

Geofutures

Exploring area-based vulnerability to gambling-related harms:

Results from the gambling-related harm risk index for Newham



Prepared by Geofutures for

The London Borough of Newham

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Executive Summary

Background

- The London Borough of Newham commissioned Geofutures to explore the extent and nature of gambling-related harms in Newham.
- Geofutures have previously developed risk indices for Westminster and Manchester City Councils, highlighting areas where it is likely that greater number of people who may be vulnerable to gambling problems may be.
- These risk models focus on identifying areas with greater numbers of young people and those considered vulnerable to harm. The Gambling Act 2005 singles both of these groups out for special regulatory attention, with the aim that the young and the vulnerable should be protected from being harmed or exploited by gambling.
- A primary aim of the risk models is to help industry operators to produce local area risk assessments, which are now a regulatory requirement, and to use this heightened understanding of local area risk to protect vulnerable people from harm by developing appropriate policies and procedures.

Methods

- The methods used replicate those developed for Westminster and Manchester. First, a list of people who were more likely to be vulnerable to gambling-related harms was developed. This was based on research evidence and included: young people, those who were unemployed, those from minority ethnic groups, those with economically constrained circumstances, those with diminished cognitive capacity and those with certain mental health conditions or substance abuse disorders. Research evidence shows that each of these groups are more likely to experience gambling problems.
- 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 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 Newham. These results were displayed visually on maps to highlight the locations which had relatively higher risk profiles.

Results

- There are three areas around Stratford, Forest Gate and East Ham which have the highest levels of risk of gambling-related harms relative to other places in Newham.
- Careful consideration of each area is needed, as the maps show that risk in each place is driven by different factors. For example, in Stratford, risk appears to be driven much more by the services offered in that locality, which may attract vulnerable people into that space. In East Ham, risk is driven more by the profile of people who live there.
- There are some places which also have relatively high risk based on the characteristics of people who live in these spaces, for example the area around Woodgrange Road. It is therefore important to look at these types of places too, and not concentrate just on the highest risk areas.

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 harms. The models may be conservative as gambling-related harms are broader than problem gambling.

1 Introduction

Overview of project

This project aims to explore area-based vulnerability to gambling-related harms, incorporating all types of gambling activity. Whilst anyone can experience gambling problems, the evidence shows that gambling behaviour and those who experience harm is socially patterned, meaning that both 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 the local environment where people live, such as deprived areas. The political, cultural and commercial 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 been little explored. This project aims to fill this gap by exploring this for Newham for the first time.

This project builds on our previous work developing gambling-related harm risk indices for Westminster and Manchester City Councils. This prior project included a scoping review highlighting the kinds of people and/or characteristics that may mean someone is more vulnerable to gambling-related harm.¹ This was followed by a further report which documented the development of a gambling-related harm risk model that displayed results visually using maps. Both reports were peer-reviewed and a summarised version published in the academic journal *Addiction Research and Theory* (see Wardle, Astbury and Thurstain-Goodwin, 2017). This project replicates the methods developed for Westminster and Manchester and this report outlines the methodology used to create the local area risk indexes for Newham and discusses the results.

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

Legislative and regulatory environment

The risk indices developed for Newham in this report are intended to help support local decision makers relating to gambling policy and practice. The primary audience is likely to be licensing officials within Newham who are responsible for issuing premises licences for gambling venues. The current legislative environment encourages licensing authorities to “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.

However, there has been increased focus on fostering a risk-based approach to regulation. This has been a key part of the Gambling Commission’s (GC, the industry regulator) 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 emphasis on risk-based regulation underpins the GC’s 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. For the GC, risk is defined as follows:

“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 highlights the importance of thinking about risk in a probabilistic way. 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.

Local risk assessments

Greater focus on risk underpins the GC's requirement that gambling industry operators should 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 the risks identified (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, licensees 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 recommended that licensing authorities consider producing local area profiles to support this process. 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 local authority area 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 emphasis for understanding local risk is therefore incumbent on both the gambling operator and the licensing authority. Our risk indices are intended to help support this process by highlighting the areas where greater numbers of people who may be vulnerable to gambling harms are likely to be.

Gambling as a public health issue

Another primary audience for the risk indices are those involved in public health. Gambling is increasingly being positioned as 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. Public health involvement relates to the third licensing objective of the Act, which states that vulnerable people should be protected from harm. According to the GC, vulnerable people are 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. Therefore, whilst gambling is not considered under a public health framework at national policy level, at the local level there may be many benefits from doing so, not in the least because many people vulnerable to gambling-related harm may also be vulnerable to other health issues and considered vulnerable more generally.

More recently, the wide-ranging harms which occur from gambling have been recognised (see Box 1).² This outlines the impact on resources, relationships and health that arise from gambling and articulates the consequences that this has on both individuals, their families and society more generally. This recognition underpins the Local Government Association of their “whole council approach” to tackling gambling harms, recognising that the harms from gambling reach into many areas of health and wellbeing and outlining that a joined-up

² Wardle, H., Reith, G., Best, D., McDaid, D., Platt, S. (2018). *Measuring gambling-related harms: a framework for action*. Birmingham: Gambling Commission. Available at: <https://www.gamblingcommission.gov.uk/PDF/Measuring-gambling-related-harms.pdf>

approach across council departments is needed to tackle the ranges of harms caused by gambling.³

Gambling-related harms are the adverse impacts from gambling on the health and wellbeing of individuals, families, communities and society.

These harms are diverse, affecting resources, relationships and health, and may reflect an interplay between individual, family and community processes. The harmful effects from gambling may be short-lived but can persist, having longer-term and enduring consequences that can exacerbate existing inequalities.

In terms of **resources**, harms generate instability in economic lives, undermine productivity in the workplace, lead to the accumulation of debt and, in more severe cases, bankruptcy and engagement in criminal activity. There is a further range of related consequences, some concerning material impacts such as housing instability, others concerning loss of opportunities and future wellbeing. The impact of these harms can be experienced by individuals, families and communities.

In terms of **relationships**, harms include disruption or erosion of partnerships, familial relationships and friendships, including emotional and social isolation from family, friends and communities. This can lead to erosion of community cohesion and resources. In families, harms erode trust and reduce emotional and financial stability in households. This diverts money, time and attention away from familial roles and responsibilities. At a societal level, these harms demand resources from wider medical, social and judicial infrastructures.

In terms of **health**, harms relate to physical ill-health, psychological distress *(such as feelings of shame, stigma and guilt), mental health problems (including anxiety and depression) and, in some cases, suicidal behaviour. These harms may be felt by both individuals and families. At a societal level these harms lead to major demands on healthcare services, increased use of social care and welfare services, all of which have negative economic impacts.

Box 1: definition of gambling-related harms (from Wardle et al, 2018).

Contribution of our project to this policy environment

It is against this policy and regulatory background that this project has been commissioned. Our research explores what area-based vulnerability to gambling-related harms looks like and how it can be visualised geographically across Newham. By conducting spatial analysis and producing maps that highlight areas where those who are more vulnerable to harm may be present, we provide tools to help understand local area risks. We hope these tools can be used

³ Local Government Association (2018). *Tackling gambling-related harm: a whole council approach*. London: Local Government Association. Available at: https://www.local.gov.uk/sites/default/files/documents/Tackling%20gambling%20related%20harm_LGA_10%2023.pdf

as the basis for developing strategies 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 Newham. Chapter 2 gives a short 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 Newham whilst Chapter 5 summarises key themes from this research.

2 Developing the risk index models: theoretical basis

Overview

In order to develop an index of risk to gambling-related harm, it was first important to establish the theoretical and empirical basis of the models. To do this we consulted a range of experts and key stakeholders to understand which groups they felt may be vulnerable to harm and why. The groups mentioned by stakeholders were then assessed against the empirical evidence to understand the extent to which evidence shows that these groups do have different patterns of gambling behaviour and may experience heightened levels of gambling problems. Finally, the list of 'potential' groups more vulnerable to gambling problems was then compared against local level data to see whether good quality data on each characteristic was available at the local level.

The original primary research underpinning the Newham risk model was conducted in 2015/16. We reviewed each area to determine if a) new evidence suggested that specific characteristics were no longer an issue, or strengthened the case and b) to see if new evidence on previously omitted characteristics meant they should now be included in the models.

Who is vulnerable?

Stakeholder perceptions

From stakeholder interviews, common themes around which 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 incomes 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. In the sections that follow, we outline key themes only, greater detail can be found in our previous reports for Westminster and Manchester (see Wardle, 2015a).

Who is vulnerable? Findings from the scoping reviews

Figure 1 shows the full range of people/characteristics of people which stakeholders felt indicated increased vulnerability/risk to gambling-related harm. This is based on the original reviews conducted in 2015/16. Assessment of new research evidence since then tends to support the conclusions drawn. For example, Forrest & McHale's (2018) recent analysis of youth gambling problems over time highlighted those aged 18 as being very vulnerable to the onset of gambling problems, and called for consideration of special regulatory protections for those aged 18-21. Further research in the USA has highlighted the strong link between gambling and homelessness (Nower et al, 2015). Finally, research from the Health Surveys in Great Britain, particularly Scotland, has highlighted an association between gambling and low household income. However, this is based on bi-variate analysis only and it is unclear the extent to which this relationship holds when other factors are taken into account. Therefore, our assessment is that new evidence generally supports and strengthens the theoretical underpinning of the models produced in 2015/16 with little need for change.

In Figure 1, 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.

Figure 1: People vulnerable to gambling-related harm, by theme

Demographics	Socio-economic	Poor judgement/ impairment	Other
Youth	Unemployed	Low educational attainment	Poor mental health
Older people	Low income	Low IQ	Substance abuse/misuse
Women	Deprived areas	Under influence alcohol/drugs	Problem gamblers
Ethnic groups	Financial difficulties/debt	Learning disabilities	
	Homeless	Personality traits	
	Immigrants		
	Prisoners/ probation		

As can be seen from Figure 1, 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 girls⁴. 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 recognise that these groups may experience social change and that

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

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 1 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 draw 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 complex 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 local authorities have responsibility for planning and development, gambling premises licensing, safeguarding vulnerable people and protecting the health of the public.

Our modelling approach

Overview

We have used spatial analysis techniques to examine local variation in vulnerability to gambling-related harm in Newham. 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.

Our models only include factors reflecting the characteristics of individuals and not the current location of gambling venues themselves. These risk indexes are likely to be used by licensing authorities in making decisions about the location of gambling venues. The Gambling Act 2005 is unequivocal in that when these decisions are made, existing or potential demand should not be a consideration. In doing so, this also means that existing supply is also sidelined as a consideration (i.e., in the eyes of the Gambling Act it is irrelevant whether there are already many venues which could be said to meet demand). Therefore, because this cannot be legally used in the decision making processes, we have excluded it from our model.

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, however this was not included in our model as there were no relevant treatment locations in the study area
Substance abuse/misuse	Strong support for those with other substance issues as vulnerable	Away from home and at home
Poor mental health	Strong support for those with poor mental health as vulnerable	Away from home and at home
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
Homelessness	Emerging evidence that homeless population groups are vulnerable	Away from home only

Table 1: continued...		
Characteristic	Supporting evidence	Local small area data available
Deprivation	Support for those living in the most deprived areas as vulnerable	Modelled by the above ⁵
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	At home only
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

⁵ 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:

- Substance abuse/misuse
- Poor mental health
- Unemployment
- Ethnic groups
- Youth
- Financial difficulties/debt.

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, or relevant services in the study area:

- Problem gamblers who are seeking treatment
- Low IQ
- Personality traits and cognitions
- Immigrant population
- Under the influence of alcohol
- Homelessness.

Further information about the exact data used 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. 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 or specific organisation.

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.

Risk factor: problem gamblers seeking treatment

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

These locations were not included in the model, as there are no relevant treatment centres located in the Newham study area.

Risk factor: people with substance abuse or misuse problems

Dataset used: *Alcoholics Anonymous and Narcotics Anonymous meetings, treatment clinics for persons with substance misuse, and needle exchanges*

These treatment centres, meetings and pharmacies are likely to act as 'pull' for potentially vulnerable people to these locations. This dataset is an amalgamation of Alcoholics Anonymous and Narcotics Anonymous meetings, locations of treatment for people with substance misuse problems from NHS Choices, accommodation locations and needle exchanges from the London Borough of Newham. The analysis is dependent upon the sources being well informed, managed and current; further sense-checking of the input data using local knowledge is recommended. NHS data are a robust and complete national dataset.

There is variation in the 'type' 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.

There are many treatment locations relating to both mental health and substance misuse - as our weighting schema is slightly higher for substance misuse and so as to not overstate these locations, we have referred to places where an aspect of substance misuse is treated in this category.

Accommodation for persons with substance misuse

This data is gathered from the Care Quality Commission (CQC) list of services inspected. It is a complete national dataset.

Risk factor: people with poor mental health

Datasets used: Number of patients recorded on the GP register with schizophrenia, bipolar affective disorder and other psychoses, and other patients on lithium therapy

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 NHS Quality Outcomes Framework (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.

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 acute mental health conditions.

Treatment clinics for people with poor mental health

These locations are likely to act as 'pull' for potentially vulnerable people to these locations. This dataset details locations of treatment for people with substance misuse problems from NHS Choices. It is a complete national dataset.

Accommodation for people with poor mental health

This data is gathered from the Care Quality Commission (CQC) list of services inspected. It is a complete national dataset.

Risk factor: Unemployed people

Datasets used: 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 a freedom of information request at the Department of Work and Pensions and should provide a complete and current list of job centre locations.

Number of economically active unemployed residents

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 six 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. Counts in areas with prisons are removed.

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 data 2011 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. Counts in areas with prisons are removed.

Risk factor: Youth

Datasets used: *Number of residents aged 10-24 years*

The data is derived from the 2011 census. 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. Again, counts in areas with prisons are removed.

Education institutions with students of 13-24 years

These data list all known educational institutions for people aged 13-24 and are derived from the English Department for Education data.

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 to 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: 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 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.

The data has been sourced by web searches.

Food banks

The 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 is no central database managing these locations as they are usually not council-led services or officially part of government policy or welfare state provision.

Our data is a combination of the main bulk of food banks managed by the Trussell Trust, as appear on their website, supplemented by web searches.

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

Criteria	Indicator/measure	Dataset name	Reference date	Geographic scale/ aggregation	Dataset owner and copyright	Geographic availability	KDE band-width	Weighted by	Missing areas
Substance abuse/ misuse	Alcoholics Anonymous meetings	AA listings	08/2018	Unit postcode of the meeting location	http://www.alcoholics-anonymous.org.uk/	National	400m	None	None
	Narcotics Anonymous meetings	NA listings	08/2018	Unit postcode of the meeting location	https://ukna.org/	National	400m	None	None
	Treatment for people with substance misuse	NHS Choices / London Borough of Newham Public Health	08/2018	Unit postcode of the service location	NHS Digital / London Borough of Newham Public Health	National	400m	None	None
	Accommodation and clinics for people with substance misuse	Care Quality Commission (CQC) services inspected	08/2018	Unit postcode of the treatment centre location	Care Quality Commission (CQC)	National	400m	None	None
	Needle exchanges	Pharmacy needle exchanges	08/2018	Unit postcode of pharmacy	London Borough of Newham Public Health	LB Newham	400m	None	All surrounding

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	Quality Outcomes Framework (QOF) GP statistics	April 2016 – March 2017	Unit postcode of the GP practice	NHS Digital	National	400m	Number of patients	None
	Treatment for people with poor mental health	NHS Choices	08/2018	Unit postcode of the treatment centre location	NHS Digital	National	400m	None	None
	Accommodation and clinics for people with mental health problems	Care Quality Commission (CQC) services inspected	08/2018	Unit postcode of the accommodation	Care Quality Commission (CQC)	National	400m	None	None
Unemployment	Jobcentre Plus offices	FOI request of Jobcentre Plus office locations	08/2018	Unit postcode of the job centre location	Department for Work and Pensions (DWP)	National	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).	National	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)	National	750m	Number of residents	None
Youth	Education institutions with students of 13-24 years	https://www.get-information-schools.service.gov.uk/	08/2018	Unit postcode of institution location	England Department for Education. Available under Open Government Licence (OGL)	National	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)	National	750m	Number of residents	None
Financial difficulties/ debt	Loan shops	Web searches	08/2018	Unit postcode of the shop location	Web searches	National	400m	None	None
	Food banks	Trussell Trust / web searches	08/2018	Unit postcode of the food bank location	Trussell Trust website / web searches	National	400m	None	None

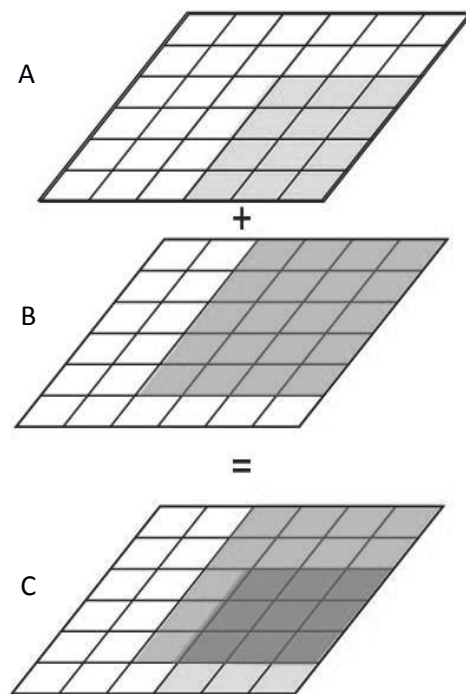
Spatial analysis techniques

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 Newham. 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.⁶

Figure 3: visual representation of overlay



⁶ 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).

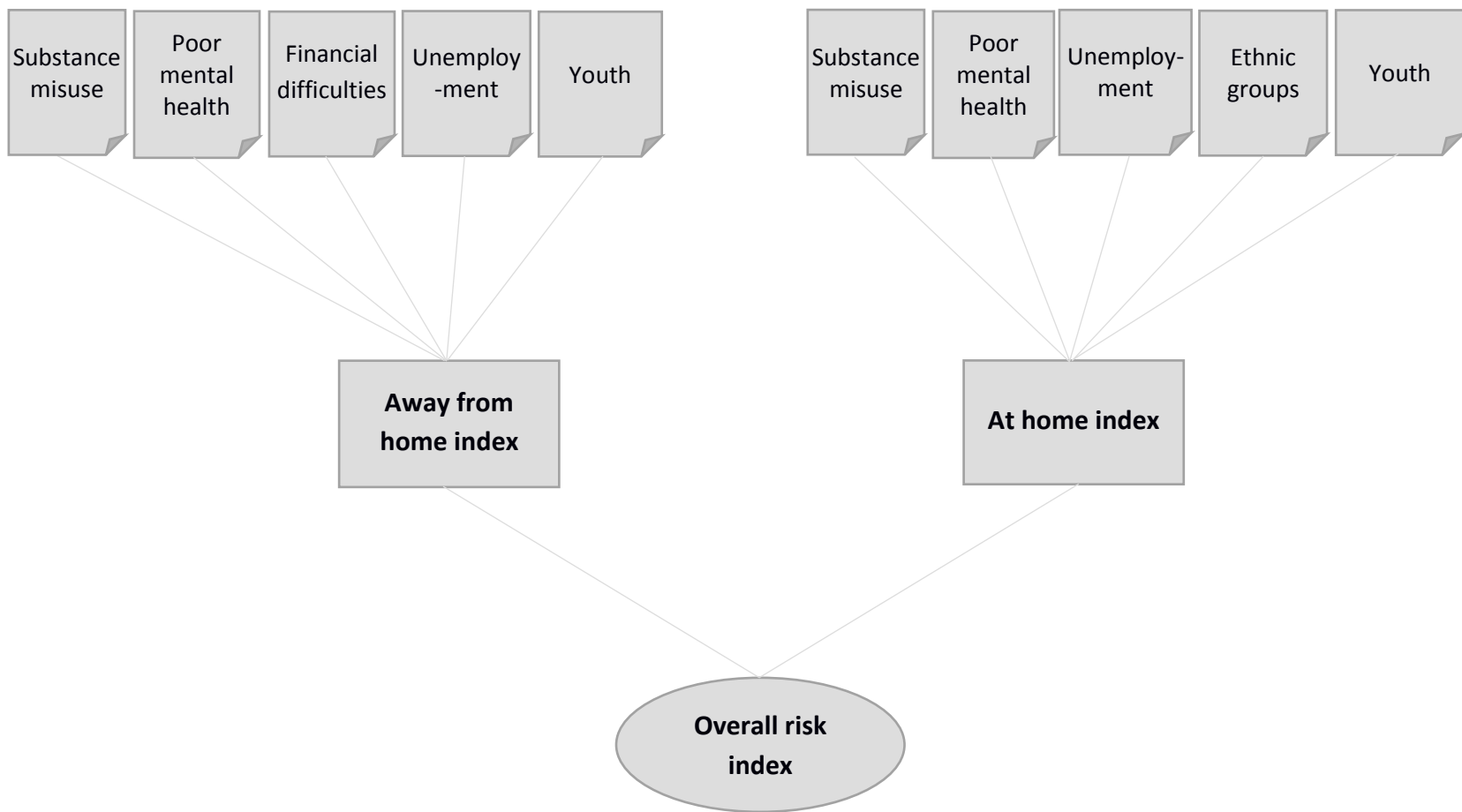
A tree-based approach is the conceptual model showing how all indicators are structured within our models. This structure then guides the method and order in which the final indices are calculated. For example, the tree-based structure is used to define which layers of data represent certain risk factors 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 structure is shown in Figure 4.

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 local authorities will vary and may be different in structure meaning that each local authority will likely have a slightly different model. The tree-based model offers a simple way of identifying those small differences. The tree model used for Newham is shown in Figure 4.

Figure 4 also shows the 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 model 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' population 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 Newham gambling-related harm risk index



Modelling factors and equations used

The risk index shows the places where there are higher numbers of people relative to other places who might be at risk of experiencing gambling-related harm. The risk indexes have not been normalised to reflect the underlying density of the population. This is for three main reasons:

- 1). Part of the index focuses on the 'away from home' population and includes services which are likely to pull vulnerable people into an area. To normalise this to the overall population we would need definitive data about how many people use each service, which does not exist.
- 2). As a result of point 2, our spatial modelling approach uses Kernel Density Estimates to create surface representations of geographic patterns. The most appropriate type of input data to these density estimates are count-based data, rather than rates.
- 3). Further to this our 'at-home' indicators mostly use Census-based indicators at small areas. These small-area units of aggregation are engineered to include similar resident population levels (around 300 people in 2011 for each output area). The results of each indicator are normalised before being combined. As a result of the similar base-populations, the patterns of z scores created for risk using these indicators will be similar whether using counts or rates. Whilst there will be some error introduced by some variation in base populations, this error will be relatively small when looking at broad patterns generated from these small area data.

Whilst there are many possible valid approaches to identifying and representing risk populations, our methodology is appropriate for practitioners using these results for licensing decisions and the identification of treatment resources at the strategic level, amongst many other uses.

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 normalisation 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:

$$(a - b)/c$$

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.⁷ 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 3 below, along with a brief justification of the value assigned.

⁷ 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.

Table 3: Strength of evidence weighting domain		
Risk factor	Value	Explanation
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.

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. Results are shown in Table 4.

Table 4: Relative risk of gambling problems weighting domain

Risk factor	Value	Explanation
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 4: Continued...		
Risk factor	Value	Explanation
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.

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 5. These were the final weights used in our models.

Table 5: Weightings applied to the model characteristics

Risk factor	Strength of evidence	Relative risk	Final weight
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

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:

$$(50/\text{maximum cell value}) * \text{cell value}$$

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.

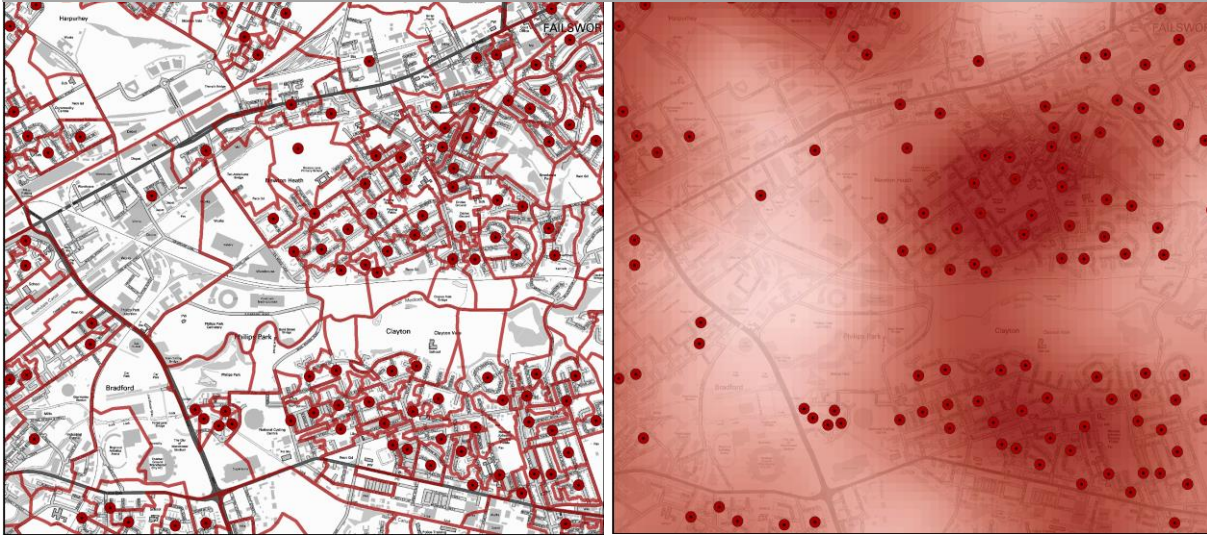
Input dataset modelling

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 5 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.⁸

Figure 5: example spatial representations of small area census data: areal units vs kernel density estimations (KDE)



⁸ A unit postcode centroid represents, on average, the centre around 15 geographically contiguous addresses

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 Newham, 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. Other potential reports to reference include UK Planning Policy Guidance 13: Transport, which gave some useful guidance on walking and cycling distances, but was withdrawn in 2012 and the IHT's 2000 report, Providing for Journeys on Foot and Planning for Public Transport in New Development. However these documents have limited

evidence to support the advice given. The recent Transport for London Travel in London report 9, states the mean walk trip length to a public transport terminal is 0.5km, although the data suggests a smaller modal and median distance (page 122, figure 5.7). This distance is also related to public transport which may or may not be considered synonymous to other local services. Some of our previous research examining loyalty card data of fixed odds betting terminal users identified a modal distance of 400m from player residences to machines as-the-crow-flies. The median and mean were larger, although the data captured shops being used at distances from residences akin to workplace and holiday locations and therefore skewed the reliability of local-level measurements (Astbury & Thurstain-Goodwin, 2015). Continuing to use the 400m 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 Table 2, 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 Newham Local Authority boundary, real-life geography is continuous, so wherever possible we have gathered data from the Local Authority border and extended the modelling past this 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 Newham.

Z scores are calculated on Newham plus the 1km surrounding area, so the normalised scores represent a 'study area' average of 1km past the Newham boundary. Where extra data are not available from surrounding Local Authorities we have flagged this in Table 2.

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 previous rapid scoping review report (see Wardle, 2015a).

The rationale for the choice of risk factors included in the models was based on research from the previous rapid scoping review into who may be vulnerable. Whilst this 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 seven years old. If there has been significant neighbourhood 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 relevant authority or organisation. 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 within the resident 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, showing where greater numbers of people who are potentially vulnerable to harm are more likely to be. Each square cell (50m x 50m) has a value indicating the relative risk. These values are a measure of 'high' and 'low' risk relative to other places within Newham 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.

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. 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, 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? We illustrate these processes in a number of case study areas. The individual maps for the study area are presented in Appendix 1.⁹

Overall, three local areas in Newham stand out as having the highest levels of risk to gambling related harms (see Appendix 1). These are areas around Stratford, Forest Gate and East Ham. The case studies below explore each area in more detail, looking at the specific drivers of risk in each area. There are other areas which have heightened risk relative to the rest of Newham, for example, around Upton Park and Woodgrange Road. In these places, risk tends to be driven by the profile of people who live in these spaces rather than the services offered. For example, Woodgrange Road has a relatively higher numbers of people from Minority Ethnic Groups and those who are economically inactive in its vicinity. It is important, therefore, to look at both the at-home index and the away from home index separately as these show quite different distributions in risk based on who lives in an area and what services for potentially vulnerable people are available in an area.

Case study 1: Stratford

Stratford was one of three areas with the highest levels of risk to gambling-related harm in Newham. Unlike the other two areas, risk in Stratford was driven more by the services for vulnerable people in its local area than the profile of residents living in its locale. Figure 4.1 shows the location of substance abuse/misuse services, which are located centrally in Stratford.

⁹ Hospital episode statistics data on mental health have been omitted from the Appendix because of data confidentiality at this fine geographic scale.

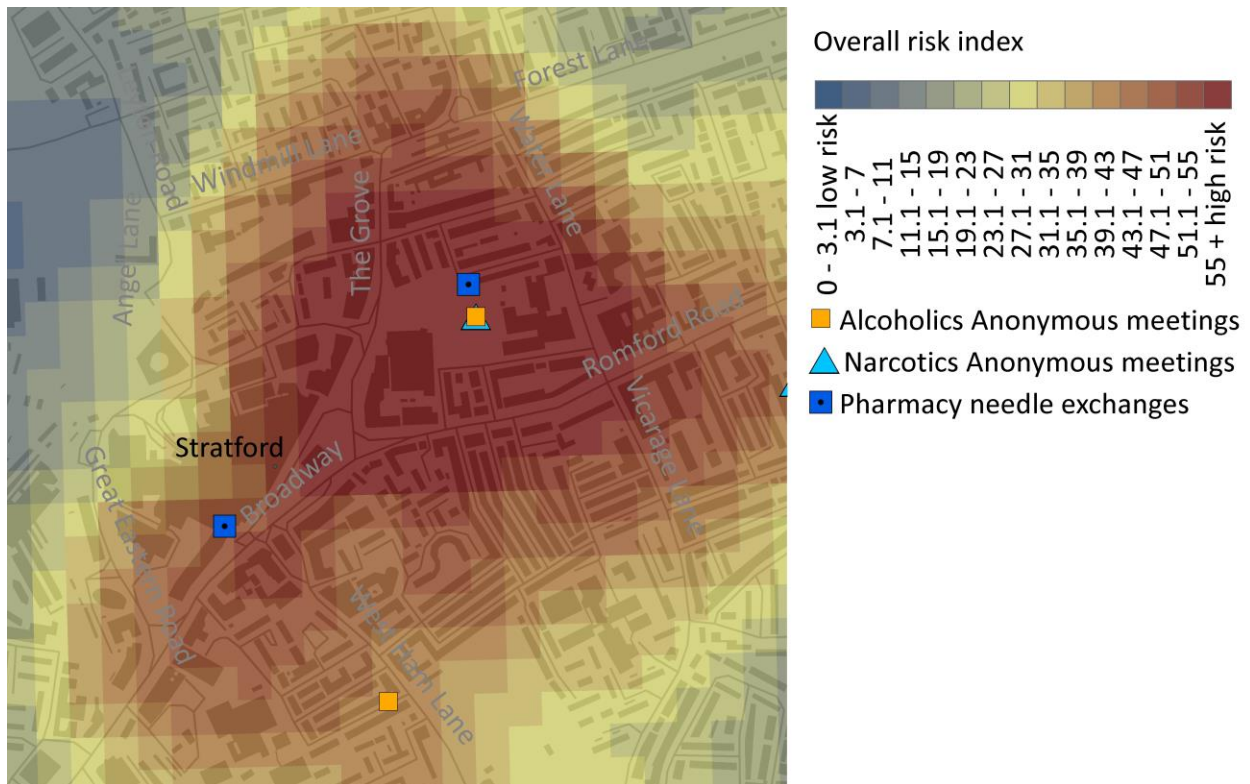


Figure 4.1: location of substance abuse/misuse services

Figure 4.2 shows a number of educational institutions in the Stratford area but also how many of the output areas have relatively low numbers of young people living in these spaces. This suggests, that the youth population in Stratford is likely to be more transient, travelling into this space for education (or entertainment) rather than being local residents.

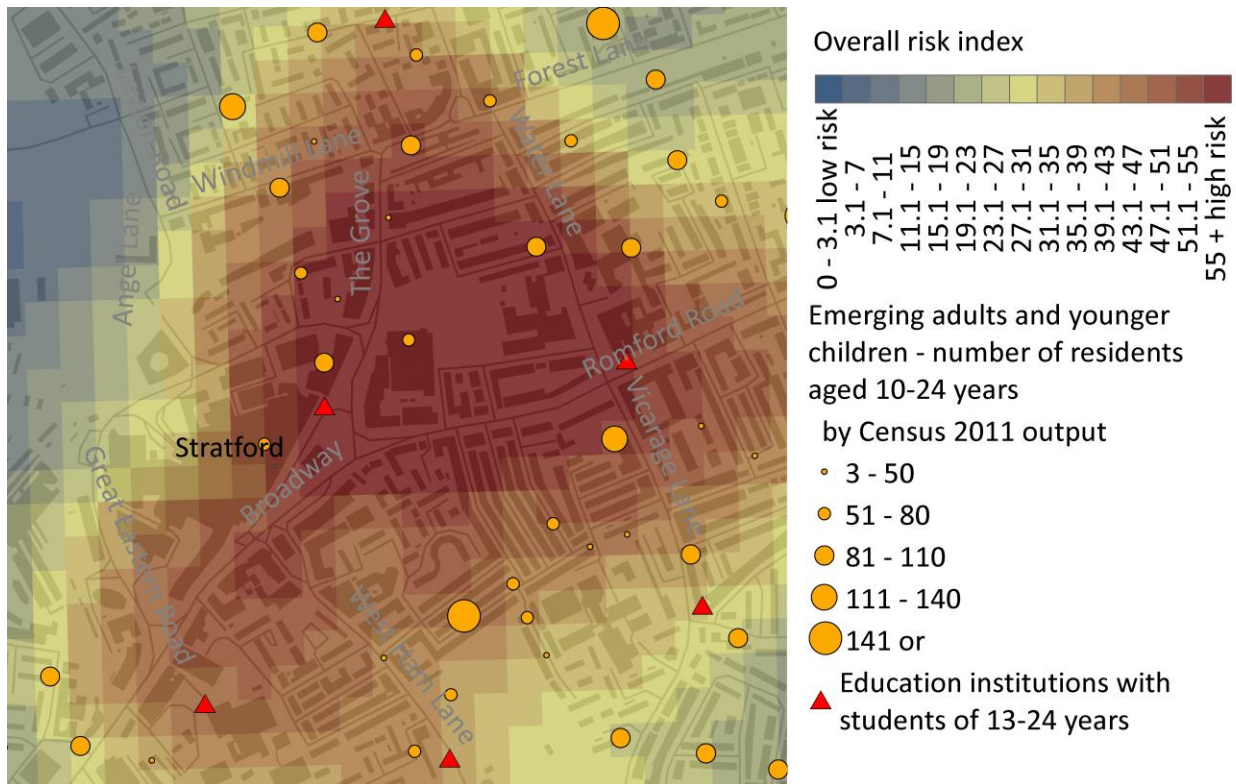


Figure 4.2: Number of young people living in Stratford and educational institutions.

Finally Figure 4.3, shows the relatively low number of people in Stratford who are economically inactive, further highlighting that risk in this area is driven more by the services it offers rather than the profile of local residents.



Figure 4.3: number of economically active people in Stratford

Case study 2: Forest Gate

In Forest Gate, risk was driven by both services offered to vulnerable people in the area and the profile of the resident population. Figures 4.4 and 4.5 show the location of services for substance abuse/misuse and provision of food banks and loan shops in this area. Figure 4.6 shows a high number of people from Minority Ethnic Groups living in this area, with some output areas having between 300-400 people from Minority Ethnic Groups. Likewise, Figure 4.7 shows that some of the output areas towards the south of Forest Gate have a greater number of young people resident. The output areas in Forest Gate also tend to have greater numbers of people who are economically inactive.

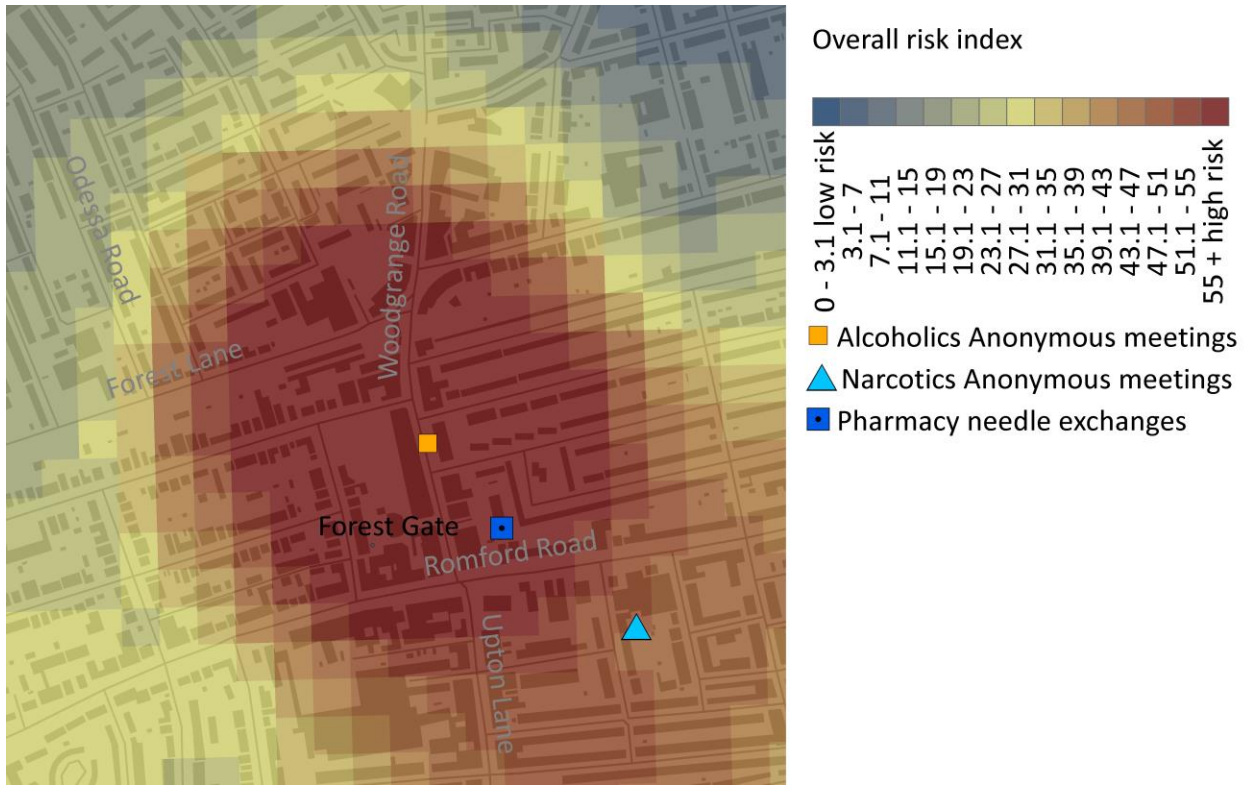


Figure 4.4: Location of substance abuse/misuse services in Forest Gate

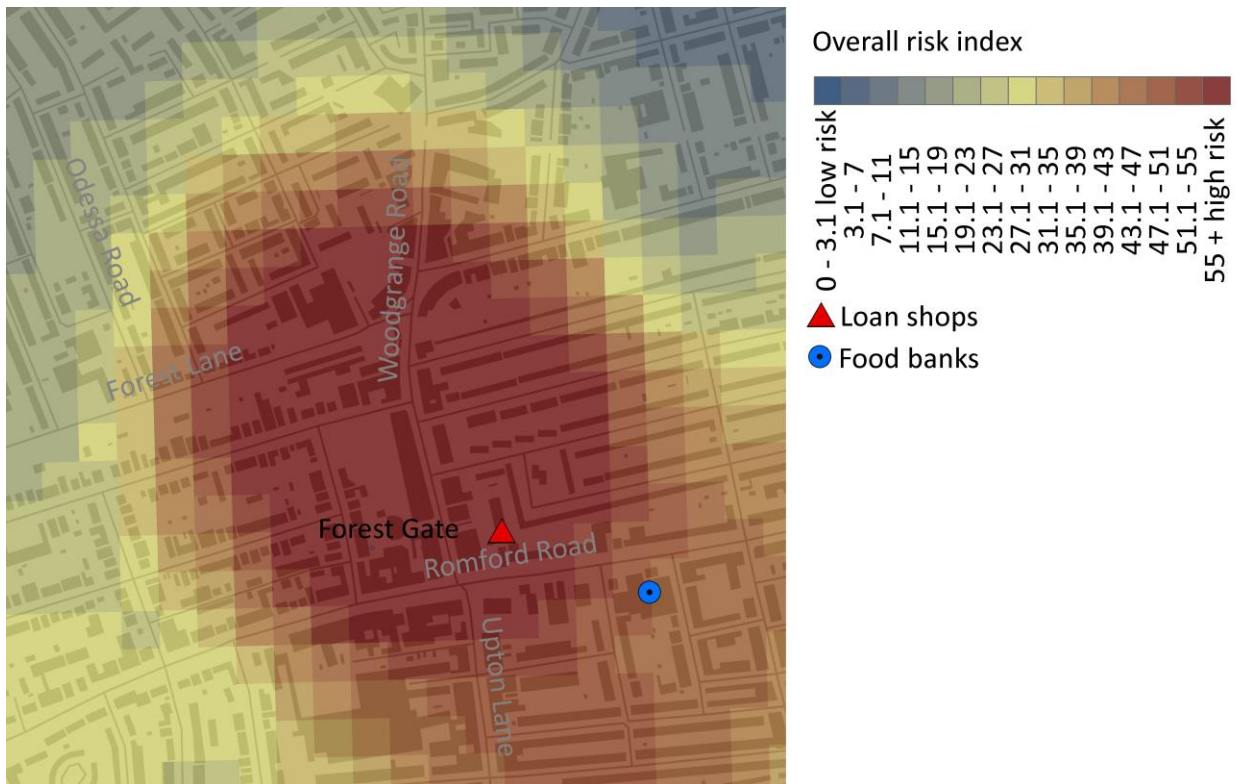


Figure 4.5: Location of food banks and loan shops in Forest Gate.

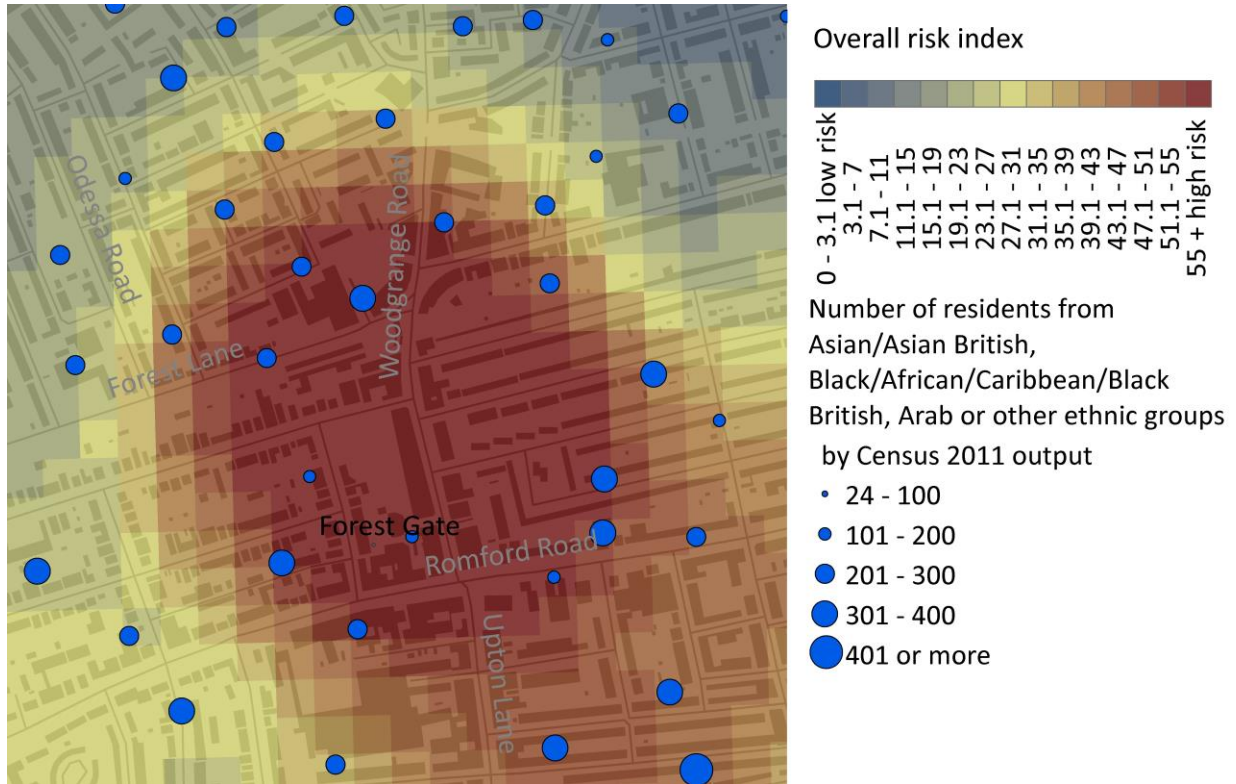


Figure 4.6: Number of residents from Minority Ethnic Groups in Forest Gate

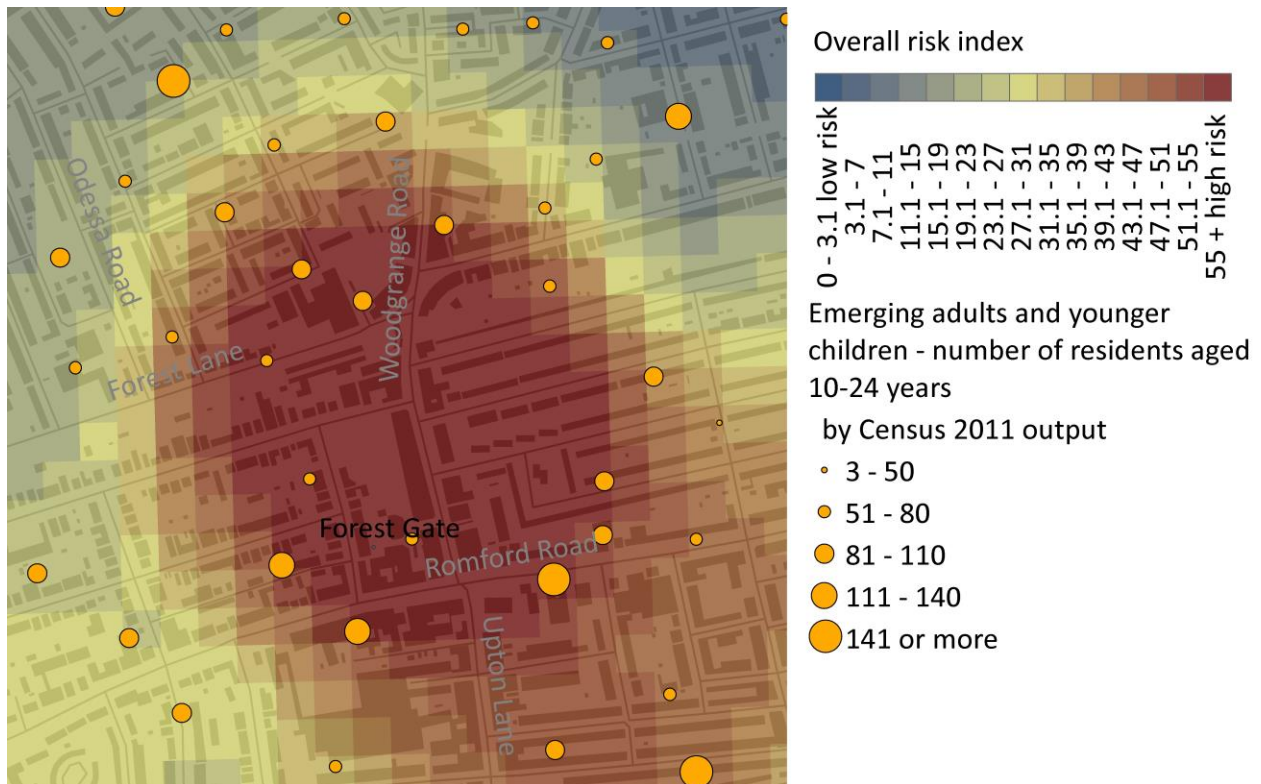


Fig 4.7: Number of young people living in Forest Gate.

Case study 3: East Ham

In East Ham, the risk is driven much more by the local resident population profile than services in the local area. There is only one service for substance abuse/misuse in this area and one foodbank on the periphery of the area. By contrast, there are greater numbers of people who are economically inactive (Figure 4.8) or from Minority Ethnic Groups (Figure 4.9) and some output areas with higher numbers of young people, alongside two educational institutions in this space (Figure 4.10).

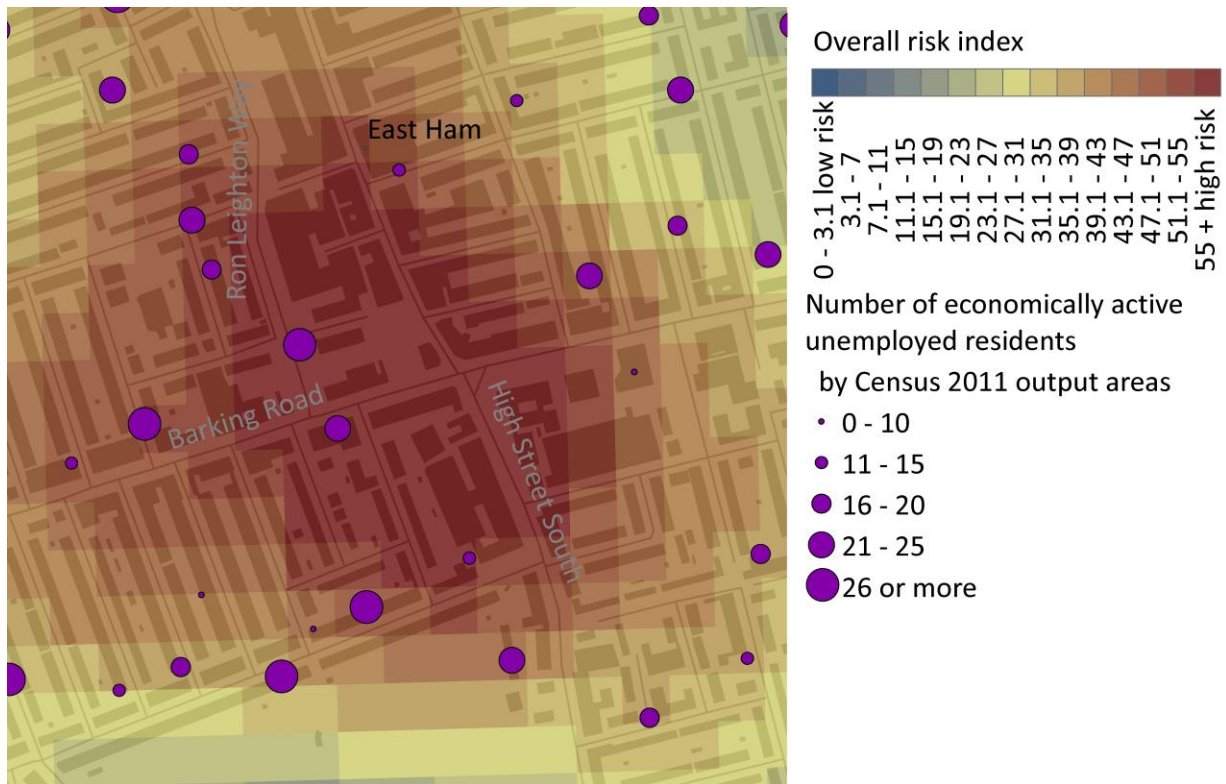


Figure 4.8: Number of economically inactive people in East Ham



Figure 4.9: Number of people from Minority Ethnic Groups in East Ham

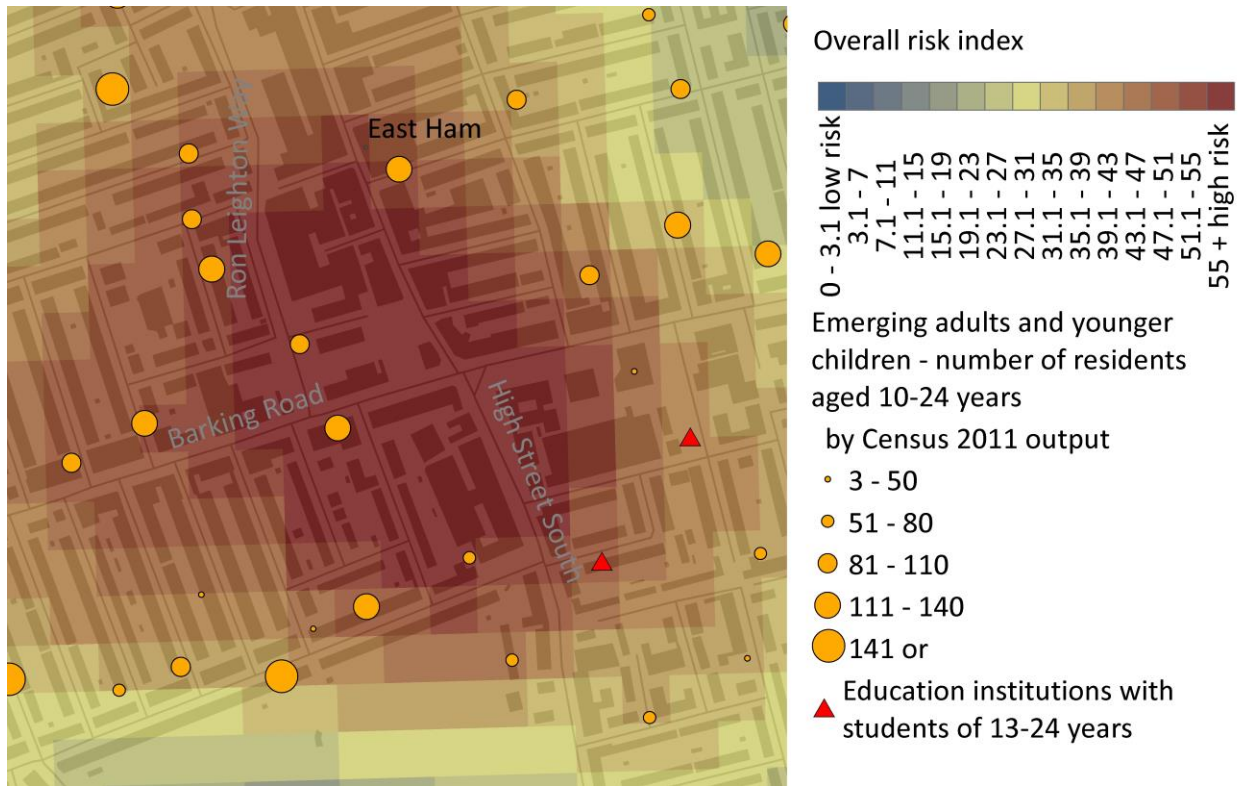


Figure 4.10: Number of young people and educational institutions in East Ham

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. The Gambling Commission now requires that both gambling operators and Licensing Authorities need to consider local area risks and take steps to mitigate against harm.
- This project systematically considers who might be vulnerable to harm in Newham and, using this information, create a risk index so that areas of higher or lower potential risk can be easily identified.
- We have highlighted the areas where risk of harm may be greatest in Newham. 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

- Findings show that risk within Newham varies and that the drivers of risk are different for different places. Of the three areas with the highest rating on the risk index, risk in Stratford is driven more by the types of services it offers, potentially attracting vulnerable people into this space whereas risk in East Ham is driven much more by the characteristics of local residents.

- Aside from the three main areas discussed, there are other areas in Newham which have relatively high levels of risk according to the 'at-home' risk index. An example of this is around Woodgrange Road. This area has relatively low risk according to the 'away from home' index but has much higher risk on the 'at home' index. Because our overall index balances these two, it does not appear as one of the highest risk areas but there are still relatively high numbers of potentially vulnerable local residents living in this area, which should be considered.

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. 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.
- 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 licensing authorities. Our research shows that deprivation is not necessarily an appropriate proxy for risk of gambling-related harm. The key UK measure available: 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 the 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, the 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. Focus on the 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 mitigate 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.
- 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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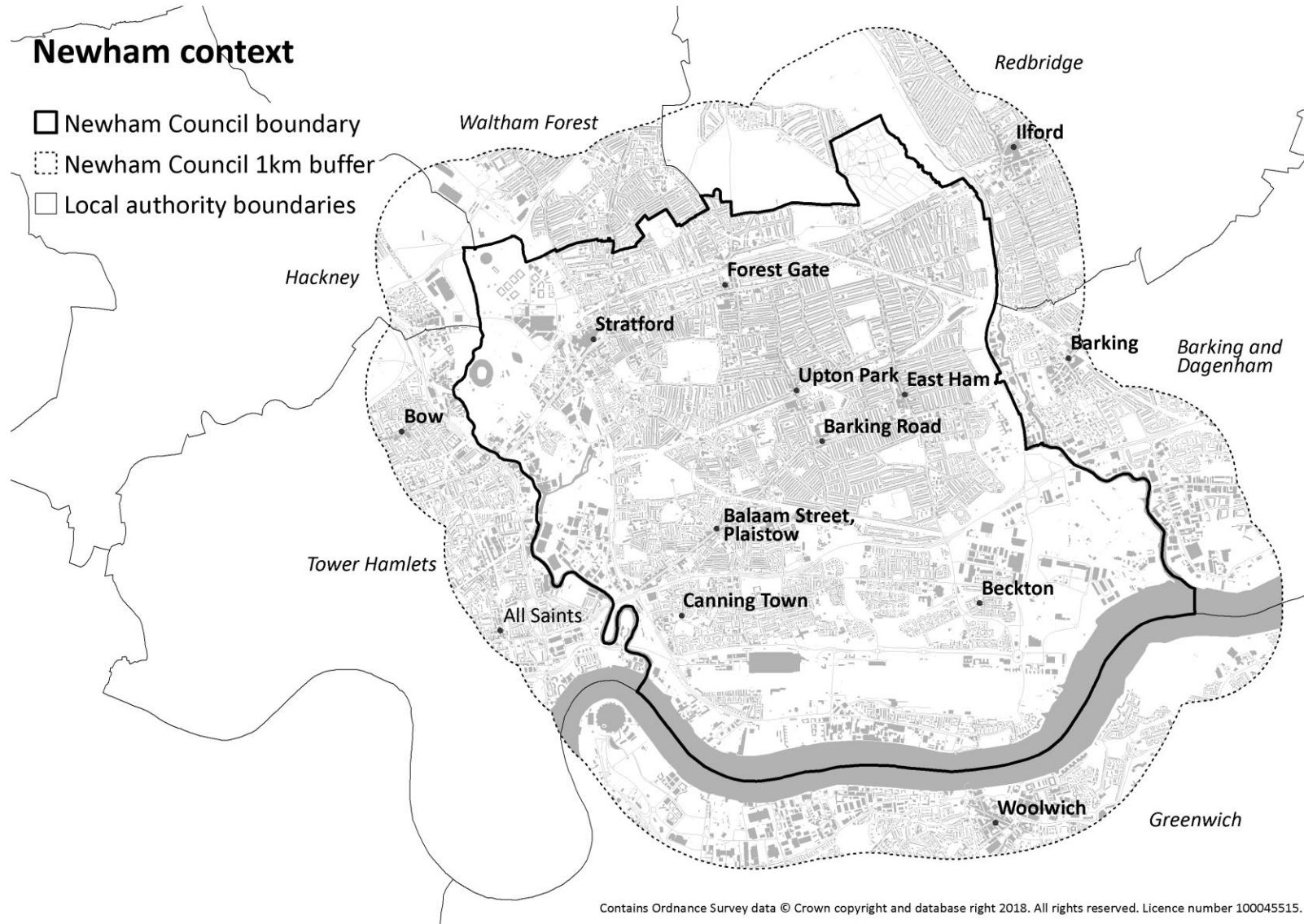
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





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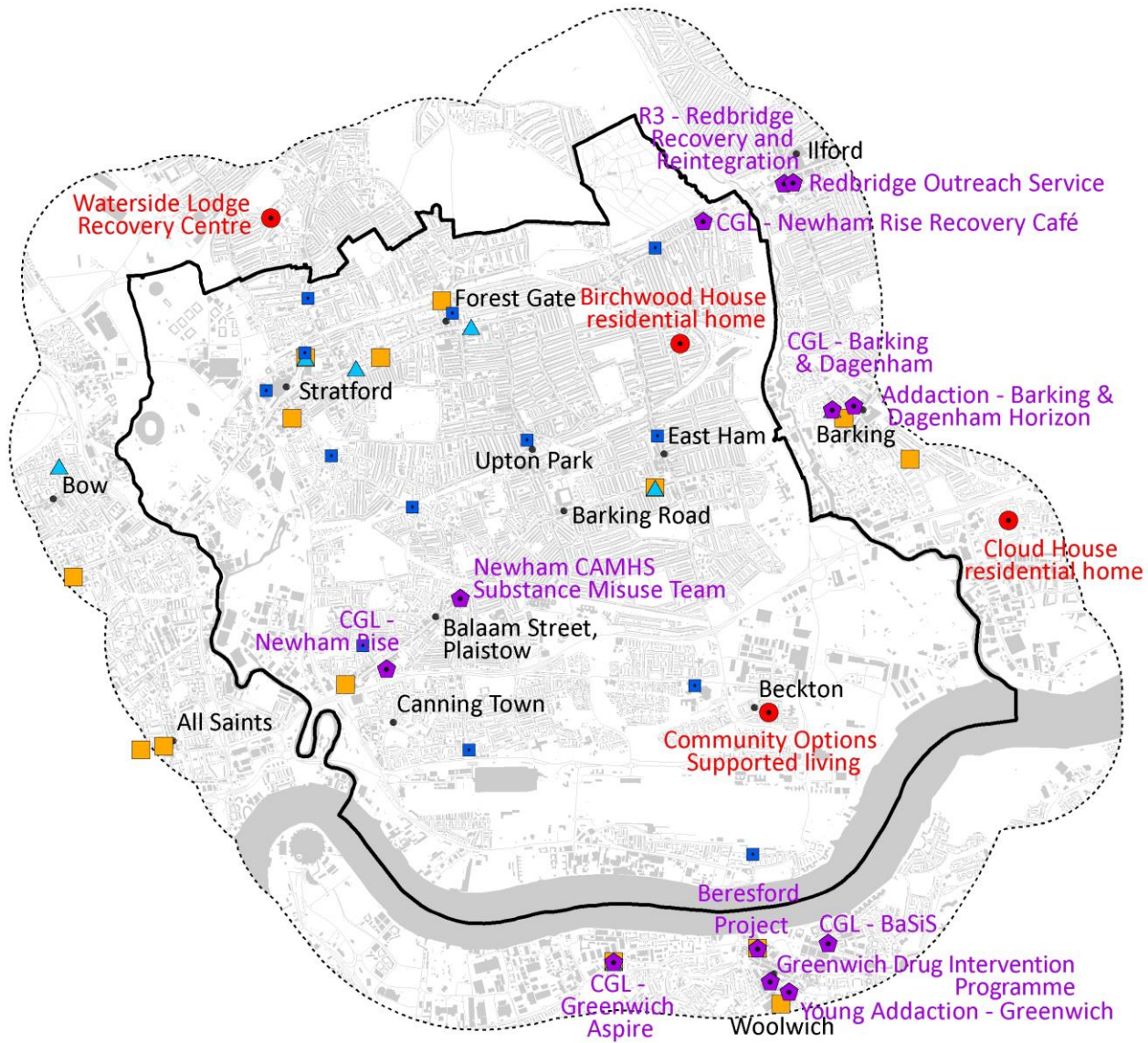
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Appendix 1



Substance misuse

-  Newham Council boundary
-  Newham Council 1km buffer
-  Substance misuse treatment locations
-  Accommodation for people with substance misuse
-  Alcoholics Anonymous meetings
-  Narcotics Anonymous meetings
-  Pharmacy needle exchanges



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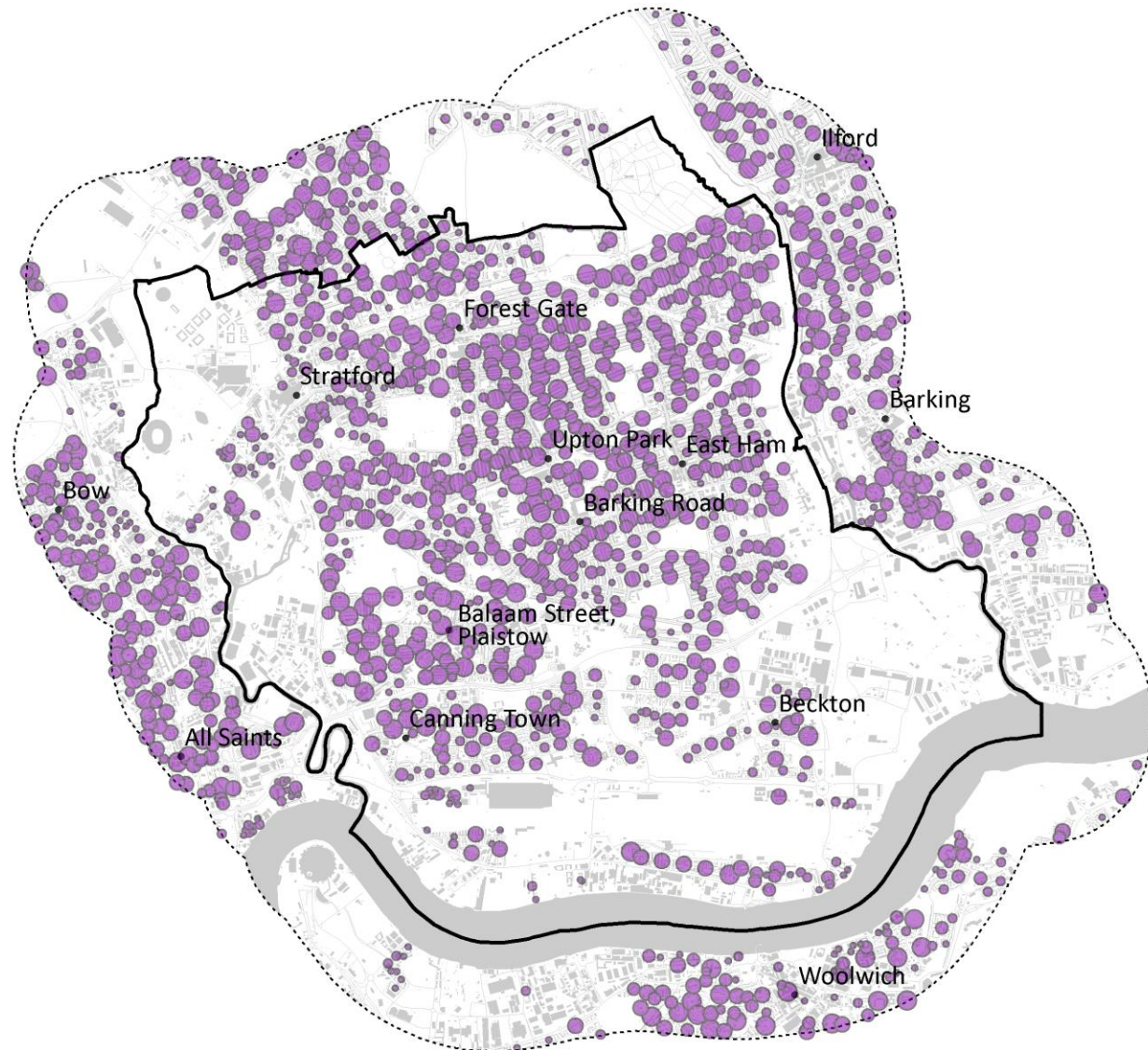
Unemployment

- Newham Council boundary
- Newham Council 1km buffer

Number of economically active unemployed residents

by Census 2011 output areas

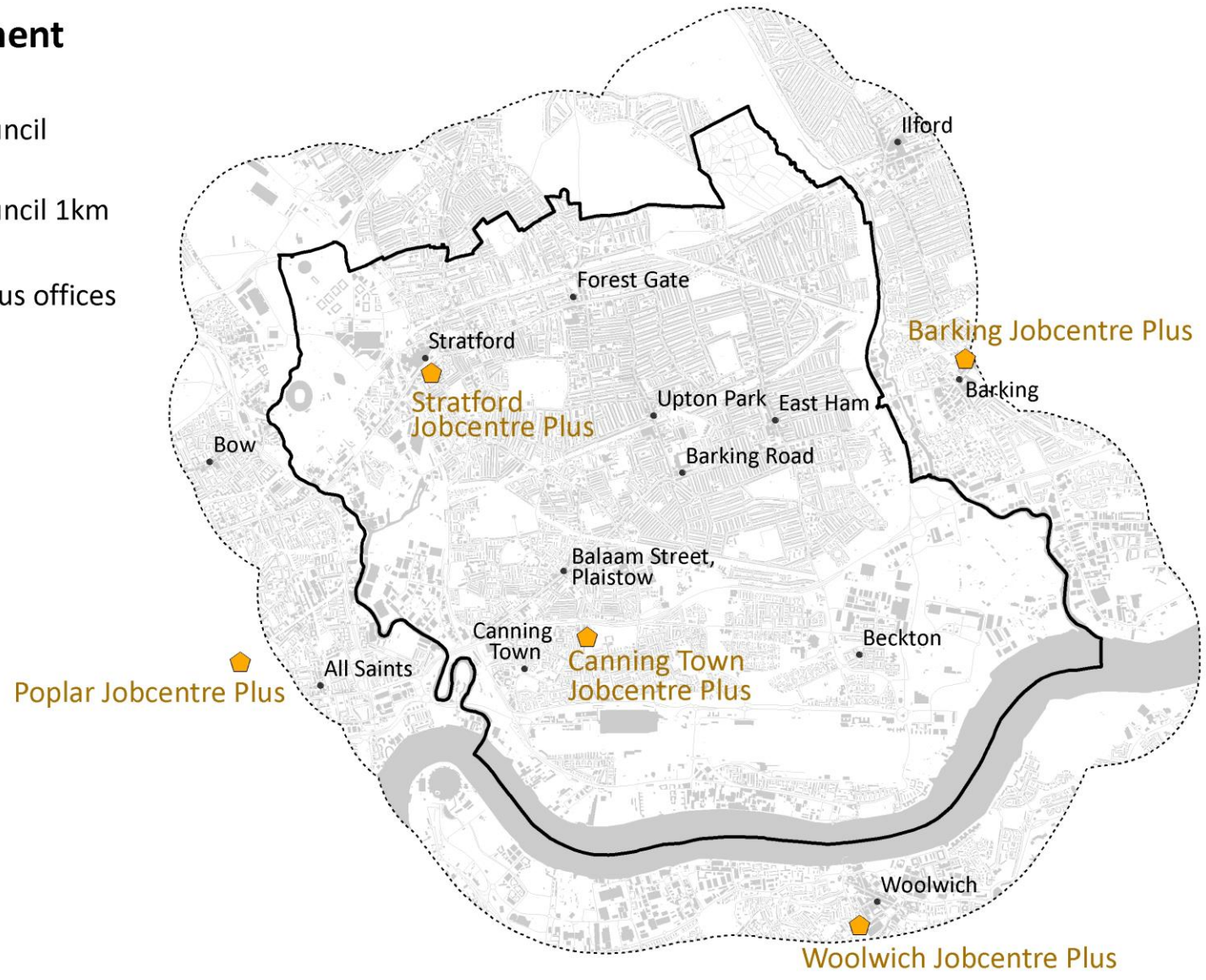
- 0 - 10
- 11 - 15
- 16 - 20
- 21 - 25
- 26 or more



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Unemployment

- Newham Council boundary
- ⋯ Newham Council 1km buffer
- 📍 Job Centre Plus offices



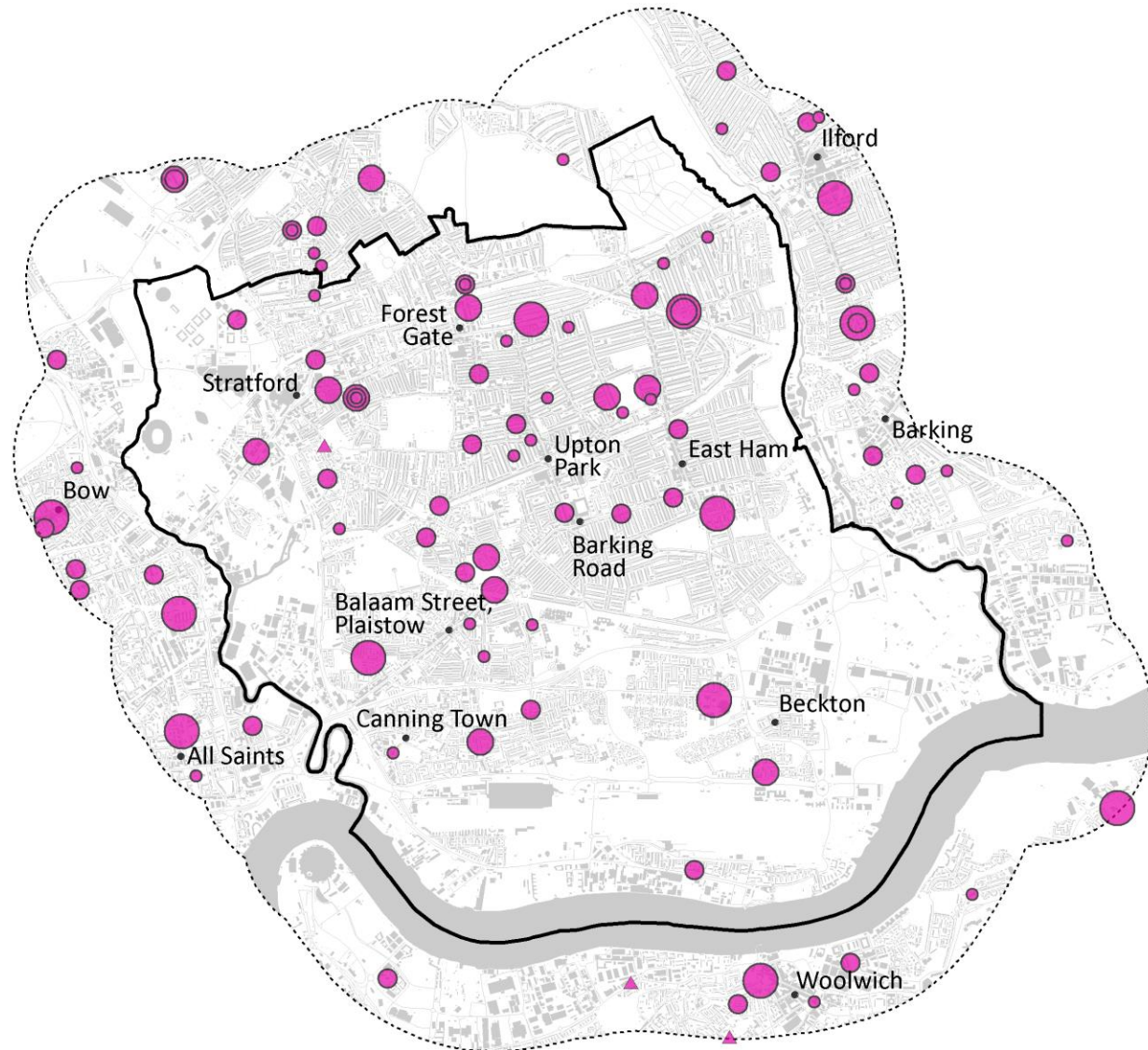
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Mental health

- Newham Council boundary
- Newham Council 1km buffer

Number of patients recorded on the GP register with schizophrenia, bipolar affective disorder, and other psychoses, and other patients on lithium therapy

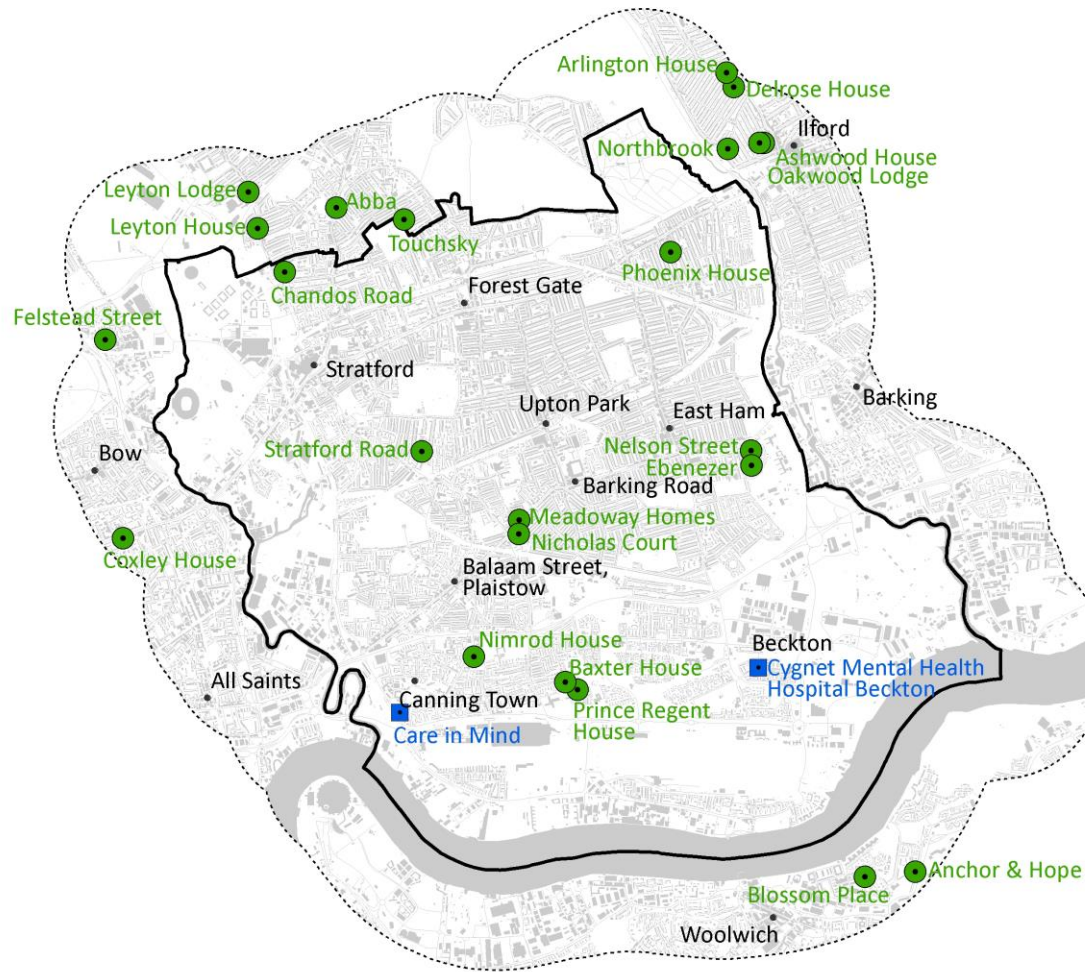
- April 2016 - March 2017
- ▲ *no information available*
 - 1 - 50
 - 51 - 100
 - 101 - 150
 - 151 - 464



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Mental health

- Newham Council boundary
- ⋯ Newham Council 1km buffer
- Mental health treatment
- Accommodation for those with poor mental health



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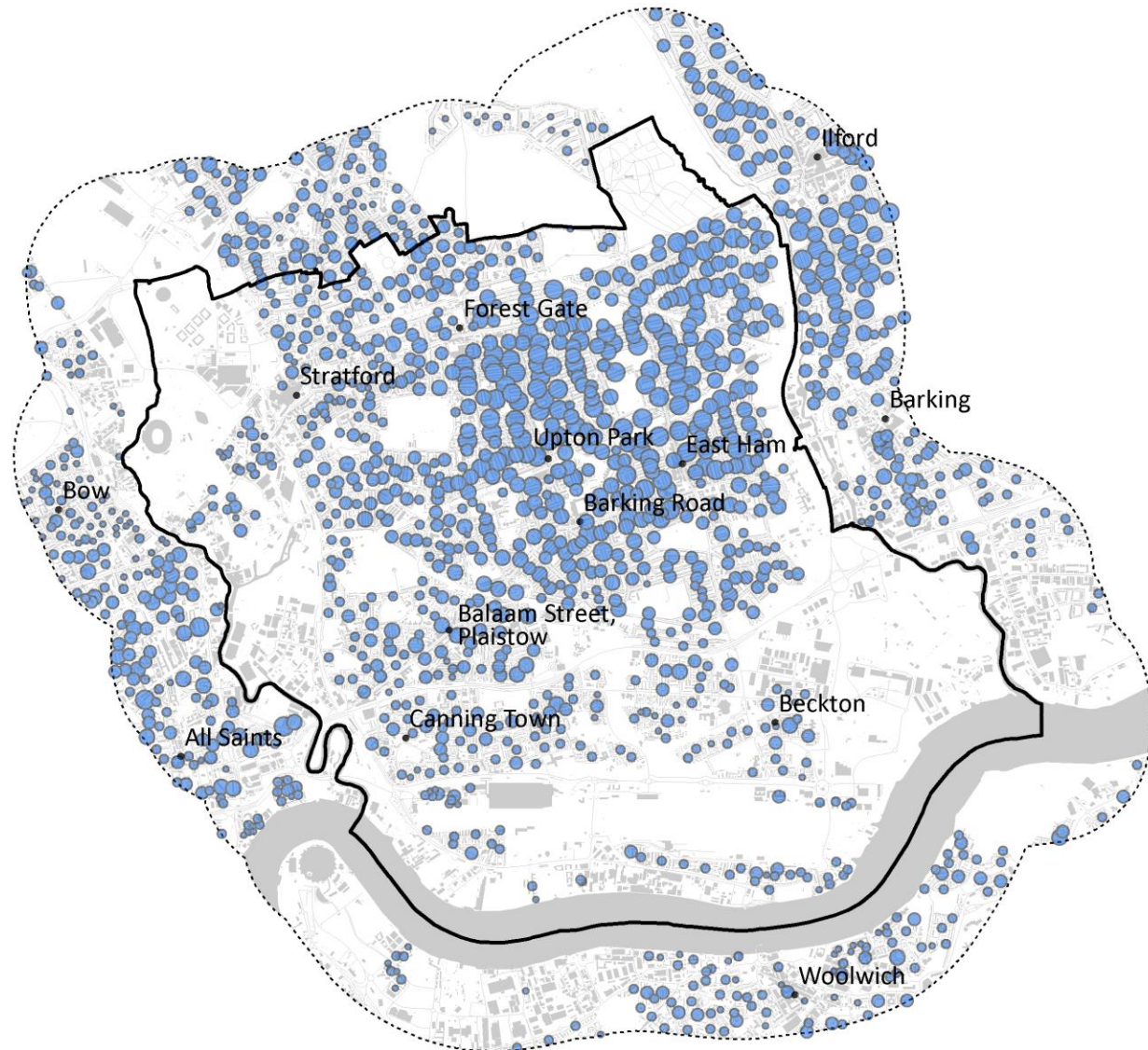
Ethnic groups

- Newham Council boundary
- ⋯ Newham Council 1km buffer

Number of residents from Asian/Asian British, Black/African/Caribbean/Black British, Arab or other ethnic groups

by Census 2011 output areas

- 24 - 100
- 101 - 200
- 201 - 300
- 301 - 400
- 401 or more



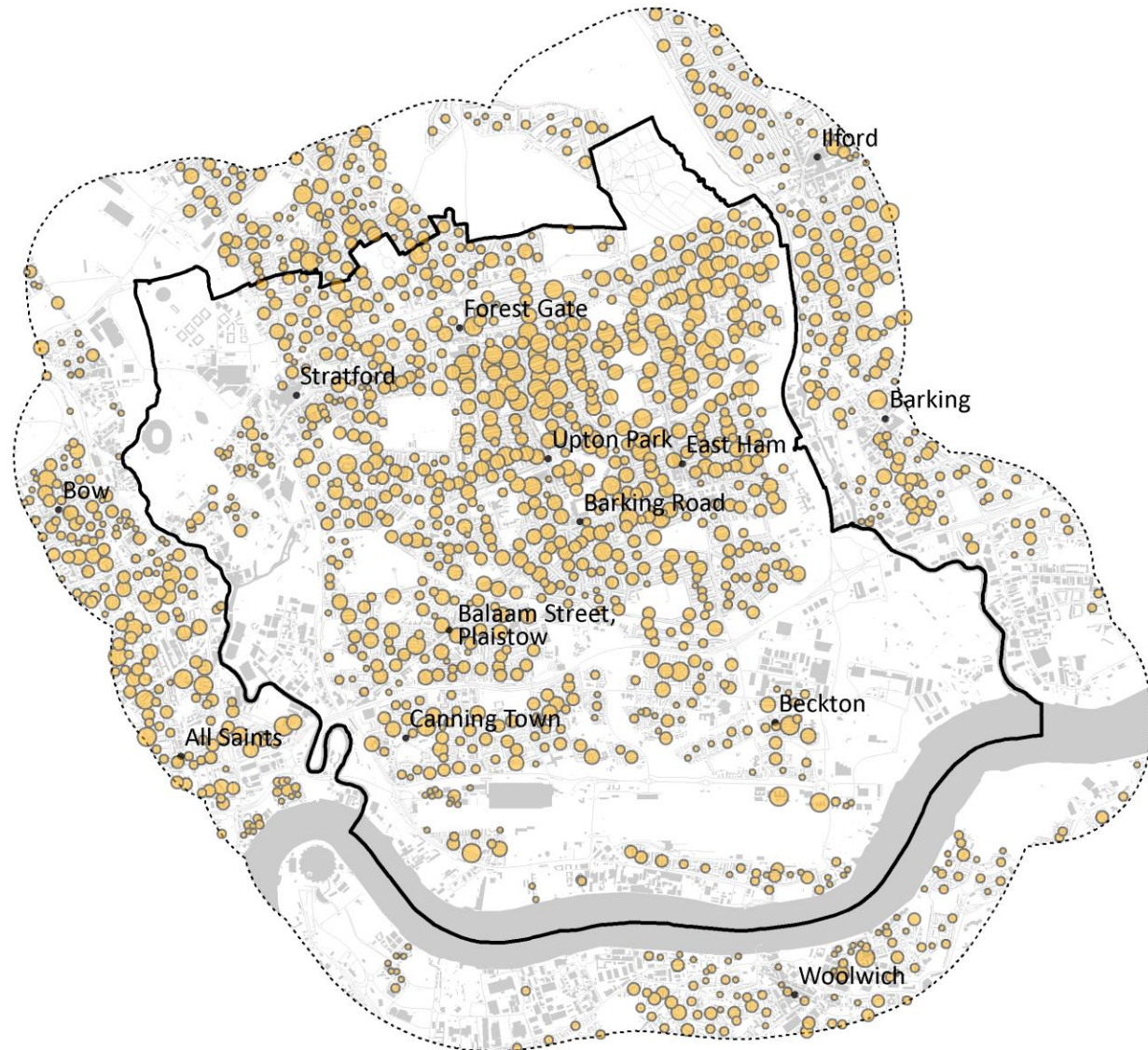
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Youth

- Newham Council boundary
- Newham Council 1km buffer

Emerging adults and younger children - number of residents aged 10-24 years by Census 2011 output areas

- 3 - 50
- 51 - 80
- 81 - 110
- 111 - 140
- 141 or more



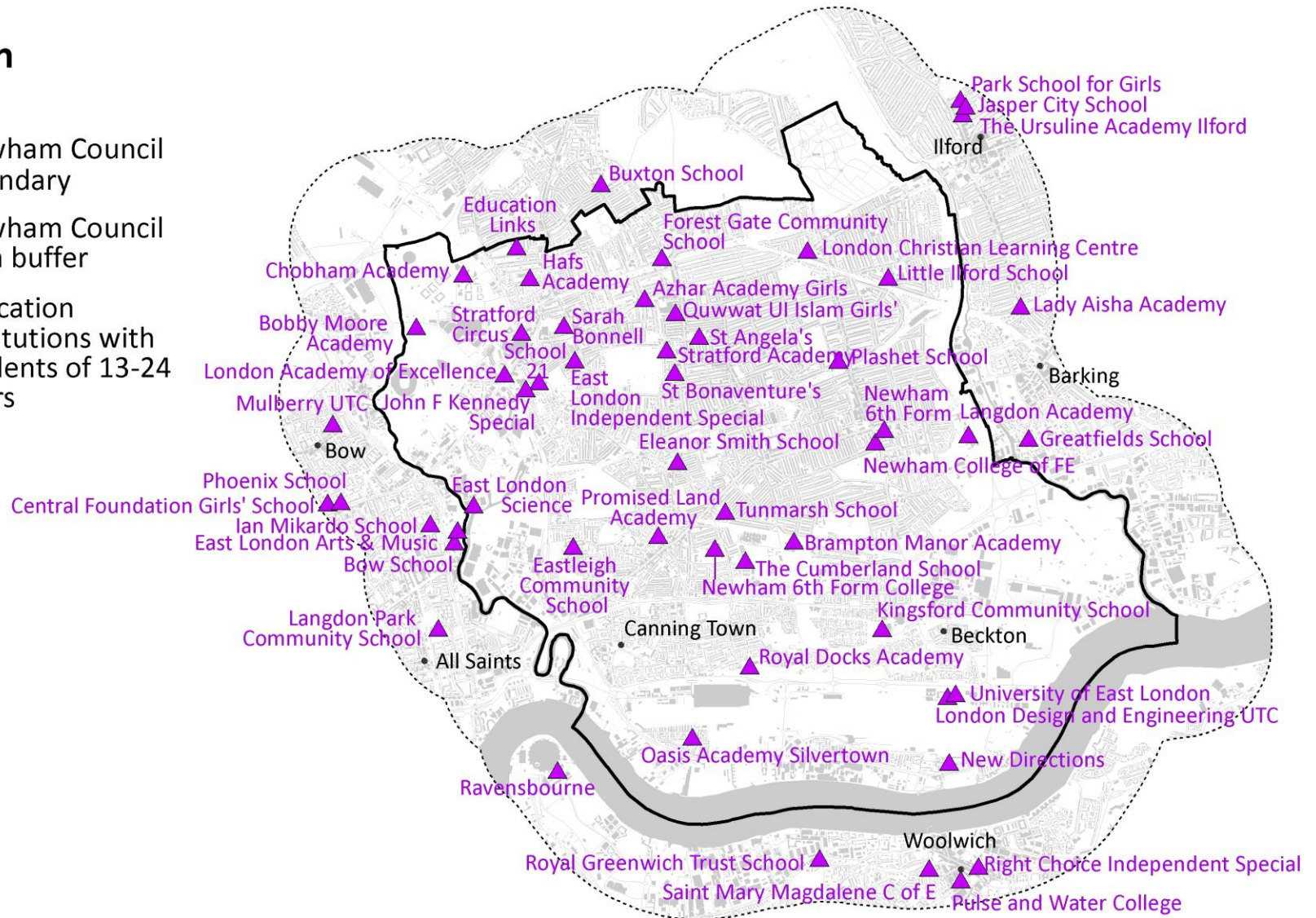
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Youth

□ Newham Council boundary





⋯ Newham Council 1km buffer

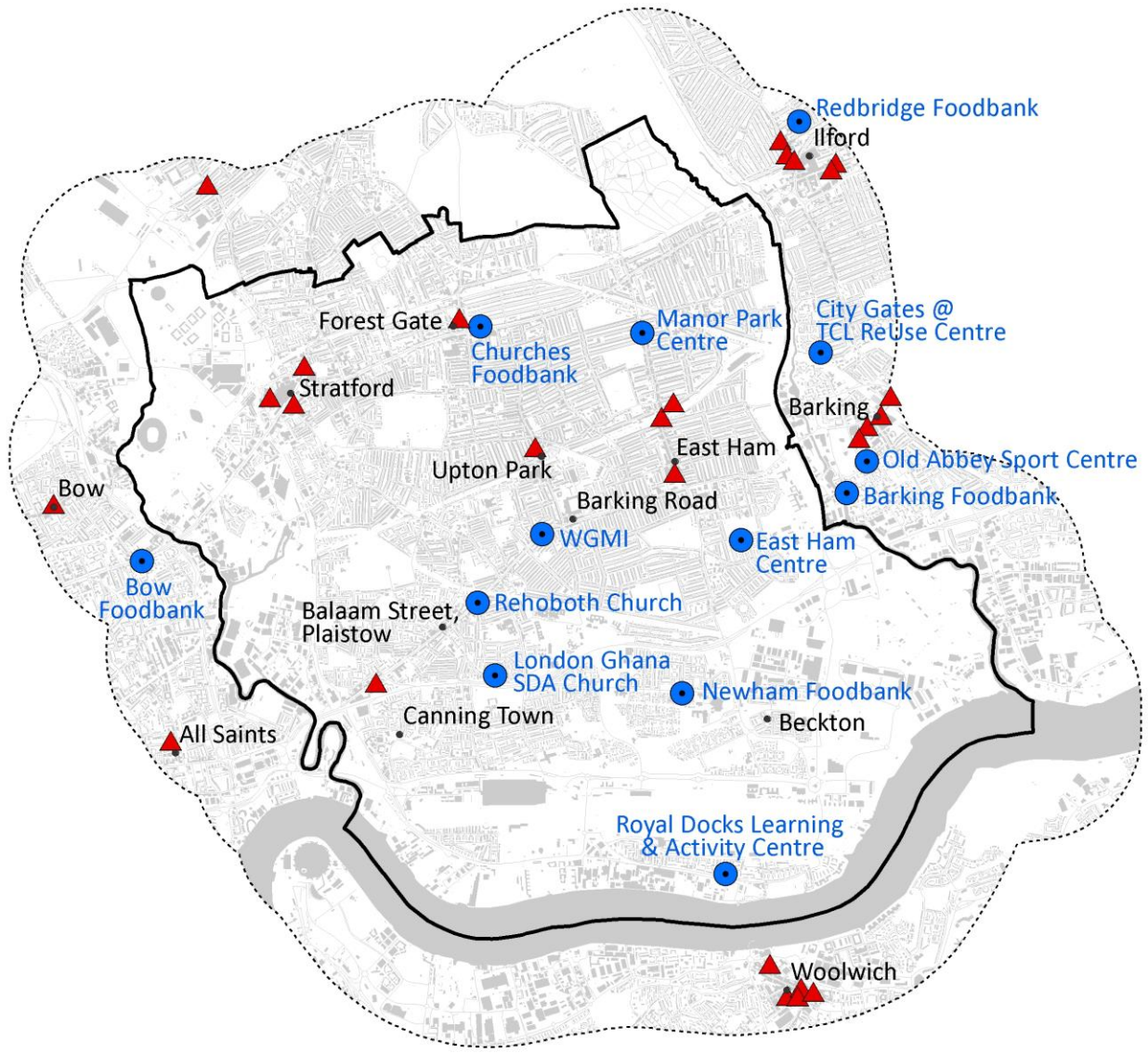
▲ Education institutions with students of 13-24 years



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Financial difficulties

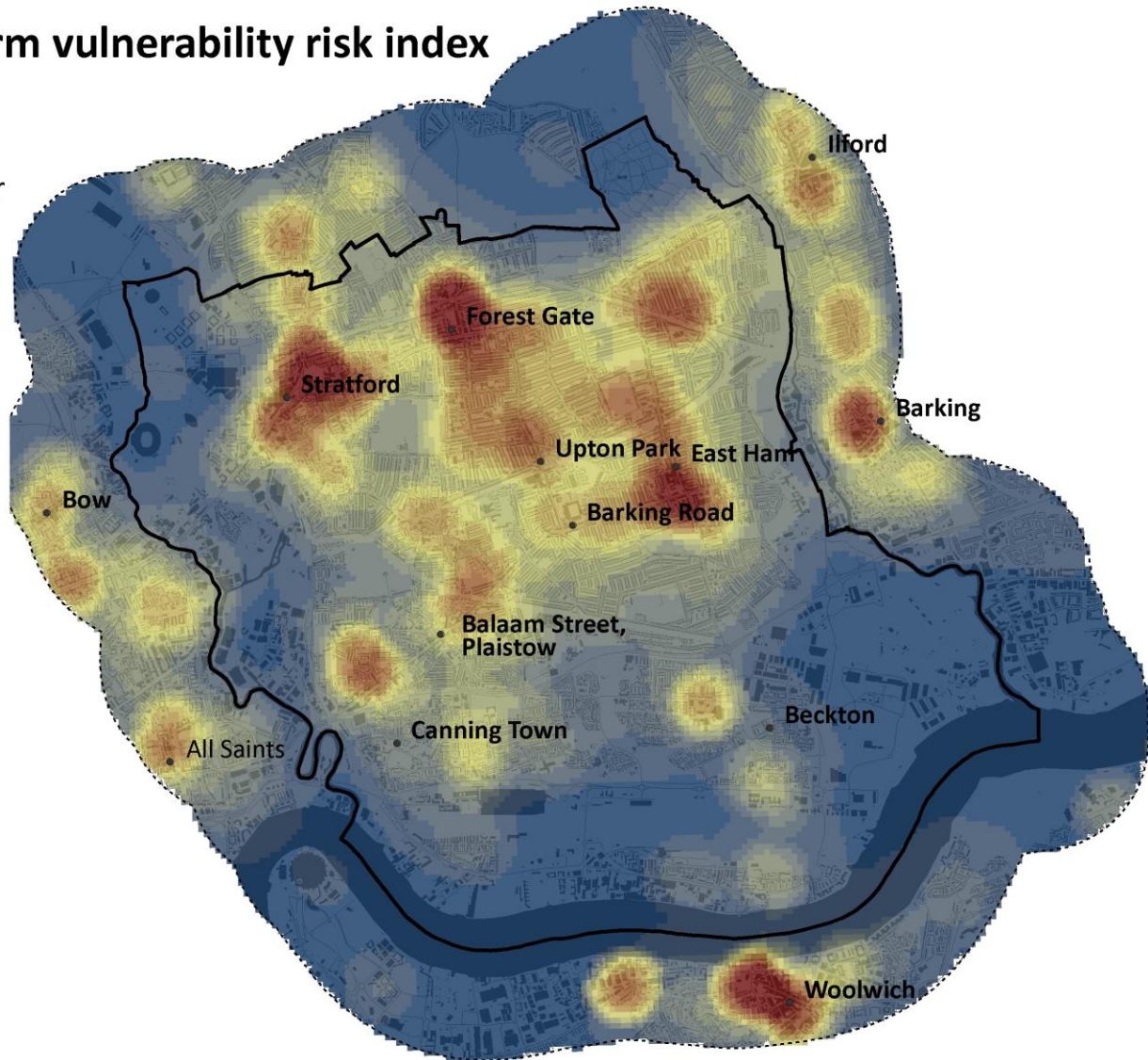
-  Newham Council boundary
-  Newham Council 1km buffer
-  Food banks
-  Loan shops



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Gambling related harm vulnerability risk index

- Newham Council boundary
- Newham Council 1km buffer
- Composite index
- less than 3.1
- 3.1 - 7
- 7.1 - 11
- 11.1 - 15
- 15.1 - 19
- 19.1 - 23
- 23.1 - 27
- 27.1 - 31
- 31.1 - 35
- 35.1 - 39
- 39.1 - 43
- 43.1 - 47
- 47.1 - 51
- 51.1 - 55
- more than 55



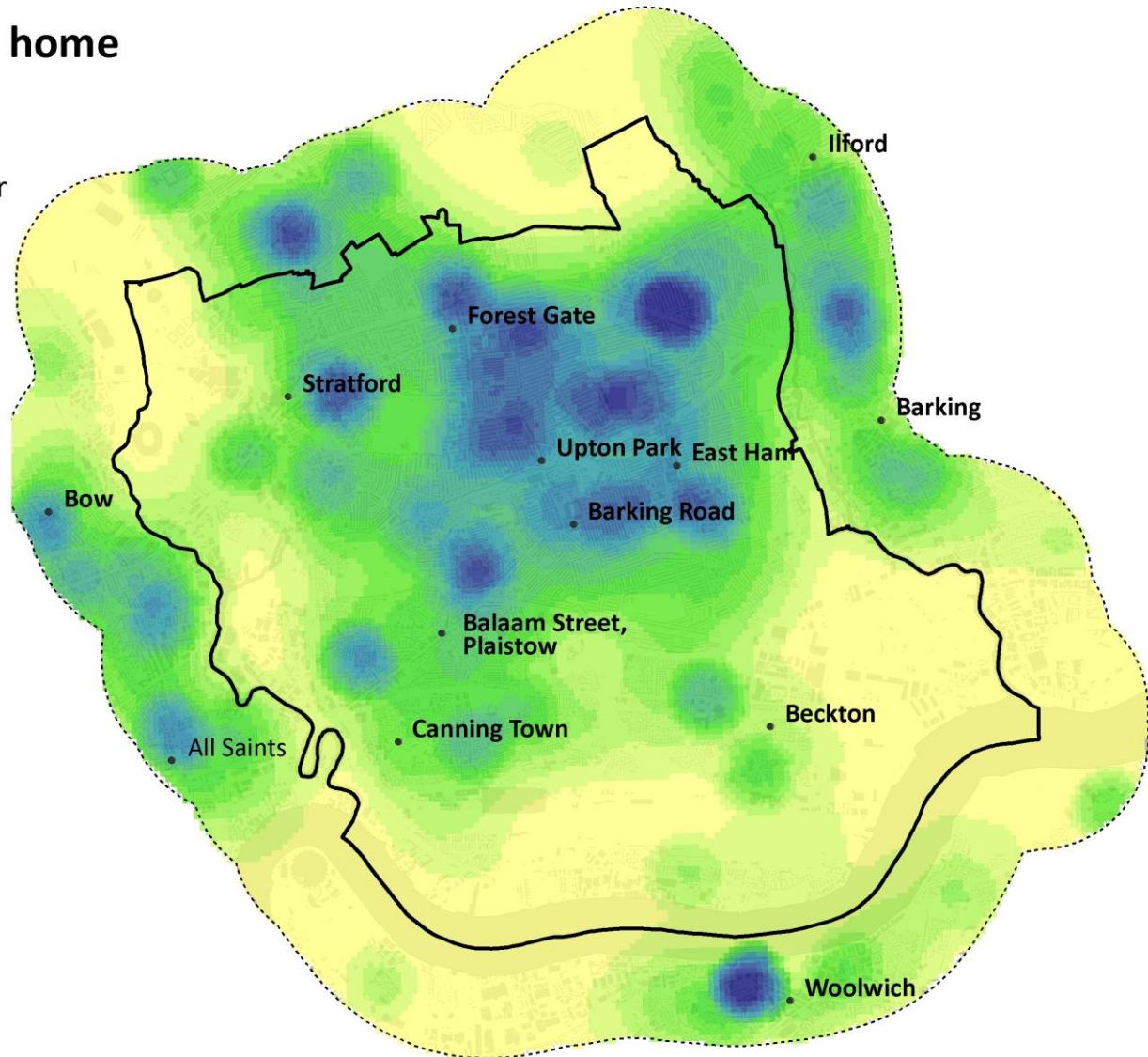
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Risk index: people at home

- Newham Council boundary
- ⋯ Newham Council 1km buffer

People at home index

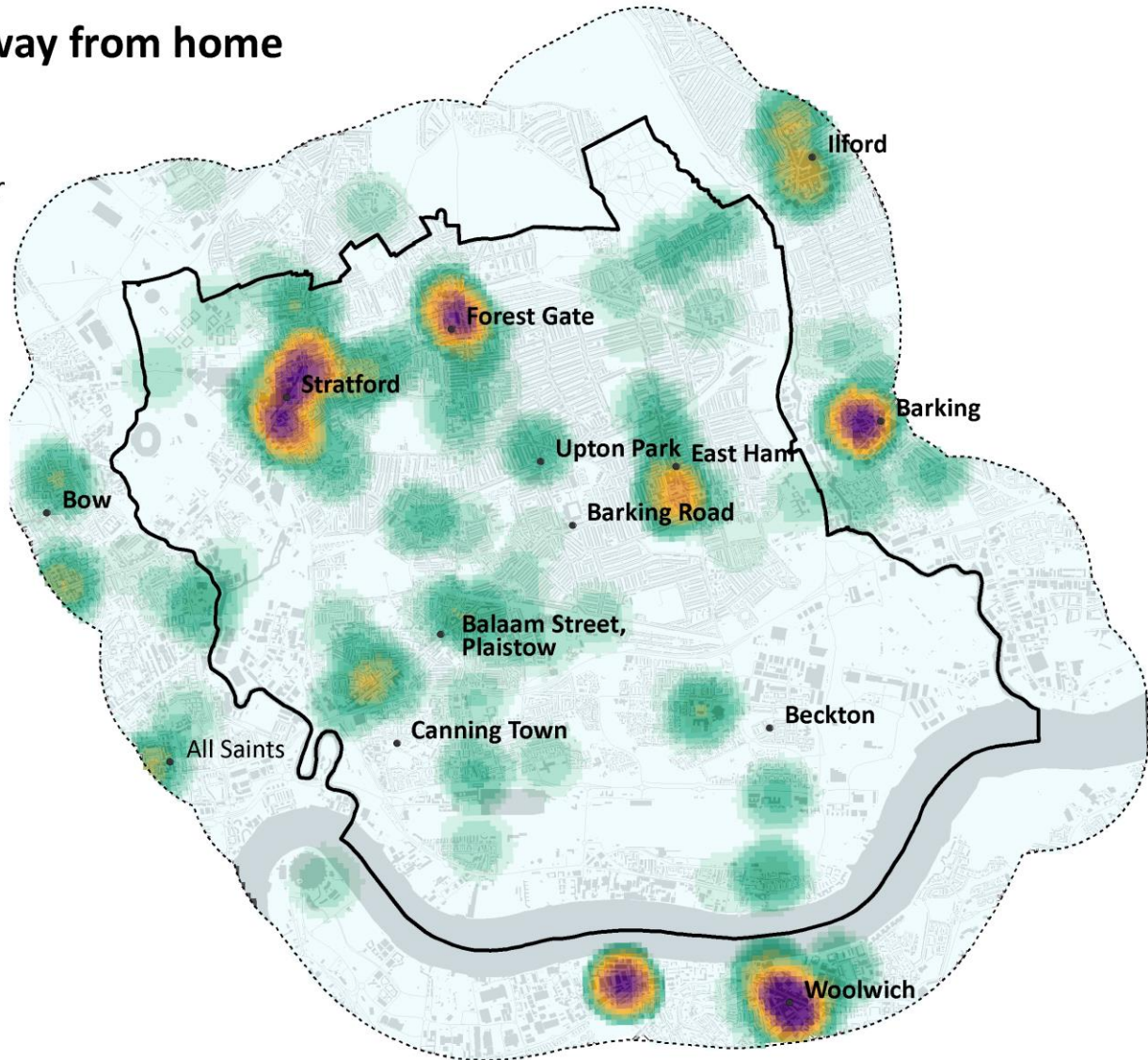
- less than 3.1
- 3.1 - 6
- 6.1 - 9
- 9.1 - 12
- 12.1 - 15
- 15.1 - 18
- 18.1 - 21
- 21.1 - 24
- 24.1 - 27
- 27.1 - 30
- 30.1 - 33
- 33.1 - 36
- 36.1 - 39
- 39.1 - 42
- more than 42



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Risk index: people away from home

- Newham Council boundary
- ⋯ Newham Council 1km buffer
- People away from home index
- less than 1.1
- 1.1 - 3
- 3.1 - 5
- 5.1 - 8
- 8.1 - 11
- 11.1 - 14
- 14.1 - 17
- 17.1 - 20
- 20.1 - 23
- 23.1 - 26
- 26.1 - 29
- 29.1 - 32
- 32.1 - 35
- 35.1 - 38
- 38.1 or more



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