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RESEARCH ARTICLE

Diversity and burglary: Do community differences matter?

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Abstract

Diversity within a population has been linked to levels of both social cohesion and crime. Neighborhood crimes are the result of a complex set of factors, one of which is weak community cohesion. This article seeks to explore the impacts of diversity on burglary crime in a range of neighborhoods, using Leeds, UK as a case study. We propose a new approach to quantifying the correlates of burglary in urban areas through the use of diversity metrics. This approach is useful in unveiling the relationship between burglary and diversity in urban communities. Specifically, we employ stepwise multiple regression models to quantify the relationships between a number of neighborhood diversity variables and burglary crime rates. The results of the analyses show that the variables that represent diversity were more significant when regressed against burglary crime rates than standard socio-demographic data traditionally used in crime studies, which do not generally use diversity variables. The findings of this study highlight the importance of neighborhood cohesion in the crime system, and the key place for diversity statistics in quantifying the relationships between neighborhood diversities and burglary. The study highlights the importance of policy planning aimed at encouraging community building in promoting neighborhood safety.

1 | INTRODUCTION

The measurement of crime is necessary for any quantitative assessment of crime policy change (Ludwig & Marshall, 2015). Knowledge of how crime patterns are distributed over space can also enhance the effectiveness of police operations and collective community programs such as Neighbourhood Watch in the UK (Brunsdon, Corcoran,

& Higgs, 2007). For example, local knowledge of where crime is clustered will increase the capacity of the police to employ prevention measures, thereby improving the safety of communities (Bruce & Santos, 2011; Moore & Trojanowicz, 1988). Therefore, urban and regional planners, policy makers, and policing agencies have all recognized the importance of better understanding the dynamics of crime (Murray, McGuffog, Western, & Mullins, 2001). A common method of understanding both short-term crime and its longer-term drivers is through correlation with socio-economic and demographic factors in the areas where it occurs, an important component of environmental criminology (Andresen, 2014). Socio-economic and demographic factors such as wealth disparity, education attainment, proportion of young people, and deprivation are commonly found to correlate with crime rates in urban areas (Bandyopadhyay, Bhattacharya, & Han, 2010). Such variables act as proxies for, or direct measures of, the underlying causes of crime in a system that links offender drivers, victim lifestyles, and environment-related opportunities. However, the accuracy and representativeness of variables that act as proxies vary considerably, and many variables, such as metrics of multiple deprivation, could be seen as "catch-all" variables that encompass a wide variety of underlying factors. Additionally, traditional operationalizations of socio-demographic variables used when exploring explanations for neighborhood variation in crime rates do not measure diversity, and traditional measures of diversity in the crime context do not cover diversity across those various socio-demographic dimensions. The term "diversity" describes the level of variety in racial or ethnic composition, age, gender, religion, philosophy, physical abilities, socio-economic background, and sexual orientation among a group (Goodin, 2014, p. 7).

In this article, we will suggest that the treatment of standard regression variables can be adjusted to better capture a range of loci in which diversity plays a part across the crime system. In addition, we show that when these adjustments are made, these variables become more strongly predictive of crime than standard treatments, suggesting the significant part diversity plays in the crime system and the significant part it plays as the link between standard regression variables and crime rates. We will examine the relationship between crime and a series of standard socio-economic and demographic variables. We argue that such variables, while acting to represent components of the crime system, capture the effects of social cohesion acting within those components in a weak manner. In contrast, we generate a new set of alternative representations of these variables, centered on diversity statistics. For example, rather than looking at the percentage of a specific age group, we look at the diversity of ages within a community. We then include these statistics within a stepwise regression, along with the more standard metrics, to show their worth. As with most statistical treatments, ours is only a proxy for the real factors in the system, which, as we shall see, is multifaceted and sometimes contradictory. Nevertheless, we see that, empirically, diversity statistics must capture some elements of these complex relationships better than standard treatments. We consider diversity in a more general sense of variation within a population (such as age, education, employment, and family) beyond ethnic diversity, as is commonly used in this sense.

The article is organized as follows: Section 2 draws out some of these complexities from the literature on the relationship between diversity and crime (Section 2.1) and discusses the theoretical justification for the explanatory variables (Section 2.2); Section 3 describes the data, diversity statistics, and analysis approach; Section 4 presents the results of the analysis; while Section 5 discusses the findings and Section 6 provides some conclusions.

2 | LITERATURE REVIEW AND EXPLANATORY VARIABLES

2.1 | Exploring the relationship between diversity and crime

In the context of the UK and the USA, socio-economic and demographic diversity has been linked to decreased social cohesion and the variation of crime in neighborhoods (Sampson & Groves, 1989; Bursik Jr & Grasmick, 1993). Diversity may hinder informal communication within neighborhoods and tends to negatively affect the establishment of social interactions across groups (Browning, Burrington, Leventhal, & Brooks-Gunn, 2008; Laurence, 2011; Letki, 2008). In the Netherlands, for example, Meer and Tolsma (2014) have found that heterogeneity in a community leads to low levels of trust and meaningful interactions and tends to undermine intra-neighborhood social cohesion. Employing the Metropolitan Police Public Attitude Survey (METPAS) of London, studies have found that ethnically diverse communities—especially with large transient populations—are often characterized by distrust, low levels of social cohesion, and high levels of dispute (Sturgis, Brunton-Smith, Kuha, & Jackson, 2014), with potential negative consequences for the individual as well as the community at large (Mellgren, 2011). Recent research in Japan consistently shows that areas characterized by ethnic diversity, wealth diversity, and age diversity (calculated at individual level with surveys) have high rates of crime (Takagi & Kawachi, 2014). However, this relationship needs to be investigated in the UK context.

Researchers have employed the social disorganization theory of Shaw and McKay (1942) to explain the variation in crime rate in different neighborhoods. Social disorganization theory posits that high levels of ethnic heterogeneity, residential instability, and socio-economic disadvantage undermine social networks, which in turn increases delinquency and crime rates (Shaw & McKay, 1942). Sampson and Groves (1989), in their empirical extension of Shaw and McKay's theory, showed that disorganization in a community lowers the ability of residents to work together toward problem solving, while collective efficacy among neighborhood residents mitigates crime rates (Sampson, Raudenbush, & Earls, 1997). Additionally, Kristjánsson (2007) stressed that weak networks of social ties decrease informal social control in the community, which increases deviant behavior.

Burglary, specifically, is a crime that thrives in socially disorganized and less cohesive communities (Weisburd & Piquero, 2008). It is likely that disorganized neighborhoods tend to have higher burglary crime rates because of weaker social cohesion than affluent areas where strong social connectedness facilitates the ability of residents to be on the lookout for criminal behavior (Dunaway, Cullen, Burton, & Evans, 2000). Routine activities theory (RAT) (Cohen & Felson, 1979) is regularly used by scholars to explain the occurrence of crimes such as burglary. This is based on the premise that a crime requires the simultaneous presence of three elements: motivated offenders, suitable targets, and the absence of capable guardians. A recent study shows that neighborhoods with diverse characteristics (occupation, education, income, ethnic, and residential instability), with low social cohesion and capable guardianship, may experience higher levels of burglary rates (Louderback & Sen Roy, 2018). Thus, social disorganization theory and RAT may help to explain the occurrence of neighborhood crime (Eck & Weisburd, 1995).

In a study of community integration in Berlin neighborhoods, Gruner (2010) employs Bourdieu's concept of "habitus" (socialized norms that guide behavior) to explain the distribution patterns of neighborhoods in terms of socio-economic and demographic structure. He found that the patterns and distributions of neighborhoods are associated with different cultural norms and the unwillingness of minority groups to integrate, describing it as self-segregation. Bourdieu's theory of habitus postulates the effects of physical embodiment of cultural capital: individuals who grow up in similar conditions develop similar habitus (Bourdieu, 1989). People with similar habitus feel attracted by and are more comfortable with each other (Bourdieu, 1989). The theory is extended to the study of social problems such as crime and perceived problems associated with migration flows in urban neighborhoods (e.g. Shammas & Sandberg, 2015). For example, growing up in a socially disorganized and crime-ridden neighborhood might greatly influence the behavior of people, especially the young (O'Connor, 2004), thereby facilitating delinquency (Tricia, 2016). This is especially pertinent to the local context in which this research is set. The conclusion from this set of studies is that high diversity in communities is acting to reduce social cohesion, consequently increasing neighborhood crime. There is some evidence that diversity reduces social cohesion (Meer & Tolsma, 2014) and this seems especially true where diversity is found in conjunction with deprivation (Cooper & Innes, 2009). However, it is important to note that diversity and cohesion levels are not always related in a simple manner, and that cohesion has the opportunity to be affected both positively and negatively, and by more than just ethnic or economic diversity (Ariely, 2014). Potentially, high diversity may have net positive impacts in terms of multiculturalism and the disruption of embedded cultural processes, despite negative impacts in other areas.

This article will model a number of socio-demographic factors and compare the impacts of standard variables representing those factors directly (for example, the proportion of young people) with variables representing their diversity (for example, age diversity). As study site, we focus on Leeds, UK, a city of approximately 750,000 people situated in the north of England (ONS, 2011).

2.2 | Theoretical justification for the explanatory variables

Although the relationship between community composition and crime is complex and multifaceted, there are some core factors that regularly emerge as important determinants of crime rates. This section will outline the most common factors used to explain variations in neighborhood crime rates; it is from these that the variables used in the later modeling work are derived. In each case, we will cover the more traditional variable, and then the diversity variable. The specific diversity equations used will be covered later.

2.2.1 | Age distribution

An age distribution is defined as the proportional numbers of persons in each age category in a given population. Previous studies have indicated that offenders are commonly drawn from younger age groups (Kongmuang, 2006). The age–crime curve tends to increase from the adolescent years, reaching a maximum at adulthood and then sharply declining (Blonigen, 2010; Farrington, 1986; Gottfredson & Hirschi, 1990; McCall, Land, Dollar, & Parker, 2013; McVie, 2005; Sampson & Laub, 2003; Sweeten, Piquero, & Steinberg, 2013), although this varies by the type of crime (Tittle, Ward, & Grasmick, 2003). Burglary is therefore likely to be affected by the absolute proportion of young (age 16–24) people. For example, according to Fagan and Western (2005), the incidence of crimes related to vehicles and drugs tends to be higher in early adulthood than in adolescence. Further, while homicides tend to be committed by adults, theft-related offences including burglaries are more prevalent in the younger age groups than the elderly (Loeber et al., 2012).

However, crime may also be affected by age distributions. A mixed population may put more or fewer offenders near more or fewer victims, but will also affect social cohesion. Younger people are less likely to build social cohesion (especially face to face) than older people (Johnston & Matthews, 2004; Takagi & Kawachi, 2014). Although offending is skewed toward the young because older adults have less opportunities for crime (Feldmeyer & Steffensmeier, 2007), the challenge is in accurately measuring the age effect on crime. Previous studies relied on raw numbers and proportions and did not use age standardization techniques (Hirschi & Gottfredson, 1983). Additionally, the tendency to commit crimes can change over time, regardless of age (Piquero, Farrington, & Blumstein, 2003). Recent comparative studies that used crime data from Taiwan and the USA found a considerable divergence from the age effect on crime (Steffensmeier, Zhong, & Lu, 2017). We therefore include population age diversity as a variable to investigate its relationship with crime, but with a prediction that different measures of diversity will identify different relationships. In this study, it is hypothesized that age diversity would be positively associated with burglary rates.

2.2.2 | Family structure

Family structure refers to whether the family unit includes children or not, both parents or a single parent. The family is generally regarded as an important social institution that shapes behavior, especially that of children (Nam, 2004). Maginnis (1997) has argued that the children of some single-parent families are more likely to have behavioral problems, because they tend to lack economic support and have lower parental input (Cheung & Park, 2016). In the UK, single parents continue to suffer from inequalities of employment and housing, creating a gap between couples and lone parents (Berrington, 2014). Additionally, single parents are also more likely to be victims of crime due to social marginalization in terms of living conditions (Wikström & Wikström, 2001). Given this, we include the proportion of single parents with children as an indicator from the traditional literature.

In terms of diversity, it seems likely that the distribution of family structures constitutes an important determining factor in social cohesion among community residents. For example, two-parent families with children tend to form social groups within the community that are distinct from single-parent families (Kanazawa, 2003; Sampson & Wooldredge, 1987). Community support within single-parenting groups is undoubtedly strong in some areas, but is likely to be more geographically variable. The determinants of community support are largely the presence or absence of children, and the presence or absence of single parents, bearing in mind that the number of children is largely random in most populations (Umberson, Pudrovska, & Reczek, 2010) and ethnically controlled otherwise (Lee & McLanahan, 2015). Not having children encompasses populations that are both very young and very old, and little else (Rees & Butt, 2004). According to Tasgin and Morash (2016), different family characteristics (e.g. economically disadvantaged families and families with parents who have limited education) can have a negative impact on children's upbringing and behavior. Additionally, family indifference (lack of interest in a child's behavior), as characterized especially in communities with a diverse family structure, has been found to be a major cause of delinquency (Baek, Roberts, & Higgins, 2018; Bobbio, Lorenzino, & Arbach, 2016). Furthermore, family diversity may have a differential impact on urban crime rates, which suggests the need for including measures of family structure beyond traditionally used variables (such as the percentage of single parents) in urban crime studies (Parker & Johns, 2002). We offer diversity of family structure as a variable in the model based on these factors, with the hypothesis that it would be positively correlated with burglary rates.

2.2.3 | Ethnic identity

Ethnic identity is defined as the extent to which an individual identifies with an ethnic category (Chandra, 2006). Identity plays an important role in the likelihood that people will connect and form social relationships (Gilchrist & Kyprianou, 2011), and plays an important part in the integration of migrants into local neighborhoods (Kindler, Ratcheva, & Piechowska, 2014). Migrants—especially from black and minority ethnic (BME) populations—often lack the wealth, social integration, or formal crime-prevention connections to protect themselves (Sharp & Atherton, 2007). Because of these factors, the size of an immigrant population in an area positively correlates with the incidence of property crime (Bell & Machin, 2011). Empirical evidence from the US also demonstrates links between the size of an immigrant population and the occurrence of motor vehicle theft and robbery (Bholowalia & Kumar, 2014). However, previous studies in the UK have yet to empirically establish the link between increases in the size of the immigrant population in an area with the incidence of property crime specifically (Papadopoulos, 2014).

Ethnicity has a well-established relationship with crime (Tonry, 1997; Piquero & Brame, 2008; Unnever, 2018), principally acting through socio-economic exclusion and disadvantage. There are also biases in reporting, the justice system, and policing, the latter including complex relationships between race and prejudice, most clearly expressed in the findings of the Stephen Lawrence Inquiry in the UK (Macpherson, 1999). These issues seem entrenched. For example, police figures show that stop and search of white suspects increased by seven percentage points between 2009 and 2014 (from 68 to 75% of stops) and decreased by five percentage points for black suspects (from 17 to 12% of stops) (ONS, 2015). However, research has found that defendants from a BME background are more likely to be sent to prison compared to those from a white background (Kathryn, 2016). In this study we address the relationship between residential ethnicity and reported crime, ignoring the complex and important nuances of systemic biases, the statistical representations for which are largely unresolved.

In terms of diversity, ethnic diversity might relate to crime in different ways, including offending and victimization, including hate crime as a direct effect of ethnicity (Shepherd, 2006). Moreover, Vermeulen, Tillie, and van de Walle (2012) have argued that the negative effects of ethnic diversity on social networks would probably be stronger in terms of interpersonal trust, as well as differences in interests and needs between groups which weakens networks of social interaction. Though counter-arguments can be made in areas where everyone is essentially in a minority population, the nuances of tension and disadvantage in communities of multiple ethnicities and country of origin are likely to be complex. We therefore include diversity of country of origin to capture elements of isolation and integration, and diversity of ethnicity to capture the complex elements of offending and victimhood associated with ethnicity in mixed communities. We hypothesized that these sets of diversities would be positively associated with burglary rates.

2.2.4 | Employment and income

While there is a wide range of criminality across the socio-economic spectrum, for burglary, offenders in the vast majority of cases are drawn from the poor and unemployed (Bursik Jr & Grasmick, 1993; Sariaslan et al., 2013). Given this relationship, we include the level of unemployment in those age categories that could be working as a key variable.

Additionally, in Leeds the number of students is important because of the presence of large residential educational institutions (especially the two universities). Students are more likely to fall victims of crime, especially burglary, because multiple-occupancy homes are attractive to burglars, and because students are less likely to be at home (Kongmuang, 2006; Shepherd, 2006).

Furthermore, students' residences are attractive to burglars because students are more likely to possess valuable items, especially electronic gadgets (e.g. DVDs, laptops, iPads, and mobile phones), and be less careful about the security of their personal belongings (Barberet & Fisher, 2009). Additionally, some students reside in poor accommodation that lacks security surveillance devices such as closed circuit television (CCTV) and may not be adequately patrolled (Masike & Mofokeng, 2014). Wealth diversity within a community may act to increase crime. Given that most burglars only travel a short distance to commit crimes (Ashby, 2005), there is some evidence that disparities of wealth within short distances encourage burglary (Chiu & Madden, 1998; Rufrancos, Power, Pickett, & Wilkinson, 2013; Tseloni, Osborn, Trickett, & Pease, 2002). In addition, disparity of wealth within a community can influence crime by weakening social cohesion (Fajnzlber, Lederman, & Loayza, 2002; Rufrancos et al., 2013). Equally, low wealth diversity can enhance social cohesion (Cooper & Innes, 2009). Although the picture is complicated across other types of crime (Rufrancos et al., 2013), researchers have found support for the relationship between property crime and income inequality (Demombynes & Özler, 2005; Kelly, 2000; Reilly & Witt, 2008; Witt, Clarke, & Fielding, 1998). We therefore include diversity of employment type in our assessment, as a proxy for wealth, in the absence of a household income variable not captured in the UK census statistics (House of Commons, 2011). We hypothesized a positive relationship between employment diversity and burglary rates.

2.2.5 | Deprivation

Deprivation has been defined as a lack of resources to meet the basic necessities of life (DCLG, 2015). Literature on the relationship between deprivation and crime suggests that deprived communities tend to have more crime than affluent communities (Sampson & Wooldredge, 1987; Bursik Jr & Grasmick, 1993; Krivo & Peterson, 1996; Malczewski & Poetz, 2005). Furthermore, deprivation widens the gap between rich and poor, which can reduce social cohesion (Morenoff, Sampson, & Raudenbush, 2001; Takagi & Kawachi, 2014). The Index of Multiple Deprivation is a multidimensional metric that is measured, in England, through a combination of seven distinct domains: income, employment, education, health, crime, barriers to housing & services, and living environment (DCLG, 2015).

Although deprivation is often seen as a key indicator of social cohesion, as well as propensity to commit a crime such as burglary, UK deprivation statistics include crime and therefore it is inappropriate to use them in this analysis. Deprivation is covered by the other variables, as far as demographics are concerned.

2.2.6 | Educational attainment

Educational attainment has a great influence on individuals' social behavior, as well as on participation in community activities (Sabates, 2008). The theory of human capital suggests that skills and qualifications determine wages, and the wider the distribution of qualifications, the wider the distribution of wages (Green, Preston, & Janmaat, 2006). Reynolds, Temple, Robertson, and Mann (2001) found that the propensity of individuals to commit crime is associated with their level of educational attainment, and so we include lack of qualifications as a traditional variable.

However, there is also a likely indirect relationship between educational inequality and crime. Sabates, Feinstein, and Shingal (2008) found that educational inequality is associated with violent crime. While it is unclear whether such a relationship acts at the intra-area scale independent of any effect of wealth, we include a diversity statistic centered on education to test the potential relationship and hypothesized a positive association with burglary rates.

2.2.7 | Residential instability

Residential instability has been defined as two or more residential moves within the course of one year (Foulkes & Newbold, 2008). Residential stability in a neighborhood is an important factor for the generation of social capital and place-based attachment, so it is expected that residential duration will affect crime via this effect on social cohesion (Thomas, Stillwell, & Gould, 2016). Studies have demonstrated that the creation of social ties is associated with the length of residence in an area. For example, Yamamura (2011) argued that personal relationships are built over time, tend to be more solid when people reside in a particular neighborhood, and are influenced by length of residence and home ownership. Similarly, Keene, Bader, and Ailshire (2013) point out that it takes time to create supportive social ties, therefore length of neighborhood residency may be an important determinant of social integration. Additionally, Oh (2003) shows that length of residence has a positive effect on friendships, social cohesion, and trust, which also enhance the probability of working together to solve local problems. In contrast, residential instability in a neighborhood is associated with weak social ties and a low probability of residents connecting (Sampson et al., 1997).

Crime is also more likely to occur in transient neighborhoods. For example, in the UK, the tendency to commit crime is related to length of residence, in other words, crime reduces as length of residence in a neighborhood increases (Bell & Machin, 2011). Residential instability also influences crime from the social disorganization perspective (Shaw & McKay, 1942). Specifically, research has established the relationship between residential instability and violent crime (e.g. Boggess & Hipp, 2010). However, the relationship between residential instability and burglary is likely to be complex (Markowitz, Bellair, Liska, & Liu, 2001; Martin, 2002). Given the complexity of the relationship, we include length of residence less than two years as a standard variable and diversity of length of residence as a proxy for residential instability. The hypothesis is that a positive association would be expected with burglary rates.

3 | DATA, METHODS, AND ANALYSIS

This section describes first the study area and the data used for the study. Measures of diversity statistics and the analysis approach for the study are then provided. Figure 1 shows our methodology workflow diagram.

3.1 | Study area

The city of Leeds in the north of England (UK) is a medium-sized post-industrial city of ~750,000 people. It comprises 33 *wards*, which are divided into 482 *lower super output areas* (LSOAs). Figure 2 shows the location of Leeds. The LSOAs have a minimum population of 1,000 (with an average of 1,500) and a minimum resident household number of 400 (with an average of 630) (ONS, 2011). It contains some of the poorest wards in England (DCLG, 2015), but equally has wards containing the homes of some of the most affluent individuals in the country (BBC, 2003). Leeds is an area with an increasing number of BME groups. For example, in the 2001 population census the population of BME groups was 77,530 (about 10.8% of the resident population), and this increased to 141,771 (representing 18.9% of the resident population) by 2011 (ONS, 2011). The city also has a relatively large number of burglaries (12.83/1,000 population) compared to the national average (7.5/1,000 population) (ONS, 2017) and

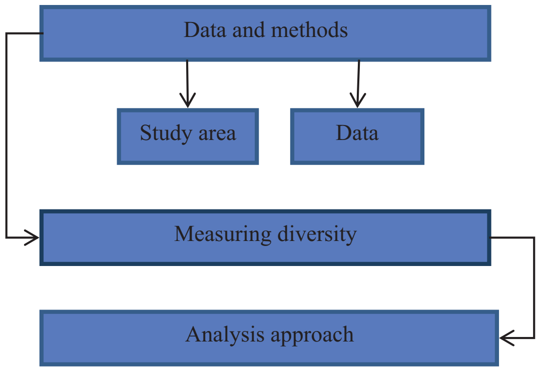

FIGURE 1 Methodology workflow diagram

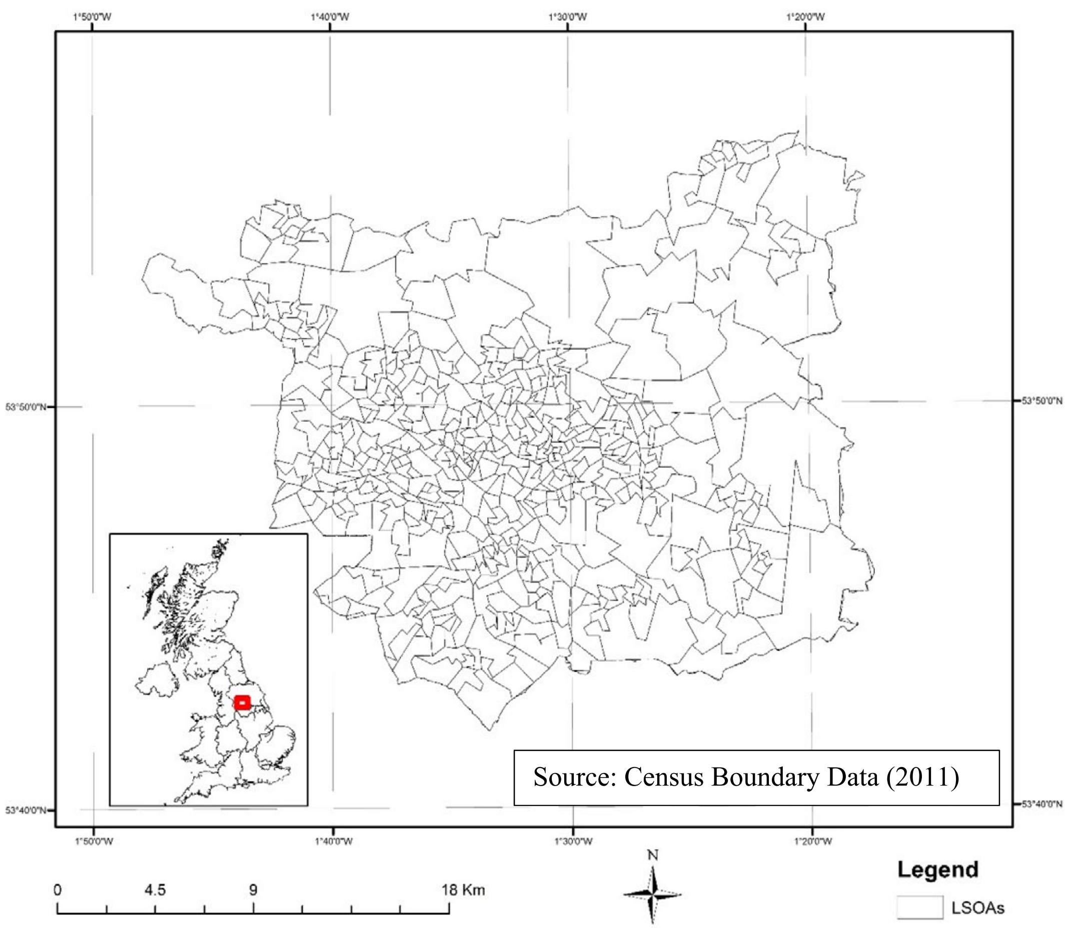

FIGURE 2 Location map of Leeds with LSOA boundaries

characteristically different types of neighborhood, which makes it suitable for examining relationships between socio-economic and demographic diversity and burglary (Hirschfield, Birkin, Brunsdon, Malleson, & Newton, 2013).

3.2 | Data

Burglaries reported between 2011 and 2015 in the city of Leeds were obtained from the "police open public monthly data of reported crimes" (https://data.police.uk/data/), a portal that provides customized crime data downloads for all police forces in England and Wales. In this case, West Yorkshire Police for the period 2011–2015 (n = 51,800). Rates per 1,000 population were then calculated over the whole data for each of the 482 LSOAs of Leeds. LSOA geography has been chosen because it is small enough to capture neighborhood effects but large enough to represent coherent community groups. The remaining data (age distribution, family structure, identity, employment, educational attainment, and length of residence) were derived from UK 2011 census data, supplied by the UK Data Service (downloaded from http://infuse.ukdataservice.ac.uk/). Figures 3a and b show the spatial distribution of independent variables (standard and diversity) in the study area.

3.3 | Measuring diversity statistics

Researchers have used a number of methods to measure diversity (Morris et al., 2014). Nevertheless, in this initial study we concentrate on diversity indices, which report the probability that two individuals taken at random are different. Such diversity indices therefore use equivalent classes weighted on the same scale, irrespective of the total community size, with each class within the community having members that share common attributes (Jost, 2006). The most widely used diversity index is Simpson's (1949) diversity index (D) (Johnson & Lichter, 2010). The range of values of D is 0 to 1; values toward 0 indicate no diversity and values toward 1 indicate the presence of absolute diversity. Simpson's diversity index for area i is written as:

$$D_i = 1 - \frac{\sum_i n_i(n_i - 1)}{N(N - 1)} \tag{1}$$

where n_i is the proportion of a population in an area falling into category i and N is the total population of that area.

3.4 | Analysis approach

In this analysis, the categories were determined by census data availability. Table 1 shows the core components of crime and community cohesion, and the variables used to represent them in the model. Table 2 shows the different categories included to measure diversity. Utilizing the variables in Table 1, we constructed a model of correlates with crime. Identifying the best model fit requires an iterative process that examines different combinations of explanatory variables. Exploratory regression analysis is important for selecting the best explanatory variables for a given model (Braun & Oswald, 2011). Exploratory regression builds ordinary least square (OLS) models using all possible combinations of explanatory variables and assesses which models pass the OLS checks (Rosenshein, Scott, & Pratt, 2011). This process is useful for ensuring that only variables with the highest significance are retained. Here, to test the strength of the relationship between the variables and crime, we utilize stepwise (a combination of forward and backward selection) linear regression. Stepwise methods are commonly used to select the best variables in a regression model, especially multiple regressions with many predictors such as in this study (Sinha, Malo, & Kuosmanen, 2015; Wooldridge, 2012). However, the process of adding and dropping variables associated with stepwise regression has been criticized in that it is possible to miss the optimal model, as removing less significant predictors increases the significance of the others, which may lead researchers to overstate the

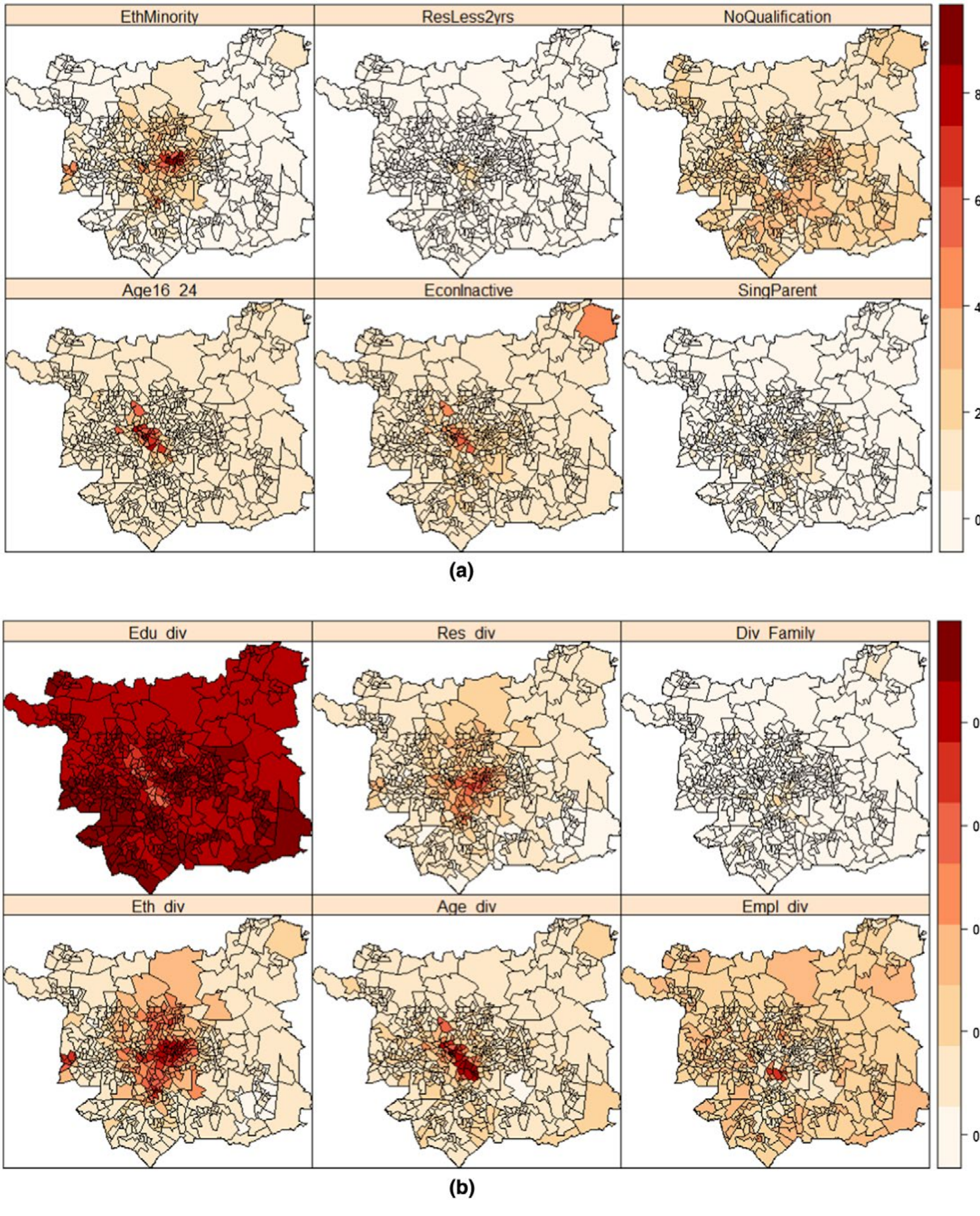

FIGURE 3 (a, b) Spatial distributions of standard and diversity metrics. Source: ONS (2011)

importance of the remaining variables (Rawlings, Pantula, & Dickey, 1998). Despite the limitations of the stepwise multiple regression method, it is widely used in different ecological studies (Caplan, Kennedy, Barnum, & Piza, 2015; Collins, Babyak, & Moloney, 2007; Meera & Jayakumar, 1995; Pitner, Yu, & Brown, 2012; Raftery, Madigan, & Hoeting, 1997).

In this study, the model was built by sequentially adding significant ($p \leq 0.05$) variables; the order of correlation between the dependent variables determines the order by which they are added to the model. The stopping

TABLE 1 The core components of crime and community cohesion, and the variables used to represent them in the model

Component	Standard variable	Diversity variable
Age distribution	Number of young persons (16–24)	Age diversity
Family structure	Lone parents	Diversity of family structure
Identity	Ethnic minority population	Ethnic diversity
Employment/income	Age 16–64, economically inactive	Diversity of employment type
Educational attainment	Age 16 over, no qualification	Diversity of educational attainment
Residential instability	Resident less than 2 years	Length of residence diversity

TABLE 2 Components used to measure different diversity metrics

Diversity	Components included
Age	10–14, 15, 16–17, 18–19, 20–24, 25–29, 30–44, 45–59, 60–64, 65–74
Family structure	Lone parent, no dependent; Lone parent, one dependent child; Lone parent, two or more dependent children; Married couple, no children; Married couple, one dependent child; Married couple, two or more children
Ethnicity	All 18 ethnic groups included
Employment	16–64 Managers/Directors, 16–64 Professionals, 16–64 Associate Professionals, 16–64 Administration and Secretariat, 16–64 Skilled Trade, 16–64 Caring, Leisure and Services, 16–64 Customer Services, 16–64 Process, Plants and Machines, 16–64 Elementary Occupation
Education	16-over qualification level 1, 16-over qualification level 2, 16-over qualification level 3, 16-over qualification level 3, 16-over qualification level 4
Residence length	Length of residence: Less than 2 years; Less than 5 years; More than 5 years; 10 years and above; Born in the UK

criterion for the stepwise process is reached when none of the remaining variables are significant ($p \geq 0.1$), then the process terminates. We first included a model using only standard variables and subsequently compared that to one including all variables (standard and diversity).

Equation (2) for linear multiple regression is given based on Charlton, Fotheringham, and Brunsdon (2009). The stepwise method adds variables (standard and diversity in this context) to the model through a series of iterations and ensures that the variables are still significant contributors to the model, removing those which are not:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n + \varepsilon \tag{2}$$

Here, Y is the value of the dependent variable, β_0 is the constant intercept, $\beta_1, \beta_2, \beta_3, \ldots, \beta_n$ are the slope coefficients of $X_1, X_2, X_3, \ldots, X_n$ and $X_1, X_2, X_3, \ldots, X_n$ are the independent variables, while ε is the standard error of coefficients. The standard error is calculated by summing the squared values of the residuals and dividing by the difference between the number of parameters subtracted from the total number of observations.

Optimal models are a balance of correlation against parsimony. Although such balances are largely subjective and centered around use cases, traditionally scree graphs have been used to help in the decision making as there is often a natural kink in the graph of, for example, R^2 versus number of model components, which indicates considerably decreasing explanatory power being provided by additional components (Mehmood, Martens, Sæbø, Warringer, & Snipen, 2011; Preacher, 2006).

Prior to building the model, the independent variables were tested for multicollinearity. Multicollinearity is present when there is a high degree of correlation among independent variables. This can significantly affect

TABLE 3 Model summary of stepwise regression

(a)	Model	R	R^2	Adjusted R^2	Std. error of the estimate
	1	0.302	0.091	0.089	32.729
	2	0.337	0.114	0.110	32.357
	3	0.359	0.129	0.123	32.115
(b)	**Model**	R	R^2	**Adjusted** R^2	**Std. error of the estimate**
	1	0.358	0.128	0.126	32.061
	2	0.447	0.200	0.196	30.746
	3	0.469	0.220	0.215	30.384
	4	0.481	0.232	0.225	30.191
	5	0.492	0.242	0.235	30.010

model performance and reliability (Wang, 1996). There is no standard rule for filtering out variables based on the issue; here, correlations of $r > 0.70$ are regarded as very significant. The proportion of *economically inactive population* correlates with the *proportion of young persons aged 16–24* (0.876); the *proportion of single parents* correlates with the *proportion of persons with no qualification* (0.709); and *ethnic diversity* correlates with *length of residence diversity* (0.971). Therefore, the following variables were removed to avoid redundancy and because of their relatively lower correlation with the dependent variable: *young persons aged 16–24* (correlation with burglary rate: young persons (0.269) compared to economically inactive population (0.276)); *single parents* (constitutes a larger proportion of those with no/lower qualifications in the UK); and *length of residence diversity* (also a useful indicator of ethnicity and has weaker correlation with burglary (0.310) compared to ethnic diversity (0.313)). No significant correlation was found between the standard variables and their diversity equivalents.

4 | RESULTS

Tables 3a and b summarize the results of the standard and combined stepwise regression models used to assess the relative importance of each variable in the models. The statistics reported are Pearson's product moment correlation (r), which shows the correlation with the dependent variable for each model. R^2 reports the percentage of variation in rate of burglary crime explained by the variables used in the model. Adjusted R^2 is the fraction by which the square of the standard error of the regression is less than the variance of the dependent variable. It increases only if the variables improve the model. It is usually used to evaluate which model performs better, where a model with a smaller standard error of estimate is likely to produce a higher adjusted R^2 (Kongmuang, 2006). In the combined analysis, model 5 is the best-performing model, represented in the form of Equation (3), while in the standard variables analysis, model 3 performed best, explaining 14% of the variation in burglary rates. Model 5 will be the subject of discussion in Section 6.

Tables 4a and b present the coefficients of the standard and combined models. The elements reported are standardized and unstandardized coefficients, standard error, t statistics and significance tests. In regression analysis, standardized coefficients are estimates standardized so that the variance of the dependent variable produced by changes in the independent variables is between −1 and 1; unstandardized coefficients express values of the relationship in raw values (Landis, 2005). The standard error is a measure of the accuracy of predictions obtained from the difference between the observed and predicted values; smaller values indicate that observations are closer to the fitted regression line (Altman & Bland, 2005). The stepwise regression results indicate that the parameters are within acceptable standards for regression modeling. An important guide for understanding this are the t statistics (Dunn, 1989). A t statistic is the estimated coefficient divided by its own standard error.

TABLE 4 Coefficients and tests of model performance

(a) Model		Unstandardized coefficients B	Unstandardized coefficients Std. error	Standardized coefficients Beta	t	Sig.
1	(Constant)	63.411	1.700		37.308	0.000
	Length of residence less than 2 years(%)	3.893	0.561	0.302	6.945	0.000
2	(Constant)	50.232	4.146		12.116	0.000
	Length of residence less than 2 years(%)	4.327	0.568	0.336	7.616	0.000
	Age 16 over, no qualification(%)	0.651	0.187	0.153	3.477	0.001
3	(Constant)	37.493	4.957		7.564	0.000
	Length of residence less than 2 years(%)	2.860	0.646	0.222	4.429	0.000
	Age 16 over, no qualification(%)	0.955	0.196	0.225	4.880	0.000
	Age 16–24(%)	0.630	0.140	0.240	4.491	0.000

(b) Model		Unstandardized coefficients B	Unstandardized coefficients Std. error	Standardized coefficients Beta	t	Sig.
1	(Constant)	53.775	2.336		23.018	0.000
	Age diversity	74.289	8.851	0.358	8.393	0.000
2	(Constant)	23.531	5.130		4.587	0.000
	Age diversity	102.110	9.490	0.492	10.759	0.000
	Age 16 over, no qualification(%)	1.273	0.194	0.300	6.554	0.000
3	(Constant)	22.092	5.086		4.344	0.000
	Age diversity	86.719	10.341	0.418	8.386	0.000
	Age 16 over, no qualification(%)	1.145	0.195	0.270	5.867	0.000
	Ethnic diversity	24.609	6.964	0.157	3.534	0.000

(Continues)

Table 4 (Continued)

(b)	Model		Unstandardized coefficients		Standardized coefficients		
			B	Std. error	Beta	*t*	Sig.
	4	(Constant)	101.265	30.075		3.367	0.001
		Age diversity	60.622	14.180	0.292	4.275	0.000
		Age 16 over, no qualification(%)	1.344	0.208	0.316	6.469	0.000
		Ethnic diversity	28.885	7.102	0.185	4.067	0.000
		Educational diversity	−93.151	34.882	−0.181	−2.670	0.008
	5	(Constant)	106.442	29.962		3.553	0.000
		Age diversity	85.607	17.060	0.412	5.018	0.000
		Age 16 over, no qualification(%)	1.509	0.216	0.355	6.985	0.000
		Ethnic diversity	32.582	7.202	0.208	4.524	0.000
		Educational diversity	−97.983	34.723	−0.190	−2.822	0.005
		Age 16–64, economically inactive(%)	−0.675	0.260	−0.163	−2.600	0.010

Dependent variable: Burglary rate.

Significant *t* statistics should be approximately 1.96 in magnitude, corresponding to a *p* value less than 0.05% or 95% confidence level (Coe, 2002). The results obtained from the stepwise regression in this analysis indicate that the values of the *t* statistics for all variables in the models were greater than 1.96, meaning that all variables are statistically significant. At each iteration of the stepwise regression, variables that are not significant are dropped and model variables that are significant are retained.

It is common practice to assess the appropriateness of a model using the coefficient of determination, although this is not an absolute indicator of goodness of fit (Reisinger, 1997) and a low effect size does not mean that the model is inefficient (Martin, 2014; Weisburd & Piquero, 2008). Although the analysis explained approximately 24% of the variation in burglary crime, that is good compared to other studies: Zhao, Lawton, and Longmire (2015), Karyda (2015), Hino, Uesugi, and Asami (2016), and Boateng (2016) have models explaining 21%, 10%, 14%, and 12%, respectively. Crime, especially burglary, is difficult to understand, predict, and model (Malleson & Birkin, 2012). The percentage of variation of the dependent variable explained in a model can sometimes be misleading, as small effect sizes can produce better and more meaningful outcomes than larger ones (Lieberson, 1985). However, this depends on the unit of analysis, the type of crime, and the underpinning theory (Weisburd & Piquero, 2008).

The final regression equation (model 5) is given here by computing the values of the unstandardized (B) coefficients:

$$\begin{aligned}\text{Burglary rate} = 106.442 + 85.606 * \text{Age diversity} + 1.509 *\\ \%\text{Age 16 over, no qualification} + 32.582 * \text{Ethnic diversity} + -97.983 *\\ \text{Educational diversity} + -0.675 * \%\text{Age 16 to 64, economically inactive}\end{aligned} \tag{3}$$

5 | DISCUSSION

The most notable result of the above analysis is the almost complete exclusion of standard variables in preference for diversity statistics (Table 4a). As seen from the unstandardized (B) coefficients of the standard only (Table 4a) and combined variables (Table 4b) models, diversity variables have shown a higher relationship in explaining burglary rates than the standard variables. Additionally, the order of the variable correlation with the dependent variables (except for the proportion of those with no educational qualification, which is the second most important variable in both models) also indicated that the diversity variables are more important. The results highlight the importance of diversity in the crime system, with a concomitant suspicion that this acts through community cohesion, but also highlight that the standard statistics probably, in part, represent community cohesion, and are being excluded here simply because the new metrics are potentially stronger correlates of burglary rates. It could equally be that diversity indicates the proximity of “haves” and “have nots” and opportunity/targets within a community, as mechanisms by which diversity impacts on crime.

In this study, diversity of age was the most important variable when regressed against the dependent variables consistently throughout the models (see model coefficients in Table 4a). As hypothesized, age diversity was significant ($p < 0.01$) and positively associated with burglary rates. Age diversity has shown that offenders are commonly drawn from younger age groups rather than elderly people, and the findings in this study are consistent with previous literature which found a relationship between age and crime (e.g. Farrington, 1986; Gottfredson & Hirschi, 1990; Sampson & Laub, 2003; McVie, 2005; Blonigen, 2010; McCall et al., 2013; Sweeten et al., 2013). However, it is likely that a wide age range puts young offenders in close proximity with older victims with, potentially, more to steal. Equally, however, we know that the young are also targets for crime (Finkelhor, Ormrod, Turner, & Hamby, 2005), and it makes some sense that the broader the range of population characteristics in an area, the more likely that there will be suitable target criteria for burglars making decisions about risk (Bernasco & Nieuwbeerta, 2005).

In this study, unexpectedly, *diversity* of educational attainment was significant ($p < 0.05$) and negatively correlated with burglary rates, meaning that the smaller the diversity of educational attainment, the more burglary occurs in an area. This finding should be interpreted with caution, as there are sophisticated crimes (such as cybercrimes) that are perpetrated by educated individuals. Although previous studies have found that educational attainment increases returns through legitimate means (Green et al., 2006), it also raises the opportunity cost of illegal behavior (Machin, Marie, & Vujić, 2011). Consistent with previous studies, we also found a significant ($p < 0.01$) positive relationship between the proportion of those with no educational qualification and burglary (Machin et al., 2011).

We also found strong support for a positive relationship between ethnic diversity and rates of burglary crime. This finding contradicts Papadopoulos (2014), who found no significant relationship between an increase in the size of the immigrant population and property crime. The findings of this study, however, are consistent with the findings of previous studies, which found a positive relationship between the size of the immigrant population in an area and the incidence of property crime (e.g. Bell & Machin, 2011). Previous research has shown that ethnically heterogeneous communities are often characterized by distrust, low levels of social cohesion, and disputes (Sturgis et al., 2014), which negatively affect individual behaviors (Mellgren, 2011). Recent studies into the spatial distribution of neighborhood crime consistently show that areas which are characterized by ethnic diversity have high rates of crime (Gartner, 2013; Takagi & Kawachi, 2014). However, the significant positive relationship found in this study could also be because migrants often lack formal crime prevention connections to protect themselves against crime victimization (Sharp & Atherton, 2007).

The feeling of disparity between wealthy and poor people increases antagonism, with a resultant increase in crime (Fajnzlber et al., 2002; Rufrancos et al., 2013). Disparity within an area also, however, implies a potential mix of richer targets and poorer offenders within the area. Given that burglars tend to be poor, and have a fairly short travel distance (see above), more diverse communities may have more targets (Demombynes & Özler, 2005; Kelly, 2000; Reilly & Witt, 2008; Witt et al., 1998). Nevertheless, in this study we found no statistically significant relationship between diversity of employment and burglary crime rate. Further study is needed to explore this relationship.

In this study, we found a significant negative correlation between the proportion of economically inactive population and burglary crime, which might be seen as counter-intuitive. Previous studies have found support for relationships between income inequality and property crime (Demombynes & Özler, 2005; Kelly, 2000; Reilly & Witt, 2008; Witt et al., 1998). However, the difference between measuring offences committed by those residing in a community and measuring offences occurring in a community could be a reason for the following preposition; this relationship might only suggest that unemployment might contribute to offending elsewhere. Recent statistics in the UK show that economically inactive people are twice as likely to be victims of burglary crime as those who are economically active (ONS, 2014), considering that this category of population comprises students, those who are retired, and people with long-term health challenges, the relationship for Leeds needs further investigation.

6 | CONCLUSIONS

This study explored the impact of diversity on burglary crime in the Leeds district, UK. We used stepwise regression models to assess the relationships between both standard and diversity-based socio-demographic variables and burglary crime rate. We showed that diversity-based statistics are a better correlate with crime than most standard metrics, highlighting the importance of diversity in the crime system, and suggesting the potential importance of social cohesion in preventing crime. It seems likely that standard statistics go some way, normally, to explaining neighborhood variations in burglary, but that this is better captured through diversity statistics.

The variables used in this study have provided useful insights into the relationship between neighborhood social context (diversity) and the spatial variability of burglary rates in Leeds. The most important predictor for modeling burglary crime rates in this analysis was age diversity. However, other predictors—such as ethnic diversity, distribution of educational attainment, proportion of those with no educational qualifications, and proportion of economically inactive population—also made a valuable contribution to the models. Notably, economically inactive population had a slight negative relationship with crime, and this needs further investigation.

It seems likely that community cohesion is an important factor in establishing social control and collective efficacy in neighborhoods with regard to crime. Here we have used a simple set of diversity statistics to highlight the possibilities for investigating this. However, there is scope, having identified the importance of diversity statistics, to investigate alternative metrics in this area to reveal different aspects of community cohesion—for example, it may be that age distributions are better represented by statistics which utilize the frequency distribution of the population in a more nuanced fashion than the standard Simpson's diversity index. As this study considered burglary crime rates, we also recommend future research to consider applying the present approach against other types of crime, in order to uncover relationships between crime and diversity metrics.

The results obtained in this study are potentially useful in prioritizing areas of policy planning for crime prevention. The study suggests that in terms of crime prevention alone, there is a need for extra support in areas dedicated to encouraging community building, rather than poverty specifically being the key, at least in Leeds[1]—although clearly poverty is at the root of additional social issues.

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CONFLICT OF INTEREST

No potential conflict of interest was reported by the authors.

AUTHORSHIP

Usman Lawal Gulma: Conceived the idea of the study, made substantial contributions in data acquisition, analysis and interpretation of the results.
Andy Evans: Critically reviewed the paper to ensure quality. Alison Heppenstall. Sufficiently contributed in revising the paper and made valuable comments.
Nick Malleson: Contributed by ensuring that issues related to accuracy of the work are appropriately followed.

NOTE

[1]It is worth noting, in this respect, that financial gain was the dominant factor identified across all burglars in recent interviews; however, over a fifth of offenders in Leeds talked about how they will also offend "for the buzz" it provides them (N. Addis, pers. comm., 2016). This may not be the case in other areas, where poverty may be more of a direct driver.

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