Using geographically weighted regression to explore neighbourhood level predictors of domestic abuse in the UK.

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Abstract

Reducing domestic abuse has become a priority for both local and national governments in the UK, with its substantial human, social and economic costs. It is an interdisciplinary issue, but to date there has no research in the UK that has focused on neighbourhood level predictors of domestic abuse and their variation across space. This paper uses Geographically Weighted Regression (GWR) to model the predictors of police reported domestic abuse in Essex. Readily available structural and cultural variables were found to predict the domestic abuse rate and the repeat victimisation rate at the Lower Super Output Area (LSOA) level and the model coefficients were all found to be non-stationary, indicating varying relationships across space. This research not only has important implications for victims' wellbeing, but it also enables policy makers to gain a better understanding of the geography of victimisation, allowing targeted policy interventions and efficiently allocated resources.

Keywords

Geographically Weighted Regression, domestic abuse, deprivation, anti-social behaviour, social policy

Introduction

The human and economic cost of domestic abuse is extensive. In the UK two women a week die as a result of their abuse and the cost to society is estimated to be around £15.7 billion per year (Walby, 2009). Having the ability to identify those at higher risk of victimisation and being able to target resources and services to the right areas is fundamental for reducing its impact.

The definition of domestic abuse used in this research is the one used by the Home Office since April 2013. This recently revised definition recognises that abuse does not always involve physical violence and that abuse can occur in relationships under the age of 18. The definition is used by all police forces in England and Wales.

'Any incident or pattern of incidents of controlling, coercive or threatening behaviour, violence or abuse between those aged 16 or over who are or have been intimate partners or family members regardless of gender or sexuality. This can encompass but is not limited to the following types of abuse: psychological, physical, sexual, financial and emotional'. (Home Office, 2013).

To date the focus of research in the UK has been on individual level risk factors of abuse, where variables such as age, gender, ethnicity and repeat victimisation have been considered. There have been substantially fewer studies that have considered the geographic variation of abuse and predictors at the neighbourhood level. A recent systemic review of neighbourhood studies of interpersonal violence found most research was carried out in urban areas in the US, with no research from the UK (Beyer et al, 2015) and the only study from Europe focused on Spain (Gracia et. al, 2014). This paper starts to address this deficit in the literature, by predicting the rate of domestic abuse at the neighbourhood level and the variation in the relationship between predictors over space. Having this knowledge not only has academic benefits, but in a time of austerity the police and other agencies need more than ever to understand the geographical demand for their services, the varying needs of the population and the interventions that will have the most impact in reducing the harm of domestic abuse.

Neighbourhood level theory

Over the last twenty years the use of GIS to explore the spatial patterns of crime has expanded dramtically, both in academic research and by researchers working for the police and other agencies (Johnson, 2017; Newton and Felson, 2015; Weisburd; 2015; Boba Santos, 2013; Chainey and Tompson, 2008; Bottoms, 2007; Weir and Bangs, 2007; Chainey and Ratcliffe, 2005; Hirschfield and Bowers, 2003).

As might be expected, crime is not distributed randomly across neighbourhoods (Brunton Smith et al, 2013; Sampson, 2012; Bottoms, 2007; Sherman et al, 1989; Brantingham and Brantingham, 1981; Shaw and McKay, 1942). As with crime more generally, the Crime Survey in England and Wales (CSEW) (formally the British Crime Survey) suggests that the distribution of abuse victims is not even, with those living in the most deprived 20 per cent of areas more likely to be victims of domestic abuse than those in the least deprived areas, with 11.1 per cent of women and 4.8 per cent of men compared to 5.6 per cent of women and 3.0 per cent of men respectively (Flatley, 2016).

Of the studies conducted at the neighbourhood level the majority have used social disorganisation theory to explore the sociological influences of domestic abuse (Ackerson et al, 2008; Frye et al, 2008; Cunradi, 2007; Raghavan et al, 2006; Dekeserdey et al, 2003; Koenig et al, 2003; Browning, 2002). Social disorganisation theory, originally coined by Shaw and Mckay (1942), studies the relationship between crime and neighbourhood structural and cultural factors. Crime was found to increase in an area when there was a lack of social cohesion, with three key variables: population exodus, ethnic heterogeneity and low economic status found to be the strongest predictors (Shaw and Mckay, 1942).

A major criticism of Shaw and Mckay's theory was the lack of testing of the measures they theorised (Sampson and Groves, 1989) and it was probable that this was a factor in the decline in support for the theory over the next thirty years. One of the first academics to openly criticise the lack of clear discussion on the causal mechanisms of the theory was Ruth Kornhauser in her book 'Social Sources of Deliquency' (Bursik Jr, 1988; Kornhauser, 1978).

Central to Kornhauser's research was the notion of informal social control. It was theorised that disorganisation resulted in a lack of trust and cohesion in a neighbourhood, which reduced the ability for informal control to be exercised over disorderly youths and criminal behaviour, resulting in a higher rate of crime (Kornhauser, 1978; Wilcox et al., 2017). It was through Kornhauser's work that an interest in neighbourhoods' influence on the rates of crime was reignited. Her work inspired a number of scholars to attempt to revive social disorganisation theory under the new branding of the 'Systemic Model' (Bursik Jr and Grasmick, 1993; Hunter, 1985; Sampson and Groves, 1989).

Using the systemic model, Sampson and Groves (1989), were the first to test the causal mechanisms between structural characteristics and crime that had been set out in social disorganisation theory. They found that the theory successfully predicted self-reported crime, using data from the British Crime Survey (BCS) (Andresen, 2010; Sampson and Groves, 1989). The research also expanded Shaw and Mckay's model, finding that communities that had sparse friendship networks, unsupervised teenage groups and low participation in organisations had disproportionately high levels of crime, which they believed mediated the effects of neighbourhood level structural characteristics (Sampson and

Groves, 1989). The systemic model took a fundamental shift away from those perpetrating the crime to the positive influence of good people in the community (Wilcox et al., 2017).

Social disorgation theory was first conceived for crimes that take place in public spaces, such as burglary and robbery. Concern was expressed that the theory would not convert to domestic abuse as its private nature means it may be difficult for a community to recognise violence between partners as deviant and intervene (Browning, 2002). However, others have suggested that factors such as higher levels of disadvantage could impact levels of abuse as it may intensify stress between partners (Ross and Mirowsky, 2009) and increases the likelihood of violence (Pinchevsky and Wright, 2012; Wright and Benson, 2011;). Variation in neighbourhood level domestic abuse has been attributed to between neighbourhood differences in cultures of violence, access to services, neighbourhood environment, quality of housing and social isolation (Beyer et al, 2015).

There is conflicting historic research on the influence of population density on levels of crime within a community. Shaw and Mckay (1942) hypothesised that urban areas were less likely to have social control, compared to rural and suburban areas and therefore weaker social ties and friendship networks, resulting in lower levels of participation in local activities (Fischer, 1982) and community attachment (Wirth, 1938; Tonnies, 1887). This in turn, is argued to have a significant affect on ability of the community to control young people, which leads to crime and anti-social behaviour (Sampson and Groves, 1989). Other studies have found little support for the influence of population density, but rather argue that length of residency in an area is a far more appropriate measure (Kasarda and Janowitz, 1974). There has been little research on the influence of population density specifically on domestic abuse; the CSEW found little difference between the numbers experiencing abuse in urban and rural areas (Flatley, 2016), whereas another study from the US found the prevalence was higher in rural areas (Peek-Asa et al, 2011). Population density could influence the amout of abuse that is reported, with those with close neighbours less likely to be able to keep their abuse hidden, compared to those living in more spasely populated rural areas. The influence of population density on the amount of abuse in an area is therefore something that should be explored further and modelled.

Previous research has focused on relationships between variables at the macro level using traditional regression methods including logistic and multivariate regression (Waller et al, 2011; Reed et al, 2009; Stueve and O'Donnell, 2008; Raghavan et al, 2006; Lauritsen and Schaum, 2004; Benson et al, 2003; Van Wyk et al, 2003). What has been absent is a methodology that accounts for the variation in the strength of coefficients across the area. Tobler's First law of Geography states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970: 234). Sampson et al (2002) echo this sentiment with a call for new analytical techniques that display the connection between social and spatial processes, a method that factors in the premise that social behaviour is influenced not only by what happens in the immediate neighbourhood, but also in the surrounding areas. Understanding how relationships vary across space has clear policy implications, with the possibility of a far more targeted and appropriate response at the local level, rather than a blanket response for a whole jurisdiction. Geographically Weighted Regression (GWR) offers a methodology in which to explore this variation, and this is the approach taken in the present research. GWR has been used to explore a wide range of phenomena, ranging from mosquitos (Lin and Wen, 2011; Ge et al, 2016) to obesity (Chalkias et al, 2013; Wen et al, 2010), participation in Higher Education (Harris et al, 2010) and school attainment (Fotheringham et al, 2001). There have only been a small number of studies where GWR has been used to understand crime. When used as a method to study urban violence in Oregon, it was found that the coefficient values for single explanatory variables varied locally, with both postive and negative values (Cahill and Mulligan, 2007). Patterns of spatial heterogeneity and non-stationality were also found in three studies of burglary, with GWR finding local variation in socio-demographic and ecological explanatory variables (Chen et al, 2017; Zhang and Song, 2014; Malczewski and Poetz, 2005). For predicting the rate of theft, GWR improved the explanatory power of the model, using population density, road network and distance to police stations as predictors (Yan et al, 2010). Finally, in a study of all crime in Korea, the pattern was primarily spatial and a mixed GWR model was found to have the best fit, with a combination of global and local predictors (Lee et al, 2009). All of these studies found that using GWR improved the explanatory power of the model.

Geographically Weighted Regression

In a standard regression model, it is assumed that the value of the coefficient is the same everywhere in the study area and that the relationship between variables is spatially homogenous. In reality this is not always the case and attributes of spatial units closer together are often more similar than those which are further apart, this phenomenon is known as spatial heterogeneity (Fotheringham, 2009). In an Ordinary Least Squares (OLS) regression this causes problems because one of the assumptions made when using a global model is that the observations that are being used are independent. A measure of this is spatial autocorrelation, with positive spatial autocorrelation showing neighbouring spatial units to have similar values. It is not only the variables that might exhibit spatial dependence, but also the model's residuals, which might result in inefficient estimates of parameters with the standard errors being too large (Charlton and Fotheringham, 2009). Whilst econometric models such as a spatial lag or spatial error model will overcome the issues of spatial dependence, they do not address spatial heterogeneity (Fotheringham, 2009). Fotheringham et al (2002) suggest that it is possible that much of spatial autocorrelation found in the residuals of global models applied to spatial data are a result of trying to fit a global model to a process that is non-stationary. GWR on the other hand allows for spatially varying coefficients by producting estimates of the parameter at each data location, factoring in spatial heterogeneity.

In this paper I employ structural and cultural variables, to see whether domestic abuse can be predicted at the neighbourhood level. Using Social Disorganisation Theory as a framework variables from the Index of Multiple Deprivation will be used to test ecomomic factors; variables from the Vulnerable Localities Index and the rate of anti-social behaviour will test social cohesion; the proportion of the population that is from a Black, Asian and Minority Ethnic (BAME) population will be used as a measure of ethnic hetrogeniety; and population density will be used as a measure or rurality. The only measure that I am unable to test is population turnover, with census information only collected every ten years. By using GWR I am able to explore the geographical variation in the effects of these predictors and the implications these findings could have on the design of relevant and targeted early intervention policy.

Methodology

Data and Study Area

The data used in this analysis came from the Essex Police Protect domestic abuse database. This is a separate database recording only domestic abuse, both incidents of domestic abuse that were recorded but not classified as crimes and those that were converted to crimes. The dataset recorded details of the incident location, the date and time, details about the age, gender, ethnicity and address of both the victim and the perpetrator and the relationship between the victim and perpetrator. The data was acquired independently as part of a broader research project. This project required a data sharing protocol and ethnical approval. If replicating this work the data could be requested aggregated to the LSOA level.

The dataset recorded three addresses, the incident location and the address of both the victim and the perpetrator. In this analysis, the address where the incident took place has been used. Whilst the focus on this paper is on the risk factors associated with victimisation, so arguably the victim address should be used, the police force acknowledge that the victim and perpetrator address are not as reliable as the incident location. Reliability issues include not having up to date address information for those involved in the incident and also the fields not being completed as regularly as the incident location. Only 75 per cent of incidents had useable victim address coordinates, compared to 96 per cent of incident locations. Where both incident and victim coordinates were available 81 percent were recorded at the same location. The period of this analysis was from November 2011 to December 2014, which was the time from which a new database was introduced. It should be noted that domestic abuse is thought to be one of the most underreported crimes. The CSEW estimates that only 21 per cent of victims report their abuse to the police (Flatley, 2016). The data is therefore thought to only estimate around a fifth of all incidents.

Essex is a large single police force in the east of England, covering a population of 1.725 million. It is one of the largest non-metropolitan forces in the UK. It has a mixture of rural, urban and coastal areas with concentrated deprivation but also some very affluent areas. In 2016 it had a total recorded crime rate of 66.0 per 1000 population (compared to a England and Wales average of 71.9), and ranked 23rd out of the 43 police forces in England and Wales (Flatley, 2017)

Before the analysis was conducted the address data was coded. There were two sources of geographic reference in the data, the postcode or a police recorded grid reference. Every postcode was assigned a grid reference (based on the postcode centroid), if the field was missing the police assigned grid reference was used, if this was blank the address provided in the incident record was matched to a postcode and a grid reference. If the address information was insufficient then the record was disregarded from this analysis. Where the police assigned grid reference was used location accuracy was checked by a random sample of 100 incidents. All of the incidents were plotted and manually checked against the address or location information given. The LSOA layer was overlaid and all the points that were checked had been recorded in the correct LSOA. There were 91,396 records in total, of which 3.6 per cent had no useable geographic reference or the address was outside the force, leaving 88,135 records for this analysis.

A problem with neighbourhood level analysis is defining the geographic areas that are to be analysed. One of the issues with aggregating data is the Modifiable Areal Unit Problem (MAUP), where changing the boundaries can alter the observed patterns and relationships (O'Sullivan and Unwin, 2003). The analysis used census Lower Super Output Areas (LSOAs), as this is the lowest level of granularity available for the deprivation data. LSOAs are census geographies and have a population of around 1,500. Using administrative boundaries does have implications for research and policy, as it is unlikely that this is the way that residents will define their neighbourhood (Sampson et al, 2002), but whilst using geographically weighted regression does not solve the MAUP, it removes the issues of trying to model continuous spatial processes without acknowledging the connection between areas and making assumptions that the relationships between variables are non-stationary by using global models (Fotheringham et al, 2002).

Two issues have been found in using crime rate data based on aggregating small counts of crime data. Firstly, as the precision of the crime rate depends on the size of the population in the area of aggegation, varying population sizes will violate the assumption that the error variance is homogenous. Secondly, when crime rates are small or zero normally distributed errors cannot be assumed. In non-spatial analysis poisson and negative bionomial models have been used to address these problems (Osgood, 2000). In this analysis the issue of varying population sizes has been addressed by using LSOAs, which have very similar population sizes. The second issue of small or low counts is not a problem for this model, as domestic abuse is a relatively prevalent crime and there were only four LSOAs with a crime count of under ten and the lowest count value was five.

All of the spatial analysis was carried out in ArcGIS desktop 10.3.1 and the spatial statistics calculated in the Spatial Analyst extension. Logarithmic transformations were also calculated in ArcGIS. The ArcGIS software provides a user friendly environment in which to carry out the GWR analysis, but the interface does not offer all the functionality that can be found in open source software such as R. This research therefore not only explores the methodology in terms of its application in understanding domestic abuse, but also tests whether the functionality available in ArcGIS is suitable for understanding non-stationality in crime predictors at low levels of geography.

<u>Model variables</u>

Table 1: Dependent and independent variables

Variable name	Mean	SD	Range	
			Minimum	Maximum
Dependent variable				
Domestic abuse rate (per 1000 population)	50.51	39.44	3.47	405.77
Victim rate (per 1000 population)	16.25	13.38	1.39	132.57
Independent variables				
Anti-Social Behaviour rate (per 1000 population)	30.60	31.05	3.50	386.74
BAME (%)	6.56	5.83	0.47	46.75
Young people aged 15-24 (%)	11.74	3.88	3.99	76.88
IMD income score	0.13	0.08	0.014	0.564
IMD health score	-0.37	0.76	-2.536	2.752
IMD education score	24.39	16.30	0.711	98.358
IMD employment score	0.10	0.06	0.012	0.568
IMD barriers score	21.68	9.38	1.785	57.29
IMD living environment score	14.09	10.73	0.45	71.692
Burglary rate (per 1000 population)	18.26	11.68	0	87.63
Criminal damage and arson rate (per 1000 population)	7.99	7.40	0	68.41
Population density	32.63	26.24	0.3	145.0

Note. N=1077

Dependent variables

The dependent variable for the first model was the domestic abuse rate per 1000 population by LSOA (using 2011 LSOA boundaries). The rate per 1000 population is the measure that Home Office uses to compare police force areas. This was calculated by aggregating incident data into LSOAs using ArcGIS and converting to a rate per 1000 population using mid year 2013 population estimates (to standardise the data). The rate of incidents, rather than rate of victimisation has been used to factor in the repeated nature of domestic abuse as it measures the increasing threat of harm (Walby et al, 2016) and the response required from the police.

In spatial analysis, a linear GWR, which allows non-stationality to be considered, requires that the dependent variable, independent variables and the error terms have a gaussian distribution (Fotheringham et al, 2002). The domestic abuse rate data showed a skewed distribution, so a logarithmic transformation was carried out, which normalised the data. As there were no zero values a natural logarithmic transformation was possible. As both the dependent and independent variables were transformed it should be noted that the interpretation of the model will be multiplicative.

The second model brings in repeat victimisation and measures the number of repeat individual victims per 1000 population by LSOA, rather than the number of incidents. Studying repeat victimisation will factor in potential interjurisdiction difference in crime rates caused by one victim reporting multiple incidents (Mukherjee and Carcach, 1998). Brimicombe (2016) found that the repeat victimisation flags used by the police are unreliable, with inadvertent errors and a lack of consistency. Essex Police also reported that this field is not reliable and always completed. Therefore, a methodology, similar to the rolling month approach that Brimicombe used was adopted. The only marked difference was that a six-month time window was used, rather than a year. This was to optimise the amount of data that could be used in the analysis (to ensure that counts were not too low at the LSOA level) and was informed by research from the British Crime Survey that suggested that domestic abuse victims experience on average 20 incidents a year (Walby and Allen, 2004), therefore suggesting six months should be sufficient. The data was divided into three-time periods; December 2011 – April 2012 was the pre-analysis period; May 2012- June 2014 the analysis period; and July – December 2014 the post analysis period. The number of incidents across the whole-time period including the pre and post analysis period was calculated for each victim (using the unique victim identifier) who reported an incident during the analysis period. This allowed a six-month window either side for a repeat to occur. If more than one incident was reported the incident was classified as a repeat. The number of repeat incidents was then calculated for each LSOA and converted to a rate per 1000 population. As there were a small number of LSOAs that did not experience any repeat victimisation, it was not appropriate to use a natural log transformation to normalise the data, so an inverse hyperbolic sine function was used in Stata instead. The number of incidents that each victim experienced is shown in table 2. One victim had experienced 128 incidents within the time frame. The median number of incidents was two.

Table 2: Number of incidents experienced by each victim

Number of incidents	Number of victims
1	23752
2	5511
3	2205
4	1132
5-9	1526
10-19	240
20+	22

N=58,904

Independent variables

The rate of domestic abuse in an area was estimated using explanatory variables based on social disorganisation theory, measures of community cohesion and population density. All variables were log transformed to normalise the distribution and aid interpretation.

Measures of community cohesion included the level of anti-social behaviour (ASB). This was measured using Essex police ASB data for 2014. The data was aggregated and converted to a rate per 1000 population at the LSOA level. Another measure of cohesion is the Vulnerable Localities Index (VLI). The VLI is used to identify residential neighbourhoods that require prioritised attention for community safety and has been used to understand issues such as riots. Analysis of reporting for other crime types has shown there to be a slight increase in reporting in areas where there is increased social cohesion and lower levels of reporting in areas where there is the highest level of socio-economic disadvantage (Tompson, 2011). The VLI is a composite measure that is calculated using six variables, and can be applied in any country where access to accurate data on these variables exists. The six variables are: Counts of burglary dwelling, counts of criminal damage to a dwelling, income deprivation score, employment deprivation score, count of 15-24 year old and educational attainment. Data for 2013 was used to calculate the VLI score and for the purposes of the analysis the data was disaggregated into the separate variables. Population density (persons per hectare) was calculated by dividing the population in each LSOA, using 2011 census data by the area (by creating a new field and using the calculate geometry option).

Social disorganisation theory was included in the analysis using deprivation and ethnicity data. The English Indices of Deprivation 2015 provide a relative measure of deprivation at small area level across England (LSOA) (Gov.uk, 2016). Areas are ranked from least deprived to most deprived on seven different dimensions of deprivation and an overall composite measure of multiple deprivation. The domains used in the Indices of Deprivation 2015 are: income deprivation; employment deprivation; health deprivation and disability; education deprivation; crime deprivation; barriers to housing and services deprivation; and living environment deprivation. The crime domain was excluded from this analysis as crime data was another variable in the Vulnerable Localities index. The proportion of the population from BAME populations (as a measure of ethnic hetrogeniety), in each LSOA was calculated using 2011 census data.

Geographically weighted regression

As a linear GWR is to be used in this the analysis, the starting point for each model was to run an OLS regression so that a single equation can be generated for the global model.

$$Y = \beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + \ldots \beta_k\chi_k + \varepsilon$$

The GWR extends this equation by generating a separate regression equation for every LSOA in the study area. The GWR equation is:

$$Y = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)\chi_{i1} + \beta_2(u_i, v_i)\chi_{i2} + \cdots \beta_k(u_i, v_i)\chi_{ik} + \varepsilon_i$$

where (u_i, v_i) represents the coordianates of the ith point in space. The weight assigned is based on a distance decay function centred at location i and observations nearer to i are given greater weight than observations further away. The distance decay function is modified by the bandwidth setting, which is the distance at which the weight rapidly approaches zero (Harris, 2016; Gilbert and Chakraborty, 2010; Charlton and Fotheringham, 2009; Fotheringham et al, 2002).

Results

Geographically Weighted Regression

Several models were run using OLS and GWR to explore the predictors of the domestic abuse rate at the LSOA level. The initial models looked at individual predictors, to see the value that they had on their own (see table 3 for the variables that offered the greatest explanation for the rate of domestic abuse), and then more variables were added (and removed if they reduced the fit of the model). Although the R-squared values were relatively high by just using one variable, the Moran's I test indicated that the ASB rate and the population density standardised residuals showed negative autocorrelation, indicating a dispersered pattern, with less that a 10 per cent likelihood that the pattern could be a result of random chance. This therefore meant that the models for these variables violate the basic assumption of independence of data that is needed by GWR. The income score, employment score and proportion of BAME on the other hand had Moran's I results that were not statistically significant, indicating a random distribution of the standardised residuals.

The Exploratory Regression tool was used in the Spatial Statistics toolbox to add more variables to the models. This data mining tool tries all possible explanatory variables to see which models pass all of the OLS diagnostic tests. The tool not only identifies the highest R square values, but reports on all the potential model violations.

Table 3: Coefficient values for the top individual predictors run as separate models with the rate of domestic abuse as the dependent variable.

	OLS			GWR			
Model	Coefficient	R2	AIC	Min	Max	R2	AIC
Model 1 Income score (IMD) (log)	0.80*	0.63	1223.9	0.11	1.41	0.73	990.0
Model 2 Employment score (IMD) (log)	1.00*	0.62	1262.9	0.13	1.79	0.74	990.4
Model 3 ASB rate (log)	0.77*	0.61	1297.6	0.31	1.17	0.70	1185.0
Model 4 % BME (log)	0.44*	0.23	2020.1	-0.31	1.74	0.50	1657.4
Model 5 Population density (log)	0.20*	0.16	2117.0	-0.73	0.87	0.44	1809.19

Note. N=1077. *p <.05. Moran's I - OLS: Income Score 0.16 (p=0.000); Employment score 0.20 (p=0.000); ASB rate 0.09 (p=0.000); % BME 0.26 (p=0.000); Population density 0.21 (p=000). Moran's I - GWR: Income Score -0.01 (p=0.31); Employment score -0.01 (p=0.14); ASB rate -0.02 (p=0.063); % BME -0.014 (p=0.15); Population density -0.18 (p=0.067). GWR bandwidth (using optimal AIC method) = Income score 47 neighbours; Employment score 37 neighbours; ASB rate 67 neighbours; % BME 42 neighbours; Population density 38 neighbours.

The good of fitness of each model was assessed with the Akaike Information Criterion (AIC), the smaller the value of the AIC, the better the fit of the model to the observed data (Harris, 2016). When considering the same independent values, the AIC value was higher for all OLS models compared to the GWR models. Furthermore, the R-squared value either improved or stayed the same in the GWR models. The GWR model with the best fit had an R-squared value of 0.82 with independent variables of the ASB rate, proportion of BAME, population density and income score. Including the employment score did lead to a R-squared value in the OLS model, but the GWR model failed because of multicollinearity, a result of a high Variance Inflation Factor (VIF) caused by adding the employment score variable.

Table 4: Coefficient values for final neighbourhood model (for OLS and GWR)

	OLS		GWR	
Variable	Coefficient	VIF	Minimum	Maximum
Anti-Social Behaviour rate (log)	0.32*	2.31	0.137	0.433
Proportion BAME (log)	0.11*	1.56	0.053	0.367
Income score (IMD) (log)	0.52*	1.90	0.288	0.723
Population density (log)	0.08*	1.28	0.019	0.147
Intercept	0.88*		1.8122	2.2407

Note. N=1077. *p <.05. AIC = 638.2 (OLS), 581.8 (GWR). R-square = 0.79 (OLS), 0.82 (GWR).

GWR bandwidth = 248 neighbours (using optimal AIC method). Moran's I = 0.0433 (p=0.000) (OLS), -0.0004 (P=0.95) (GWR)

Table 4 gives the coefficient values for the model that demonstrated the best fit. For the global OLS model the coefficients are all statistically significant and income is the biggest predictor of the domestic abuse rate, followed by the ASB rate, with a 1 per cent increase in the income score seeing a 0.52 per cent and 0.32 per cent increase in the rate of domestic abuse rate respectively, when holding all other variables constant.

The proportion of BAME population and the population density was also a statistically significant predictor, with higher rates of abuse taking place in more densely populated areas. What is not clear is whether this is because abuse is less likely to take place in rural areas or whether people are less likely to report it due to geographic isolation, which might hide violence and prevents interaction to stop it (Beyer et al, 2015).

The Moran's I score indicates that the OLS model residuals suffers from significant spatial autocorrelation. However, using GWR overcomes this issue, with the Moran's I score in the GWR model residuals suggesting that the pattern does not appear to be significantly different from random. The GWR outputs for this model had a condition number that was less than 30, meaning the results are reliable without strong collinearity. Models were run with smaller bandwidths, but these reduced the model fit, which increased the AIC value and the model condition numbers. Using just single variables in the model, such as the income score reduced the bandwith (the number of neighbours), but there then has to be a tradeoff with the model fit. The VIF for each coefficient was small and therefore did not suggest multicollinearity.

The coefficients of the GWR model in table 4 were mapped (figure 1). The relationship between the domestic abuse rate and the all of the independent variables was not consistent (stationary) across Essex, suggesting that there are other spatial processes at work, something that is supressed in a global model. All of the GWR coefficient values were positive, so the relationship is always in the same direction as the global model, but with significant variation on the coefficient values. The potential process influencing this result could include particular localised policies, variations in police reporting, reporting to other services, other characteristics of the neighbourhood or variations in wellbeing and community engagement. Further research is needed to investigate these possibilities.

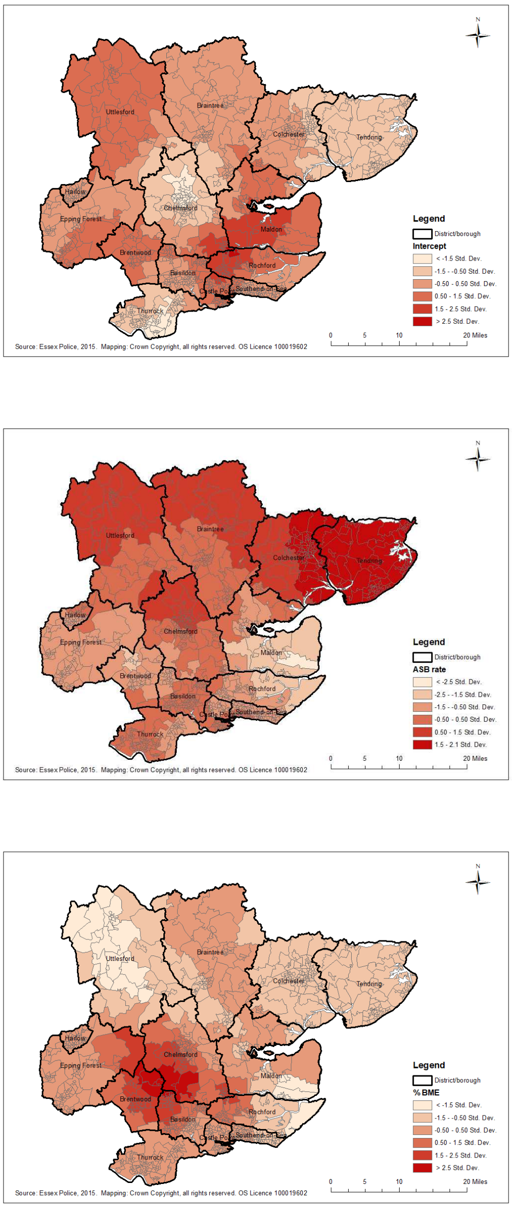
The influence of ASB is stronger in the east and north of the county. When holding all other variables constant, a 1 per cent increase in the ASB rate would see a 0.43 per cent increase in the domestic abuse in the areas shaded the darkest on the maps, compared to a 0.14 per cent increase in the lightest shaded areas. This suggests that further investigation is need into the underlying causes of ASB in an area (as this is not a causal model), to see whether these offer further explanation on the variation in the relationship with domestic abuse across space.

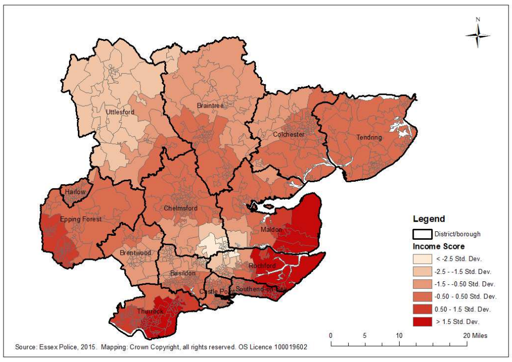
A 1 per cent increase in the proportion of the BAME population saw a between 0.05 and 0.37 per cent increase in the domestic abuse rate, with highest coefficient values in the Chelmsford, Brentwood and Basildon areas. Perhaps this is indicative of reporting patterns by different ethnicities, with previous research finding that the recognition of abuse and propensity to report varies by ethnicity, with the black Caribbean population having the highest level of recognition and black African the lowest (Mooney, 2000). Further exploration of this relationship could be useful in designing and targeting campaigns to increase the recognition of abuse and the understanding about where to report in amongst particular ethnic groups.

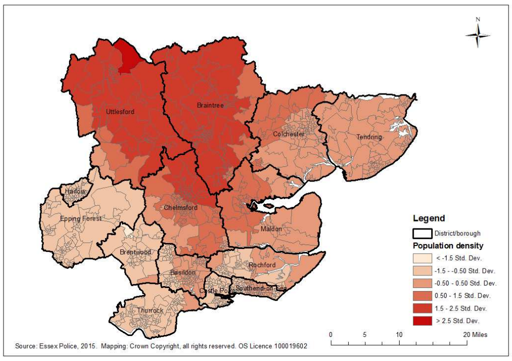
Overall income is the most influential variable in the model, but it is also the variable that shows the greatest range in coefficient values. Holding all other variable constant a 1 per cent unit change in the income score sees an increase in of between 0.29 per cent and 0.72 per cent in the domestic abuse rate, with the influence of income highest in the south and south east and lowest in Uttlesford and the south east of Chelmsford. The areas with the lowest coefficient values are some of the most affluent parts of Essex, which suggests that effect of income on the domestic abuse rate is not as pronounced in the more affluent areas and that other variables have more influence in these areas.

The overall influence of population density is small, with a 1 per cent rise seeing an increase of between 0.02 percent and 0.15 percent in the domestic abuse rate. The coefficient values are higher in the north east of the county. These are areas that are predominantly rural.

Figure 1: Coefficient maps for domestic abuse rate model

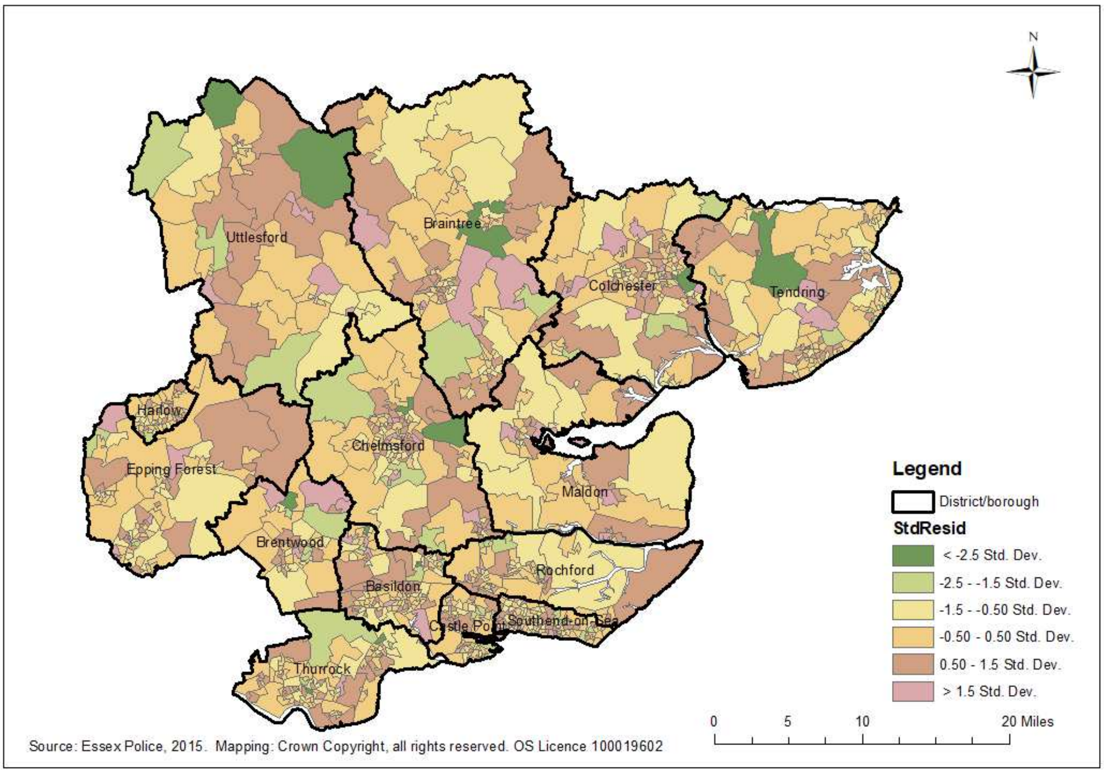






Mapping the standard residuals from the GWR models enables the model performance to be viewed geographically. The pink areas are those where the model underestimates the amount of domestic abuse in an area, and the green where it over predicts (figure 2).

Figure 2: Standard residuals of the neighbourhood model, N= 1077 LSOAs



The second model had the best fit when using the same predictors as the first model (table 5), although the overall explanatory power of the variables was lower that the first model, with an r square of 0.70 for the GWR model (compared with 0.82 for the first model). This indicates that some other factors need to be considered when focusing on repeat victimisation. Like the first model, all the OLS variables were significant. Again, the income score was the strongest predictor, followed by the rate of ASB, population density and the proportion of BAME population. The coefficients were all non-stationary and exhibited very similar distributions to the first model (see Appendix for the coefficient maps), although unlike the first model some of the coefficient values for the proportion of BAME exhibited small negative values, with the proportion of BAME population decreasing the repeat victimisation rate in a small number of areas.

Table 5: Coefficient values for the repeat victimisation model (for OLS and GWR)

	OLS		GWR	
Variable	Coefficient	VIF	Minimum	Maximum
Anti-Social Behaviour rate (IHS)	0.34*	2.31	0.039	0.521
Proportion BAME (log)	0.11*	1.56	-0.026	0.450
Income score (IMD) (log)	0.65*	1.90	0.407	0.899
Population density (log)	0.14*	1.29	0.008	0.259
Intercept	-0.02		-0.693	0.687

Note. N=1077. *p <.05. AIC = 1735 (OLS), 1705 (GWR). R-square = 0.67 (OLS), 0.70 (GWR).
GWR bandwidth = 280 neighbours (using optimal AIC method)).. Moran's I = 0.0327 (p=0.000) (OLS), -0.0006 (P=0.97) (GWR)

Discussion and implications

The particularly significant finding from this analysis is that domestic abuse can be predicted at the neighbourhood level using easily accessible structural and cultural variables. Income and anti-social behaviour are the strongest predictors of abuse in both the overall domestic abuse rate and the rate of repeat victimisation. The GWR model provides a powerful predictor of the domestic abuse rate, explaining on average 82 per cent of the variability in the dataset, the repeat vicitimisation rate is weaker, but still explains 70 per cent of the variability. The model results echo the findings of the CSEW that reported domestic abuse is more prevalent in deprived areas. These findings support the view that a social policy response to domestic abuse is needed to tackle broader issues that lead to deprivation and a break down in community cohesion, rather than just using the criminal justice system to react to incidents of domestic abuse.

The ASB rate in an area explains a staggering 70 per cent of the overall domestic abuse rate and is consistent with the modest to strong interdependence that Sampson (2012) found between perceived disorder and other neighbourhood factors. A previous link has been identified between reports of anti-social behaviour and domestic abuse in housing research, with 40 per cent of tenants who have suffered domestic abuse having had complaints made against them for ASB (Jackson, 2013). This is an important finding, with several policy implications. Firstly, domestic abuse is one of the most underreported crimes, with only around 21 per cent thought to be reported to the police (Flatley, 2016) and therefore the anti-social behaviour rate in an area could act as a proxy for the amount of domestic abuse. Secondly anti-social behaviour is also a top priority for Essex Police, so it is possible that a policy intervention that looks at both issues and explores the root causes, rather than treating them separately could be more successful.

The analysis has shown how much value a GWR model can add to understanding the relationship between the dependent and independent variables. Although a prediction and set of coefficients is available for each LSOA, the most value in policy terms is from the sub-regional coefficient clusters. For instance, ASB has a much higher coefficient value in the east of Essex. In policy terms the analysis would suggest that this is where you would focus further research and design a relevant response to ASB and domestic abuse. If resources are limited then a more targeted focus on ASB in the east may have more impact than a more dilute county wide initiative. The initiative does not have to fit rigidly to district or borough boundaries, but could follow the cluster boundaries instead. Using GWR will offer a clear way in which to evaluate the impact of any localised policies.

A limitation to this analysis is that domestic abuse is one of the most underreported crimes and assumptions have been made that the level of underreporting is consistent across neighbourhoods. Targeting resources to these hotspots assumes that the unknown cases of domestic abuse share the same geographical distribution and characteristics. Further analysis is therefore needed as it could be that this analysis is accentuating the issue in deprived areas and under reporting is more concentrated in more affluent areas or in areas where there is a variation in access to services. One way in which this could be done, would be to replicate the model with data from other agencies where abuse could be reported. This could include health data, charities, such as Victim Support and court data. Other neighbourhood studies have used survey data, but unfortunately the sample size for the LSOA at the neighbourhood level is too small. Access to services could be modelled using points of interest data.

Sampson et al (2002) question whether disorder is an explanatory mechanism or an outcome of the issues of simultaneity bias; this research is unable to answer this question as GWR does not produce a causal model. Previous research has found neighbourhood level concentrated socioeconomic disadvantage to be a precursor to violence and causes of other behaviours that influence violence, including physical and social disorder (Beyer et al, 2015; Browning, 2002; Van Wyk et al, 2003). Whilst exogenous characteristics, such as income, are known to effect an individual's risk of domestic abuse (Koenig et al, 1999; O'Campo et al, 1995), clustering was still found to be present when controlling for household and individual risk factors (Counts el al, 1999), which suggests that endogenous social effects must be at work (McQuestion, 2003). The broken windows thesis (Wilson and Kelling, 1982) supports the notion that anti-social behaviour and violent crime are linked (Boggess and Maskaly, 2014), however it has been argued that such theories fail to capture a causal link between crime and anti-social behaviour, and that crime and disorder manifest themselves when neighbourhoods lack collective efficacy (Sampson and Raudenbush, 1999). This warrants further research so that a policy response aimed at the root causes can be designed.

The method employed in this research only considers the concentration at the LSOA level; of course, the distribution within the LSOA may not be spatially homogenous. Making assumptions that everyone shares the same risk could create an ecological fallacy (Robinson, 1950). The methodology does not factor in the varying nature of abuse and the risk assigned to the different incidents, although the second model that focuses on repeat victimisation recognises those areas where domestic abuse is more than a one- off incident for the victim (in terms of reporting). In an aspatial application a multilevel model could be used to separate the individual and contextual effects, but this method implies the nature of relationship is discontinuous, and therefore would not identify the non-stationary relationships that GWR does (Fotheringham, 2002). A more recent methodology, hierarchical spatial autoregressive modelling, has been used to investigate the spatial dependence of land prices, so future work could explore the application of this methodology to personal and contextual characteristics as predictors of domestic abuse (Dong and Harris, 2015).

The use of ArcGIS placed some constraints on the scope and available approaches for this analysis. Crime data tends to have a skewed distribution and whilst tranforming the data overcame this issue, it would be interesting to compare the results with those from models that are preferred for non-gaussian distributions such as Geographically Weighted Possion Regression (GWPR) (Nakaya et al., 2005), which has been used with count data. Another method developed by Silva and Rodrigues (2014) is Geographically Weighted Negative Binomial Regression (GWNBR). This methodology has been used to overcome issues over overdispersion that have been found in poisson regression models. Unfortunately ArcGIS currently only offers the basic linear GWR. Using the GWPR or GWNBR could overcome the issue created by having zero values in the repeat victimisation model, where the logarithmic transformation offered in ArcGIS was not possible and Stata therefore had to be used to transform the data using a inverse hyperbolic sine function.

Whilst there are some limitations, this analysis has important findings and implications for social policy. It has been possible to predict the rate of domestic abuse in an area to a high degree of accuracy using data that is readily available online. A significant finding has been the variability in the coefficient values over space. In terms of social policy and criminal justice interventions this means that localised policy interventions can be designed, rather than using blanket regional or national approaches, which in a time of austerity will aid the allocation of resources to the most appropriate policies. There are real operational benefits to this methodology and a recommendation would be to explore its application with other social issues and to test it in other areas.

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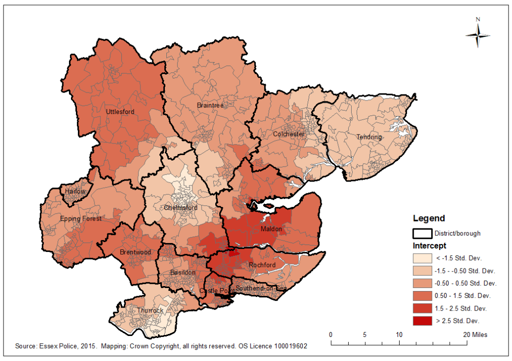
Appendix



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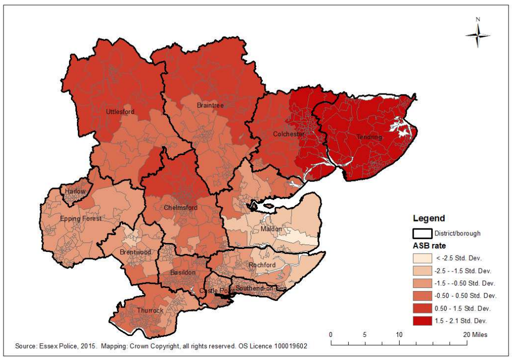
Source: Essex Police, 2015. Mapping: Crown Copyright, all rights reserved. OS Licence 100019602



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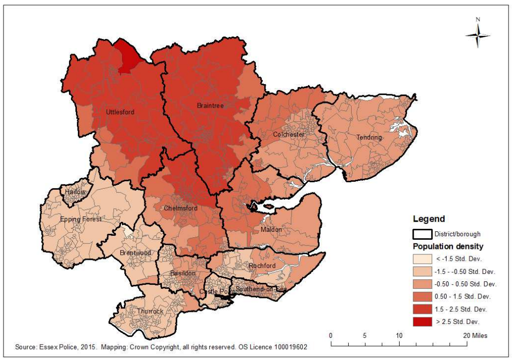
Source: Essex Police, 2015. Mapping: Crown Copyright, all rights reserved. OS Licence 100019602



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District/borough
Population density
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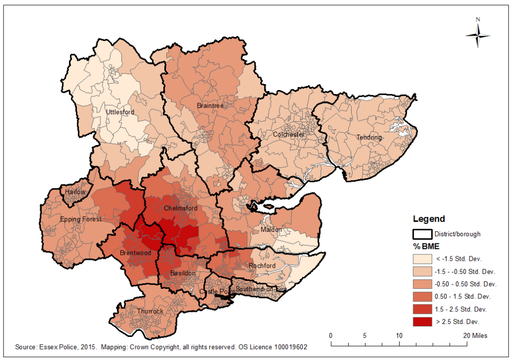
Source: Essex Police, 2015. Mapping: Crown Copyright, all rights reserved. OS Licence 100019602



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District/borough
% BME
< -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev.
0.50 - 1.5 Std. Dev.
1.5 - 2.5 Std. Dev.
> 2.5 Std. Dev.
0 5 10 20 Miles
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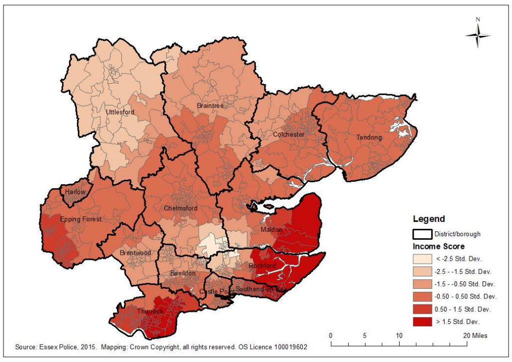

N
Uttlesford
Braintree
Colchester
Tendring
Harlow
Epping Forest
Chelmsford
Maldon
Brentwood
Basildon
Rochford
Thurrock
Legend
District/borough
Income Score
< -2.5 Std. Dev.
-2.5 - -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev.
0.50 - 1.5 Std. Dev.
> 1.5 Std. Dev.
0 5 10 20 Miles
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