characteristic data of poor mental health in Westminster

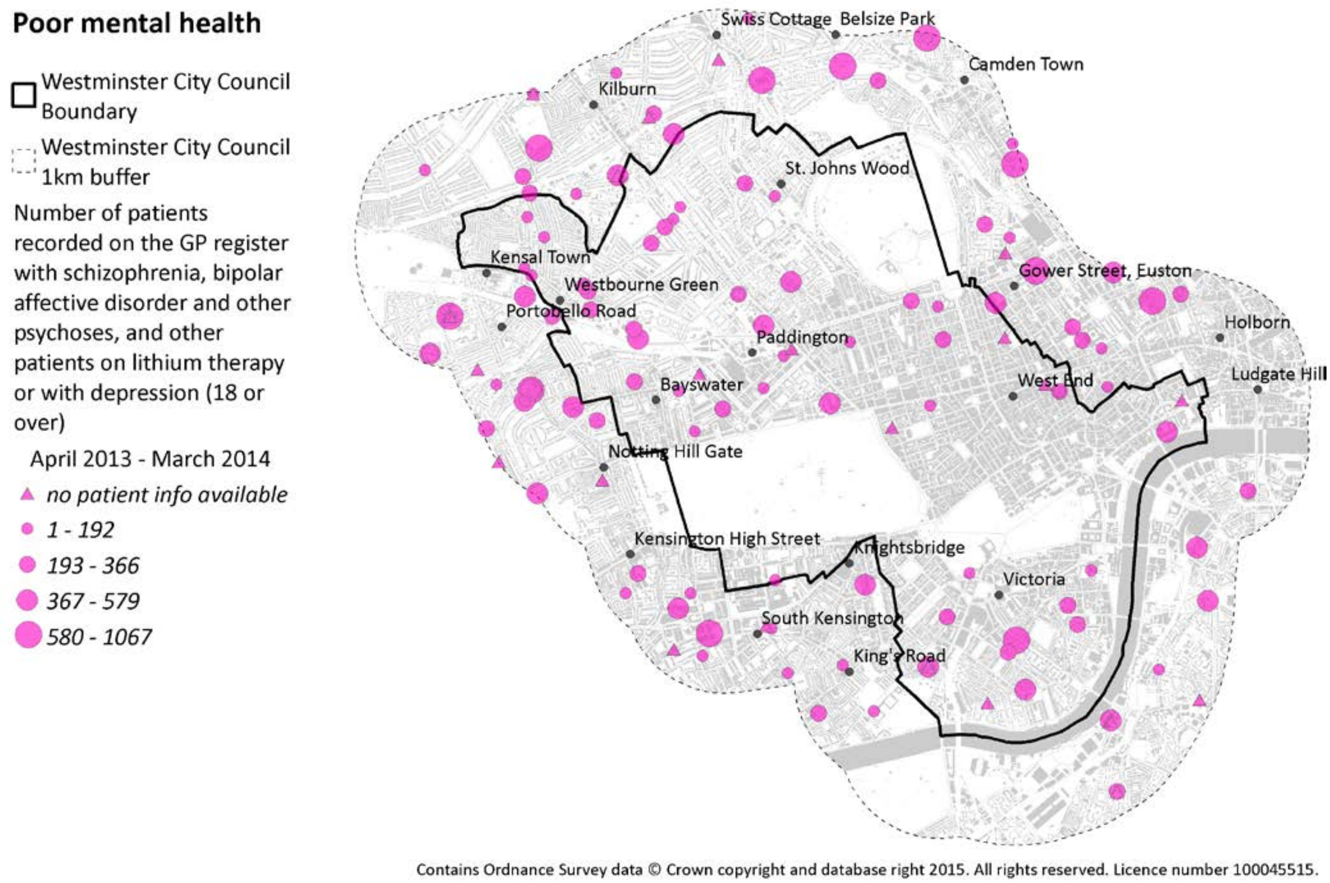


Figure A14: Map showing characteristic data of unemployment in Westminster

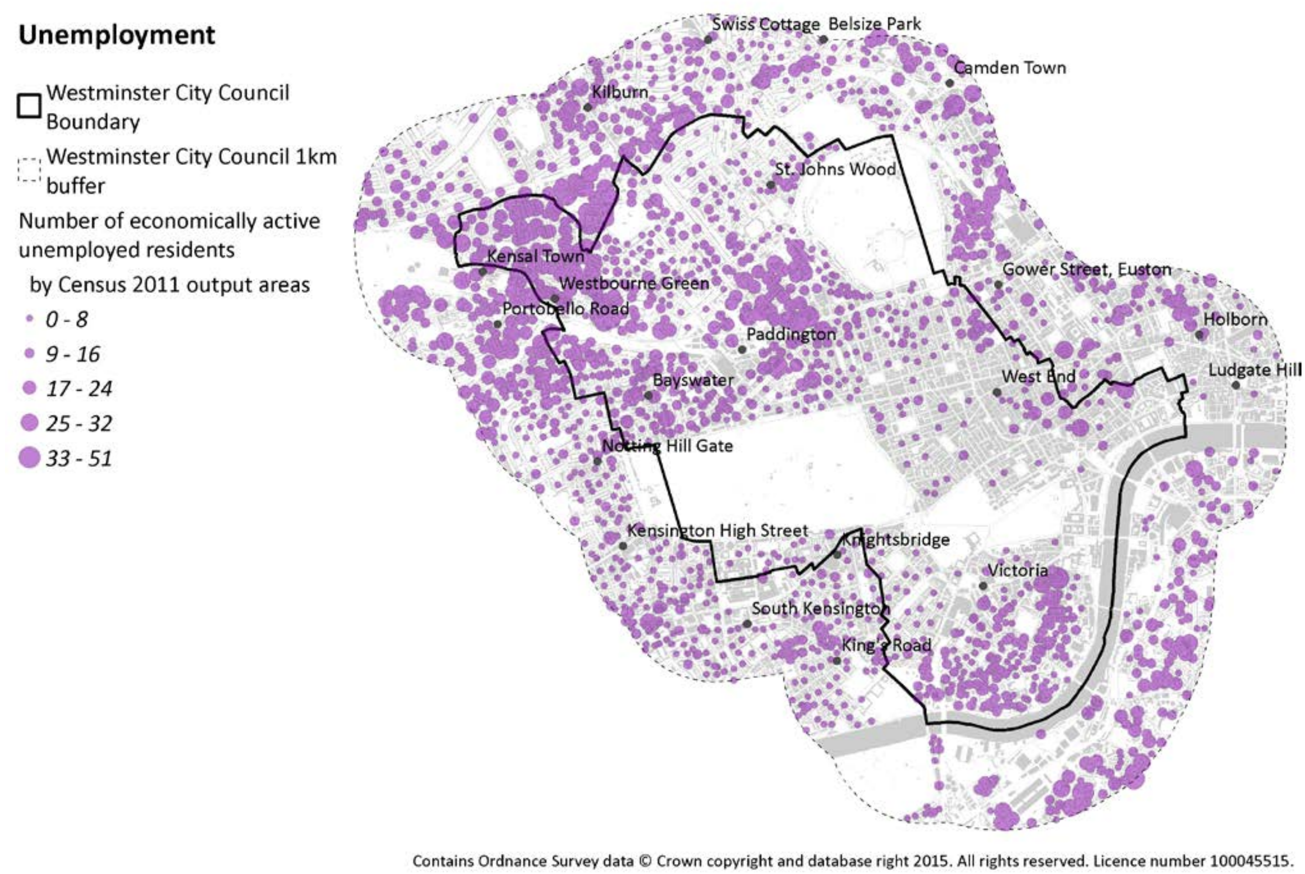


Figure A15: Map showing characteristic data of unemployment in Westminster

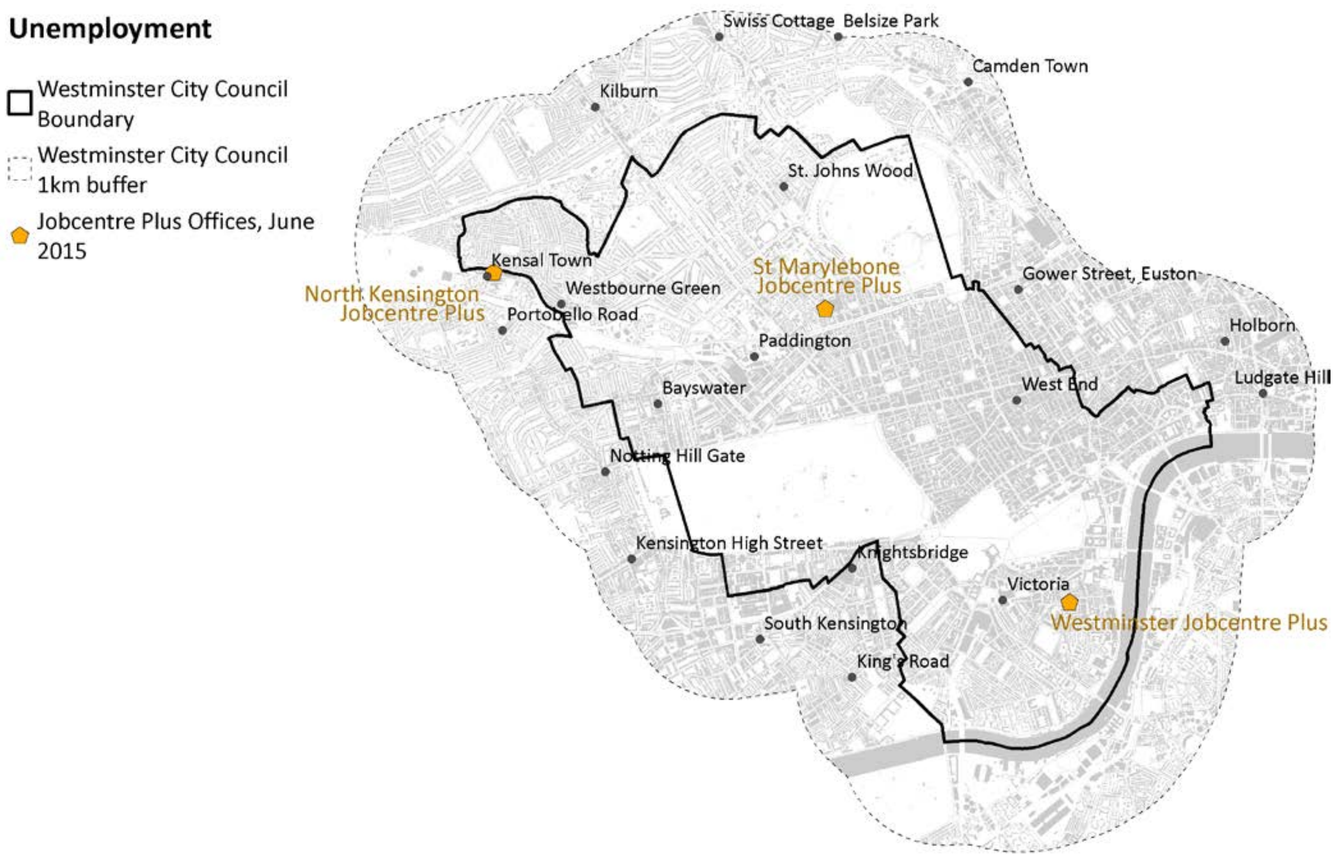


Figure A16: Map showing characteristic data of ethnic groups in Westminster

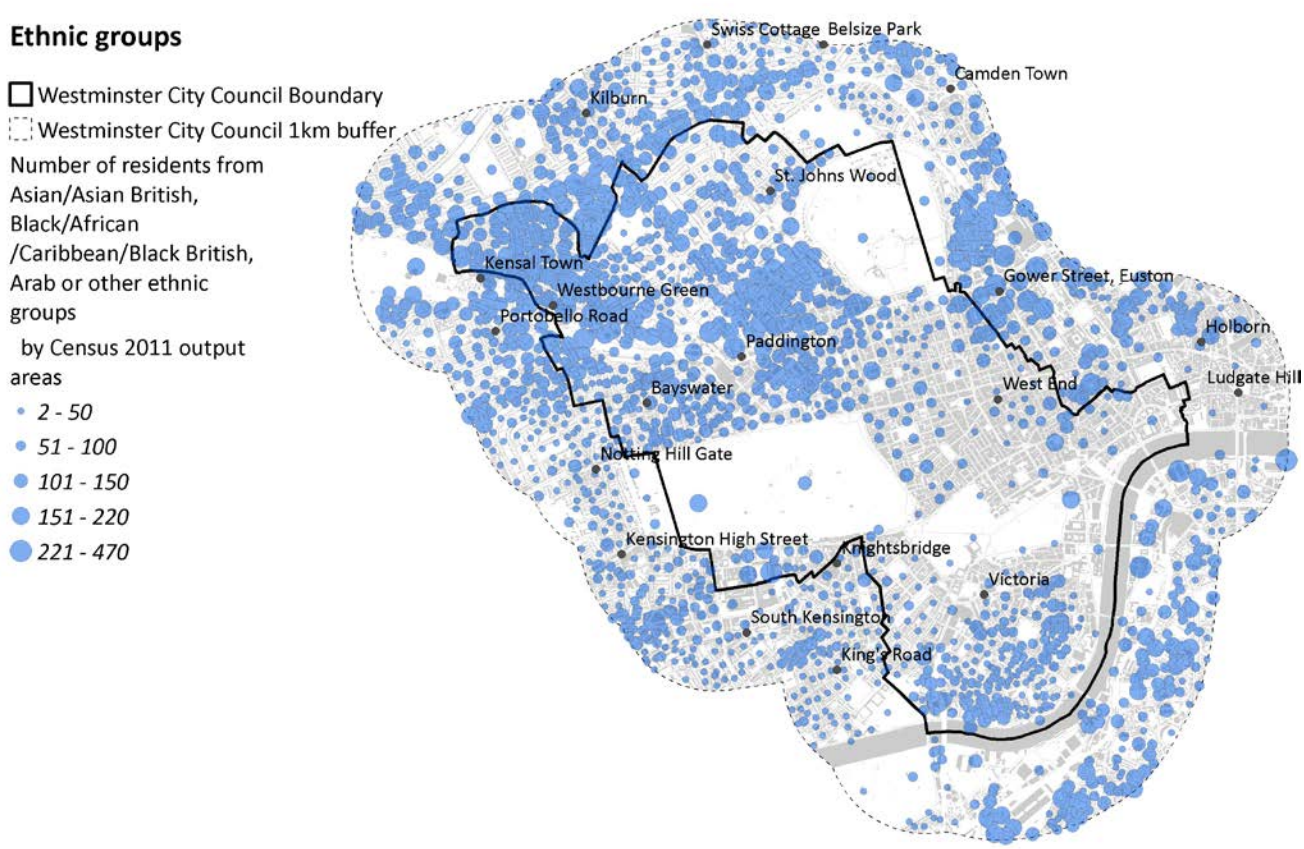


Figure A17: Map showing characteristic data of youth in Westminster

Figure A18: Map showing characteristic data of education institutions in Westminster

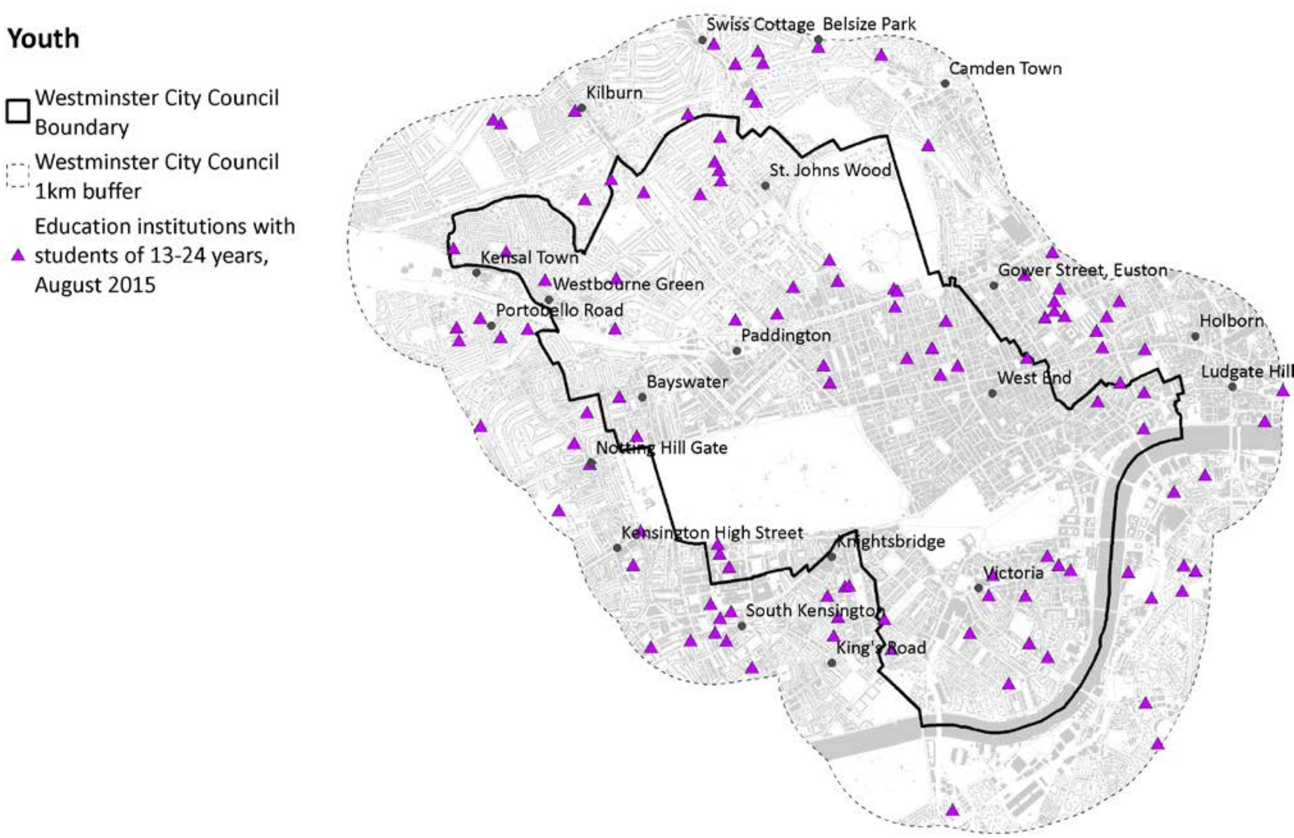


Figure A19: Map showing characteristic data of financial difficulties/debt in Westminster

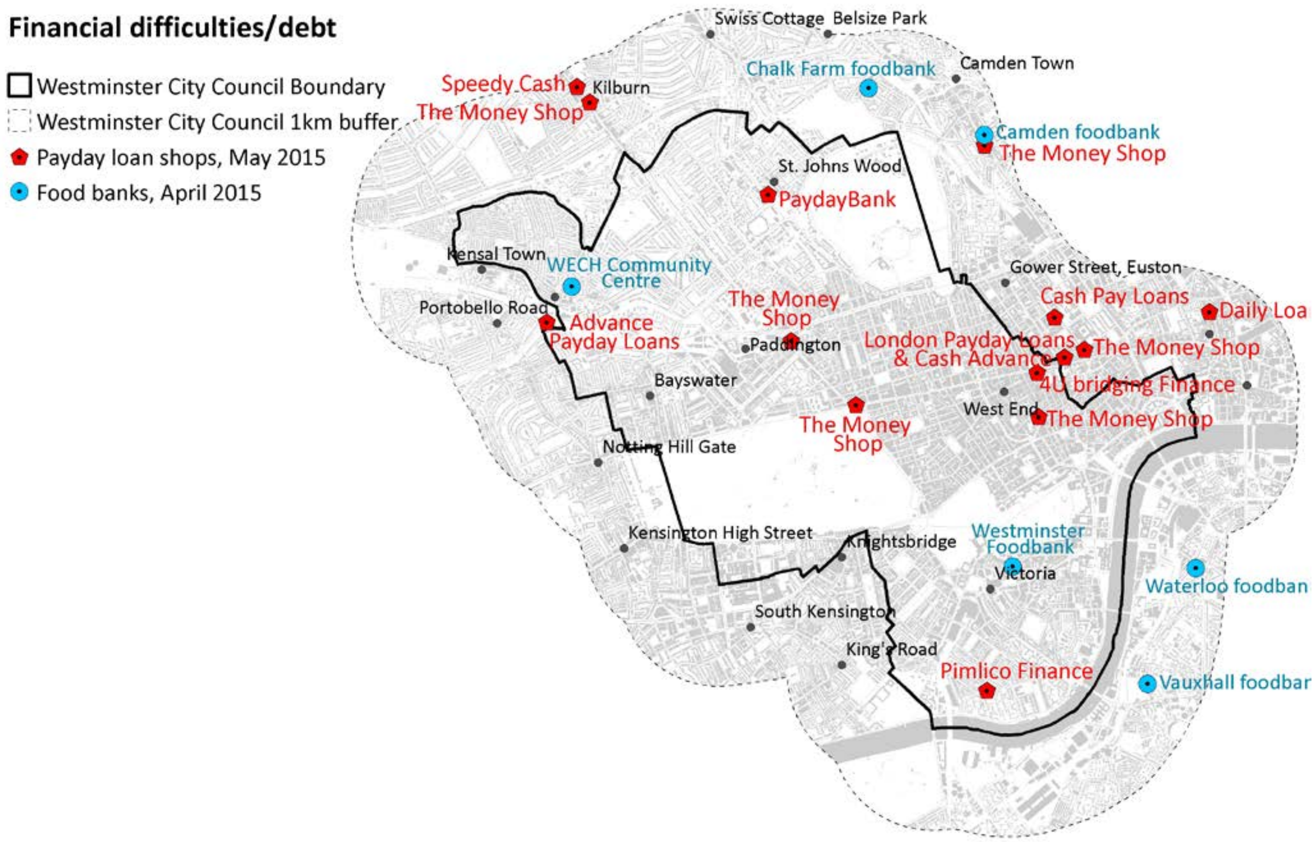
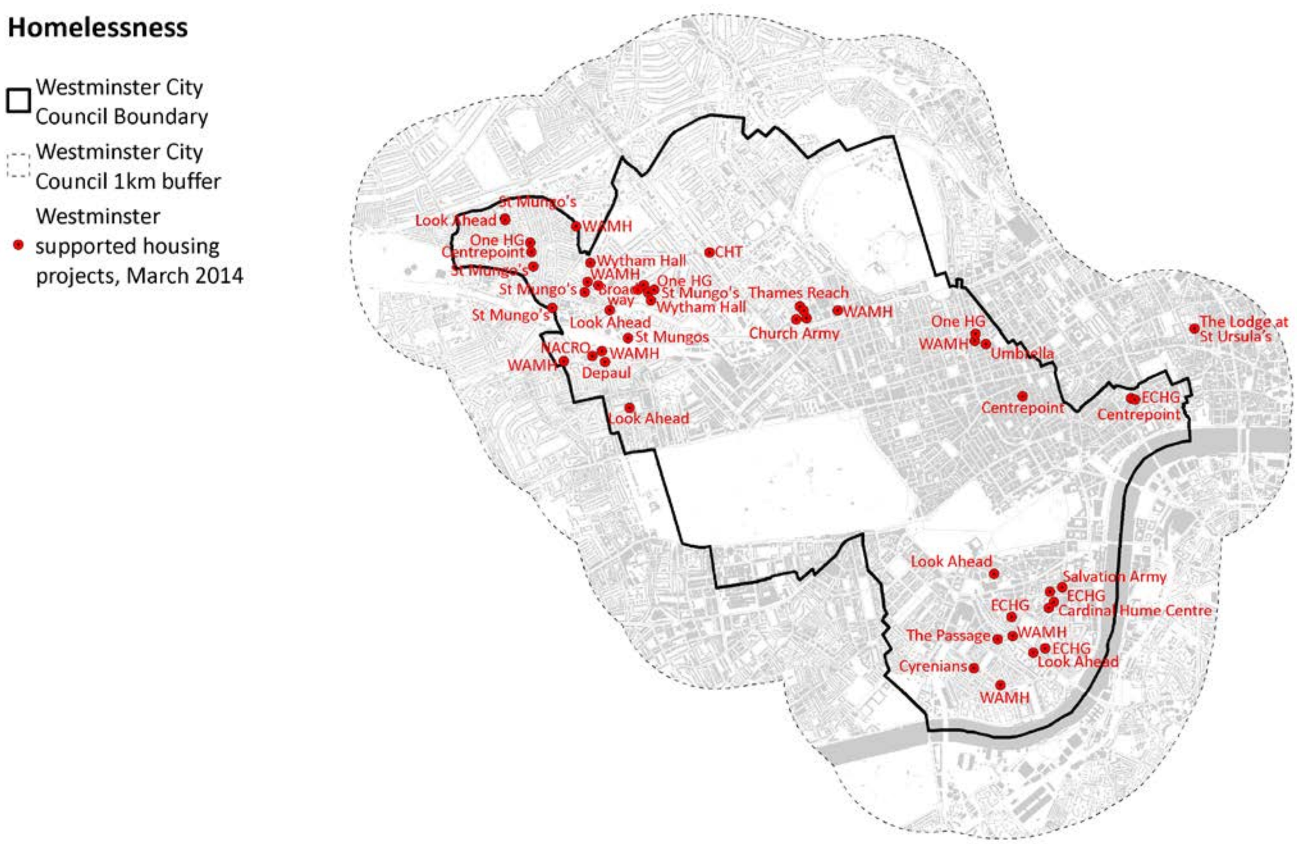


Figure A20: Map showing characteristic data of homelessness in Westminster



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Local Government Association

MANCHESTER CITY COUNCIL

City of Westminster