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Identifying predictors of harm within Black, Asian, and other racially minoritised communities

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DISCLAIMER

This report was commissioned by the Home Office contributing to a wider piece of work on perpetrators of domestic abuse. This report and its recommendations do not necessarily reflect the views of the Home Office.

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All the authors are members of the Domestic Abuse Research Network[2] which enables practitioners and academics to connect with current issues and research on domestic abuse in the region and beyond.

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[1] https://www.uos.ac.uk/content/centre-abuse-research

[2] https://www.uos.ac.uk/content/domestic-abuse-research-network

Contents

Table of Figures

Table of Tables

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Abbreviations and Terms

Term	**Meaning/Application**
DA	Domestic Abuse
CCHI	Cambridge Crime Harm Index
ONS	Office of National Statistics
DASH	Domestic Abuse Stalking and Harassment
ASB	Anti-Social Behaviour
TVP	Thames Valley Police
Pareto distribution	A probability distribution which suggests that 80% of outcomes are attributable to 20% of causes
Power Few	Term coined to reflect the Pareto principle in criminological studies but without specifically meaning 80% linked to 20%. Suggests that a small number of units are associated with a large proportion of a given outcome
Non-Power Few	The inverse of the power few, the large number or majority of units associated with a proportionally small level of the outcome
OLS	Ordinary Least Squares. OLS regression is a statistical model that estimates the relationship between one or more independent variable and the dependent variable
VIF	Variance Inflation Factor is a measure of multicollinearity, or high intercorrelations between two or more independent variables in the model
CSEW	Crime Survey for England and Wales
P value	P value refers to the probability of obtaining the observed, or more extreme, results due to chance if the ‘null hypothesis’ is true (for example, if ethnicity has no effect when other variables are controlled for) The lower the p-value, the more statistically significant the outcome
LSOA	A Lower Layer Super Output Area is a geographic area. LSOAs have an average population of 1,500 people

Notes on terminology:

- We do not use ‘BAME’ or ‘BME’ throughout the report and in the analysis. We reject the use of this term, and the practice of ‘ethnic lumping’ (Fontes, 1993), because it assumes a homogeneity that does not exist and masks differences across and within groups. Prior research with professionals from/supporting Black, Asian and other racially minoritised communities suggests that choosing language which reflects the nuances of people’s identities and experiences plays an important role in establishing trust and building good policy and practice (Adisa & Allen, 2020). Our analysis of ethnicity is not predicated on grouping of ethnicities into a binary framework. We deliberately avoid existing constructs such as ‘BAME’ or ‘BME’ and instead categorise ethnicity into the 18 categories described by the police data, mapped to six categories outlined by the Office for National Statistics (ONS) in their population statistics (White British/Any Other White/Mixed or Multiple Ethnicity/Asian or Asian British/Black, Caribbean or African/Other Ethnicities

- We have used the term ‘victims’ in line with the language used by the police and the Home Office in the recording of their data

- Similarly, we use the term ‘suspect’ as some of the crimes recorded by police may or may not have been prosecuted

- We define domestic abuse according to the Home Office definition, which encompasses “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” (Home Office, 2013)

- Unless otherwise specified, when referring to local areas, we are discussing Lower Layer Super Output Areas (LSOA), a geographical area comprising an average population of 1,500 people. LSOAs are commonly used in Neighbourhood Statistics Geography.

Executive Summary

Following the Home Office's call for research proposals on perpetrators of domestic abuse (DA Perpetrators Research Fund ITT_178) in Dec 2020, the Centre for Abuse Research at the University of Suffolk, led by Dr Olumide Adisa was granted funding to undertake work on under-researched groups, specifically to identify predictors of harm within Black, Asian and other racially minoritised communities.

What this report is about?

This report examines predictors or determinants linked to the highest harm of domestic abuse perpetration. In practice, risk assessment tools are typically focused on offending profiles and violent interpersonal behaviour. Yet, individual level characteristics of the offender/suspect can often compound the risk of injury and severity of abuse. Identifying these individual-level predictors on a larger scale will improve the evidence base regarding identifying high-risk or high-harm perpetration within Black, Asian, and other racially minoritised communities, which can be extended to other marginalised communities. The dataset analysed in this report has enabled researchers to identify hypotheses about individual-level predictors that further research can confirm and extend.

A scoping review (Arksey & O'Malley, 2005) was undertaken to give a comprehensive overview of the literature on identifying and applying predictors of harm for high-risk perpetrators in Black, Asian and other racially minoritised communities, with particular focus on highlighting gaps in the evidence base. The scoping review findings indicate that many of the relevant studies are based in the United States, and overwhelmingly focus on intimate partner violence rather than the broader spectrum of abuse covered by the Home Office definition, which encompasses violence and abuse perpetrated by a family member(s). This research aims to fill those gaps. Additionally, that research on IPV perpetration conducted in a criminal justice context points to differences in police recording, patterns of offending, prevalence and risk factors (e.g. hazardous drinking) between different ethnic groups.

The report uses police data from three police forces[3] (Thames Valley, Sussex, Bedfordshire) in England over a three-year period Apr 2017- Mar 2020.
It uses an estimate of crime harm as the key measure, the Cambridge Crime Harm Index (CCHI)[4] to identify patterns based on ethnicity of suspect, and then uses regression analysis to see which individual level and neighbourhood level variables were more strongly associated with CCHI.

It finds strong support both from the literature and our modelling work that ethnicity matters.

Additionally, for the area level analysis, the dependent variable for the model was the domestic abuse count and rate (the adjusted count per 1000 population).

The independent variables were:

- proportion of Asian people in the population
- proportion of Black people in the population
- proportion of mixed heritage people in the population
- proportion of other racially minoritised communities in the population
- female population
- police reported anti-social behaviour count
- income score from the Index of Multiple Deprivation
- median age
- population density
- proportion of single people
- population turnover
- proportion of single person households.

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[3] The original plan was to include data from Norfolk and Suffolk Constabularies, and Cambridgeshire and Hertfordshire Constabularies. However, this proved challenging for various reasons within the timeframe. We also received data from Metropolitan Police, but the FOI process that we had to go through meant that the data provided was not in a format that would allow aggregation with the three police forces data used in this report. However, the size of the dataset we arrived at was sufficient and rich enough to undertake the analysis to meet the aims of the project.

[4] Sherman *et al* (2016).

Other individual level variables included in the analysis: age, sex/gender, class[5], ethnicity, the type of relationship between the victim and perpetrator, DASH scores, alcohol, and suicide/self-harm warnings.

Other neighbourhood level variables included in the analysis: the population data used in the rates was the 2019 ONS population estimates. Variables include economic disadvantage; ethnic heterogeneity, as well as population turnover.

Aim and Objectives

The aim of this research is to assist with the prediction of future harm. To this end, we try to address seven research questions spanning the range of predictors we have access to. These questions are:

RQ1 – What is the profile of domestic abuse suspects by ethnicity?
RQ2 – What is the profile of crime harm, overall and by ethnicity?
RQ3 – What is the profile of risk assessment by ethnicity?
RQ4 – What is the profile of investigative outcome by ethnicity?
RQ5 – What is the contribution of different ethnicities to the ‘power few’ most harmful suspects?
RQ6 – Are Black, Asian, and other racially minoritised communities at increased risk of domestic abuse at the population level?
RQ7 – What individual level characteristics are associated with CCHI?

Stages in our modelling exercise

Stage 1: Cleaned the three-year police data on identified predictor variables and crime.

Stage 2: Estimated crime harm index scores using the Cambridge Crime Harm Index (CCHI) developed by Sherman *et al* (2016). The CCHI operationalises harm based on national sentencing guidelines: for example, in England and Wales the sentence for homicide starts at 15 years, which translates to a CCHI score of 5,475.

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[5] We used indices of multiple deprivation, health deprivation, housing and presence of children from the Office of National Statistics as proxies for class.

Stage 3: Used descriptive analysis to identify the patterns of domestic abuse across suspects' ethnicities.

Stage 4: Developed two regression models (individual level predictors and area level models) to identify important predictors and test the models using all the data from the police forces and national statistics data respectively.

Stage 5: The results were then compared to identify individual and neighbourhood level predictors of high harm perpetrators in Black, Asian, and other racially minoritised communities.

Key points and findings

The police data came from three police forces which was aggregated for the analysis. The final dataset consisted of 153,209 crime records across all three forces[6]. A second 'subset' dataset in which each suspect appears only once was also produced. This involved removing all crimes with no suspect record (n = 15,705) and collating data against each suspect's first known crime record (in the period of data available). This second dataset comprised of 80,768 unique offenders.

Of the combined total of 153,209 domestic abuse crimes, more than 50% were cases from Thames Valley Police (population 2.34 million). By contrast, Sussex is home to a resident population of 1.7 million and Bedfordshire 0.55 million. The recorded domestic abuse crime rates in the three forces are all between 11 and 12 crimes per 1,000 population.

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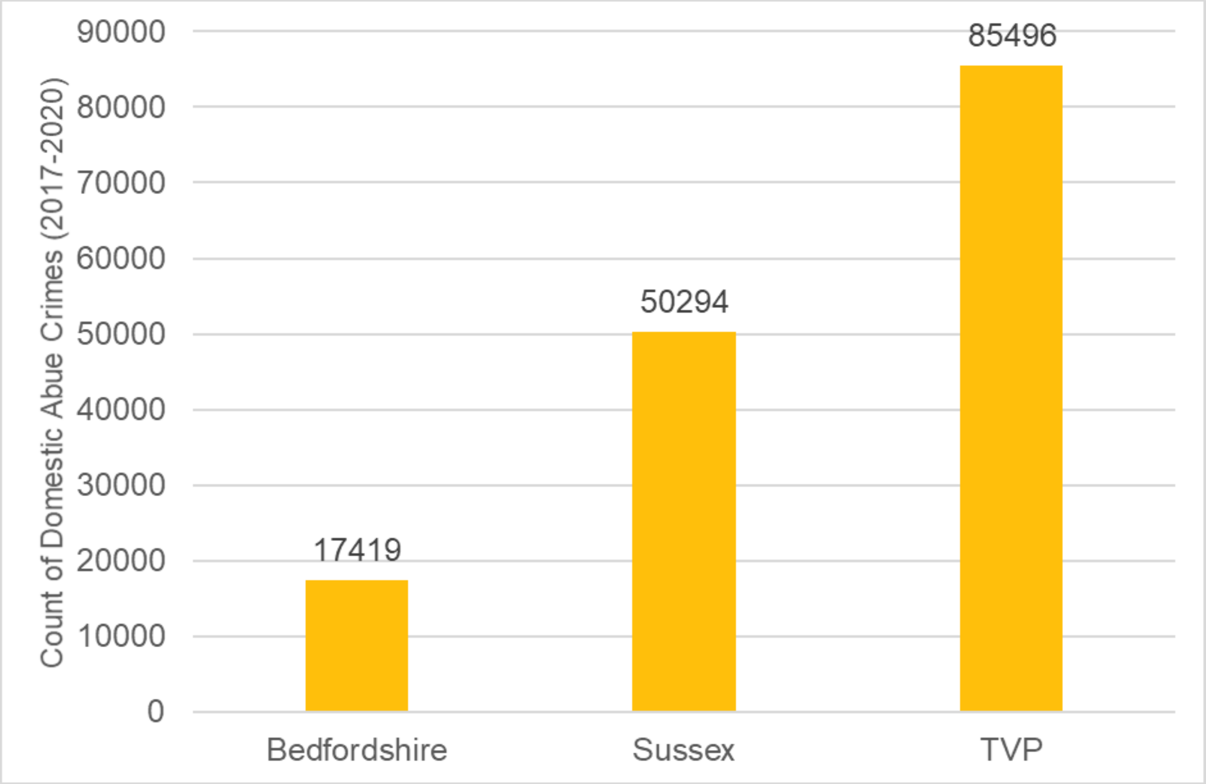
[6] Figures will not precisely match those published by the Office for National Statistics, as non-relevant records were removed during data cleaning, for example, cancelled crimes (initial investigation found no crime had taken place and it was 'cancelled').

Figure 1: Count of Domestic Abuse Crimes in Selected Forces



Patterns of Domestic Abuse Across Different Ethnicity of Suspect

The descriptive analysis based on ethnicity of suspects has been mapped to six categories outlined by the ONS in their population statistics (White British/Any Other White/Mixed or Multiple Ethnicity/Asian or Asian British/Black, Caribbean or African/Other Ethnicities).

In RQ1, regarding the ethnicity profile of suspects: a moderate proportion of self-defined ethnicity data (about 32%) are unrecorded, either due to the suspect being unidentified, refusing to answer the question, or the police failing to record the answer.

In RQ2, we identified that the distribution of harm in our datasets broadly mirrors a Pareto distribution[7], reflecting previous work on domestic abuse harm. In particular, we highlighted that 5% of suspects are associated with 65% of harm.

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[7] Pareto distribution denotes that most of the item being measured is attributed to a small fraction of units.

In RQ3, it was difficult to draw meaningful conclusions from the DASH data based on the descriptive analysis alone and disaggregating by ethnicity. They relate to just one force, and the smallest dataset among those we received. Our findings from this dataset do not indicate any strong disproportionality in grading between different ethnic groups, although there are differences.

In RQ4, we gathered data regarding solved rates in each of the three jurisdictions for which we had datasets. The results show little variation which might not be otherwise accounted for as 'statistical noise'. The low proportion of solved cases in Bedfordshire for the "other" banding pertains to a small sample size (n = 17 solved of 211 total cases) and is not a pattern repeated in Sussex or Thames Valley. One pattern that is repeated however, is that cases involving "Asian/Asian British" suspects are solved at between 0.79 and 0.86 times the rate of "White British" cases.

In RQ5, in Sussex and Thames Valley, a total score of 1,825 CCHI days (equivalent to a grievous bodily harm offence) would mean a suspect is included in the 'power few'. In Bedfordshire, the distribution of harm is more acute. A score of 400 days or above would place a suspect in the top 5%. Nevertheless, we have treated each force as discrete, to identify patterns regarding each individual jurisdiction's most harmful suspects. These analyses show that "Asian/Asian British", "Black/Caribbean/African" and "Mixed/Multiple" bandings are consistently over-represented in the most harmful group of suspects than we might expect if all things were equal.

In RQ6: Are Black, Asian, and other racially minoritised communities at increased risk of domestic abuse at the population level? To further explore to what extent ethnicity (and the need for disaggregation) matters, we undertook exploratory tests (negative binominal regression analysis) using area-level data from the ONS. When the regression model was run with just ethnicity data as independent variables, the proportion of Asian, Black and mixed heritage people in the population are all significant predictors of the count of domestic abuse at the LSOA level, but the proportion in other racially minoritised communities are not significant. The results show when holding all other variables constant, a one unit increase in the Asian population increases the domestic abuse count by a factor of 1.008, the Black population by 1.067 and the mixed heritage population by 1.094.

Following the initial modelling of just the ethnicity data, the *nestreg* function was run in Stata to evaluate the significance of blocks of other predictors. These other predictors have been selected based on previous research (Weir, 2019).

The proportions of Black, Asian and other racially minoritised communities within the population is a statistically significant predictor of the domestic count and rate at the LSOA level along with other structural and community cohesion variables, suggesting that ethnicity matters. However, the ethnicity data in the CSEW is quite old and as such we must exercise some caution in its interpretation.

Table 1: Indicators found to be significantly associated with area level variables from the CSEW

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
% Asian	✓	✗	✓	✓
% Black	✓	✗	✓	✓
% Mixed heritage	✓	✗	✗	✗
% Other racially minoritised communities	✗	✓	✗	✓
Female population		✗	✗	✗
ASB count		✓	✓	✓
Income score (IMD)		✓	✓	✓
Median age		✓	✓	✓
Population density		✓	✓	✓
% Single people			✓	✓
Population turnover			✓	✓
% One person households			✓	

Notes:
The dependent variable in all the models is the DA Count
The coefficient estimates are available in the technical appendix
✓ indicates significance at the 5% level
✗ indicates non-significance at the 5% level

Predictors found to be significantly associated with CCHI and DA count

In RQ7: based on the aggregated data, what individual level characteristics are associated with higher prevalence of high harm offending?

Table 2: Predictors found to be significantly associated with CCHI and DA count rate

Variable	**Model 1**	**Model 2 (with Alcohol and Suicide warnings)**	**Model 3 (with Area level variables)**	**Model 4 (with full set of controls)**
Ethnicity	✓	✓	✓	✓
Age	✓	✓	✓	×
Relationship with victim	✓	✓	✓	✓
Sex/Gender	✓	✓	✓	✓
Alcohol marker	—	×	—	×
Suicide marker	—	✓	—	✓
IMD	—	—	×	×
Health Deprivation score	—	—	✓	✓
% of single people	—	—	✓	×
% private rented	—	—	×	×

Notes:
Results presented in all the models are based on a hierarchical approach in that the order of entering the variables was based on past research and the predictors are entered in blocks and in some cases one by one
The dependent variable is the CCHI score
✓ indicates significance at the 5% level. We have excluded non-significant variables
× indicates non-significance at the 5% level
— variables not included
Variable descriptions – whether continuous or categorical and reference dummies are available in the technical appendix
R^2 = Model 1 (0.06); Model 2 (0.03); Model 3 (0.07); Model 4 (0.11)

Ethnicity

This was tested with 18 categories of self-defined ethnicity data from the three selected datasets. These categories were entered into the model as dummy variables (with White British as the reference group). Three of the dummy variables were highly correlated with each other (also known as multicollinearity) so were excluded. There was a significant relationship between ethnicity and CCHI (controlling for other factors), which is in line with the exploratory results using area-level data from the CSEW. In Model 1, 11 categories were statistically significant. When various controls were applied, the most likely categories to be statistically significant (consistent in at least two of the models) were “Any other Asian”; “Bangladeshi”, and “White and Black Caribbean”. Therefore, not all the categories of ethnicity were statistically significant across the models, it supports our argument for the need for further disaggregation of ethnicity categories in modelling work beyond dichotomous categories of ‘White’ and ‘Non-White’ for example.

Age

This was a significant predictor of CCHI which remained consistent across all the models, except for Model 4 suggesting that age variations are likely to matter in relation to risk profiles of suspects.

Sex/Gender

Being male and trans female was significantly associated with CCHI in relation to being female. Men were more likely to be suspects of domestic abuse harm than females (over 80% of suspects were male) and this relationship remained consistent with a full set of controls. It is important to note that the trans female category was relatively small so this finding should be interpreted cautiously. In fact, in Model 2, only the male category remained statistically significantly associated with CCHI.

Relationship with victim

This was tested with 12 categories (with acquaintance as the reference group). In line with research on victimisation, the type of relationship between the suspect and victim was a significant predictor of CCHI. Three relationship categories were excluded from the regression analysis due to multicollinearity.

Income and Social class variables

Five area-level variables from the ONS data (see Table 2) were used in the regression analysis to proxy for income and social class variables. In Model 4 (with the full set of controls), only one out of the five variables were significantly associated with CCHI.

Suicide Warnings

In Model 2, when the alcohol and suicide markers were included, both were not significantly associated with CCHI. It is important to note that while there is a lot of missing data for both the alcohol and suicide markers in the dataset, a bivariate relationship between suicide markers and CCHI provided a strong case for including this as a potential predictor. In Model 4, with the full set of controls, the suicide markers were significantly associated with CCHI.

Excluded variables

DASH Score: as noted in the earlier section, the sample size was too small to enable any reasonable conclusions to be drawn in the regression analysis. However, based on the bivariate analysis, DASH scores were positively correlated with the CCHI suggesting that it could be a significant predictor. With better quality data on DASH risk assessments, this could be a potential area of future research.

Policy implications

Our primary aim has been to identify risk factors from this work which will support the national policy effort and enable commissioners and practitioners to target their resources and services more effectively to facilitate earlier identification of perpetrators, encourage community capacity to act as ‘capable guardians’, and reduce the harm for victims and their families.

Our analyses suggest that it is important to use targeted approaches for Black, Asian, and other racially minoritised communities rather than a universal approach. The analyses suggests that risk is likely to be different across communities and at the individual level. The risk factors identified in this report may be used when selecting individuals (taking their ethnicity background into account as well as other risk factors) for different interventions. Using the more strongly associated predictors (individual and area-level characteristics) should help identify the individuals most in need of intense support. Risk assessment tools should therefore be validated with different ethnic groups to promote predictive accuracy. Further qualitative and participatory research, and greater attention to intersectionality may shed light on underlying reasons for these differences[8].

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[8] Intersectionality is a theoretical framework developed by Black feminist US legal scholar Kimberlé Williams Crenshaw. Intersectionality was originally developed as an analytical lens to understand the multiple, mutually reinforcing, and interconnected forms of discrimination experienced by Black women, which defied simple or ‘single axis’ accounts of race or gender discrimination (Crenshaw, 1989). Since Crenshaw pioneered this concept, the framework has been widely referenced, utilised and adapted by advocates and theorists subject to other intersecting forms of marginalisation, for example in relation to race, class and disability or gender and migration status.

Strength of the predictors vary based on ethnicity, holding all things constant, but this requires further research into whether this varies consistently across space and to test whether the regression models exhibit the same patterns using data in other police forces (*forthcoming Weir et al, 2022*).

Limitations of the analysis

Data quality issues: although data recording for crimes and domestic abuse in particular is subject to national guidelines, at an individual record level there are numerous discrepancies to manage when aggregating data of this nature. While the data from the three police force areas is very rich, there were some variations in reporting, recording and practice.

The consistent variables we were able to secure comprised of (1) Offence ID number, (2) Earliest date upon which the crime took place, (3) Home Office Counting Rule code, (4) Crime Classification description, (5) Investigation outcome, (6) Suspect ID number (where applicable), (7) Suspect age, (8) Suspect ethnicity as defined by themselves, (9) Suspect ethnicity as defined by the recording officer, (10) Suspect sex and various indicators of suspects prior criminal history for domestic and non-domestic crimes (see technical appendix for more information on the cleaning and aggregating).

A moderate proportion of self-defined ethnicity data went unrecorded, either due to the suspect being unidentified, refusing to answer the question, or the police failing to record the answer. For the purposes of this profiling, these records were excluded but clearly the true answers may skew our findings, even in the most optimistic case. We were unable to decipher if the gaps in recording are systematic or random and so we urge a note of caution in the interpretation of these findings.

There are a few issues with analysing neighbourhood level crime patterns. Firstly, the limitations of using aggregate data need to be considered and acknowledged, notably the problems associated with the Modifiable Areal Unit Problem, where the observed patterns and relationships can be changed by altering the boundaries (O’Sullivan and Unwin, 2003).

The CSEW finds that only 21% of DA is reported to the police. We therefore cannot be certain whether results are more indicative of reporting than actual levels of abuse and the variation that this could have within different intersections.

Lastly, as with all secondary data analysis, it is impossible to control for all variables or to fully specify a model, and therefore our results must be interpreted with that in mind. Having said that, even models with small R^2s[9] can be good models, and the statistically significant relationships of the independent variables can help to provide interesting conclusions. But it is possible that there are other potential indicators which may have impact but are not captured in this report.

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[9] This is a measure that tells us the percentage of variance in the dependent variable that the independent variables collectively explain, which can range from 0 to 100%.

1. Introduction

Background: Domestic Abuse Perpetration and Predictors

Domestic abuse perpetration remains a major threat to public health, safety and well-being, causing serious harms and contributing significantly to overall crime. ONS data for the year ending March 2020 states that an estimated 5.5% of adults aged 16-74 were subjected to domestic abuse, and 357 domestic homicides were recorded by police between March 2017 - March 2019 (ONS, 2020). Meanwhile, over one-third (35%) of all violence against the person offences, and around 16% of sexual offences – recorded by England and Wales police in the year ending March 2020 – were flagged as domestic abuse related (*ibid*).

Domestic abuse has emerged as a policing priority over the past decade, particularly following scrutiny by the national police oversight body Her Majesty's Inspectorate of Constabulary, Fire and Rescue Services (HMICFRS, 2014) regarding failings in the police response to victims. However, given reduced police capacity in the wake of significant budget cuts[10], and rising demand for interventions, police forces are under pressure to ensure that finite resources are being directed in the most effective and targeted way possible.

Recent research on the estimated economic and social costs of domestic abuse found that, for the year ending 31 March 2017, the overall cost of domestic abuse amounted to £66 billion (Oliver *et al,* 2019). This sum includes an estimated £47 billion associated with the considerable emotional and physical harms sustained by victims, as well as costs to the economy linked to reduced economic productivity and output (£14 billion), and costs for health service (£2.3 billion) and police (£1.3 billion) (Oliver *et al,* 2019). The magnitude of individual, social and economic harms incurred because of domestic abuse underlines the need to tackle the root of the problem, identifying and working with those perpetrators likely to cause the most harm.

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[10] A 2018 report from the National Audit Office found that "central government funding to commissioners has fallen by 30% in real terms since 2010-11" (National Audit Office, 2018: 7).

The Cambridge Crime Harm Index (Sherman *et al*, 2016), our choice of instrument, is an index that weights Home Office Counting Rule codes, which label different types of crime in a consistent way for all English and Welsh police forces. Sentence length, as specified by The Sentencing Council or Crown Court guidelines is the determinant of each weighting. Weights are expressed in days, as in the number of days of custodial sentence one would receive for an offence.

While there are now several crime severity or crime harm measures (see Bland and Ariel, 2020 for a thorough discussion), a consistent definition of 'harm' across the available tools remains elusive. And our choice of the CCHI has been based on practicality as well as the one of the authors' (Bland) expertise in applying this tool.

Context: legitimacy of policing in Black, Asian and racially minoritised communities

When responding to high harm domestic abuse among racially minoritised communities, it is crucial to account for historical and social context, and how this may affect confidence and trust in the police and criminal justice system and willingness to report domestic abuse.

Black, Asian and other racially minoritised people continue to be over-represented in the criminal justice system in England and Wales, and to experience disparate outcomes. For example, the 2017 Lammy Review found that, while making up only 14% of the population, Black, Asian and other racially minoritised individuals **made up 25% of prisoners, and more than 40% of young people in custody** (Lammy, 2017). This disproportionality extends to pronounced differences in sentencing for some crimes; for example, for drugs offences, other racially minoritised individuals were **240%** more likely to receive a prison sentence than White offenders (Lammy, 2017).

Concerningly, the Crown Prosecution Service has also identified significant discrepancies in the prosecution and conviction rates for domestic abuse, with a higher prosecution rate for Black, Chinese and 'Other' defendants (Lammy, 2017). This disparity indicates that other racially minoritised defendants are disproportionately likely to face imprisonment, and perhaps accordingly may be less likely to have the opportunity to access evidence-based and rehabilitative community interventions such as Respect-accredited perpetrator programmes.

These differences in treatment throughout the criminal justice system impact not only offenders but all those racially minoritised individuals disproportionately affected by policing practices such as Stop and Search, or through the increased arrest rate for Black and Mixed ethnic background people (Lammy, 2017). The pervasive “racialisation” of crime by the media, and the perception that criminal justice system structures and procedures selectively “target and criminalise” Black, Asian and other racially minoritised people (Fekete, 2018: 77), diminishes confidence in police among racially minoritised people experiencing domestic abuse, and may make it less likely that these victims will trust police to intervene and deliver just outcomes (see Adisa and Allen, 2020).

The racial disparities which exist at each stage of the criminal justice system have implications not only for the offender but for the wider community, resulting in a “trust deficit” that reduces police’s ability to safeguard survivors, disrupt perpetration and hold those using harmful behaviours to account (Lammy, 2017: 29).

When designing, commissioning and evaluating interventions for racially minoritised individuals using harmful behaviours, the legacies of this ingrained inequity must be considered. For instance, professionals from Black, Asian and other racially minoritised communities note that the use of the term ‘perpetrator’ may be experienced as alienating and associated with racialised stereotypes about criminality, deterring people from seeking help to change their harmful behaviours. Additionally, culturally specific interventions are lacking in the current landscape of perpetrator interventions which limit our understanding of ‘What works’ and ‘for whom’ within Black, Asian and racially minoritised communities (Adisa and Allen, 2020).

Currently, tailored provision for Black, Asian and other racially minoritised people seeking to end their use of harmful behaviours remains sparse; a recent rapid review of non-mandated interventions for those using abusive behaviours in intimate relationships did not include any culturally-specific or specialised programmes for Black, Asian or racially minoritised people (Callaghan *et al,* 2020).

Aims and Structure

The aims of this report are as follows:

- To use domestic abuse crime data to assess the relationship and patterns between levels of harm and potential predictor variables
- To explain the findings so that it could be used as a resource for training police officers and others to help shape preventative approaches and inform risk assessment procedures
- To help develop a future resource for using modelling techniques for understanding determinants of harmful behaviour escalation among under-researched groups which can be extended to other police forces.

The Research Team

Dr Olumide Adisa is Senior Research Fellow and Head of Centre for Abuse Research and founder of the Domestic Abuse Research Network (DARNet) at the University of Suffolk. She has a cross-disciplinary research experience straddling both economics and sociology. She is experienced in applying statistics and econometric modelling to secondary data. She has a strong research interest in evaluating community-based perpetrator programmes and domestic abuse interventions, and has built strong links with national domestic abuse organisations including SafeLives and Surviving Economic Abuse. She also supports Drive with developing evidence on Black and other racially minoritised communities to feed into their national call to action perpetrator strategy to inform policy. She is leading on Drive's systems change evaluation examining their work with perpetrators.

Dr Matt Bland is an Associate Professor in Evidence Based Policing at Cambridge University and a Research Fellow for the Cambridge Centre for Evidence Based Policing Ltd. He is a Visiting Senior Research Fellow and DARNet member at the University of Suffolk, a Fellow of the American Society of Criminology's Academy for Experimental Criminology and a Visiting Scholar at the Jerry Lee Centre for Experimental Criminology. He is the Trial Director for the national pilot of polygraph tests for domestic abuse offenders and the independent chair of the Home Office's

Technical Working Group for developing a new funding formula for policing. He was a crime analyst for Norfolk and Suffolk Constabularies for more than 15 years. His research specialisms are domestic abuse, quantitative analysis of police records and forecasting algorithms. He has published two criminology books to date, on domestic abuse, and experimental research methods.

Dr Ruth Weir is a lecturer in Sociology and Criminology at the University of Essex. She is a quantitative Criminologist specialising in the spatial analysis of crime. Her PhD identified the predictors of domestic abuse at the individual, family and neighbourhood level in Essex. Prior to her PhD, she worked as a researcher in local government and for the Home Office. Weir's research has been presented to the Home Office and she has advised the Cabinet Office on domestic abuse during the pandemic. Additionally, plans are in place to present her research findings to civil servants. Ruth is a steering group member of the Domestic Abuse Research Network (DARNet) and is a Visiting Senior Research Fellow at the University of Suffolk. Ruth is also currently writing a Routledge book with Professor Jackie Turton and senior police officers from Thames Valley Police and Bedfordshire police titled "Policing domestic abuse: risk, policy and practice".

Advisory group members and reviewers

Jackie Turton is an emeritus professor at Essex University. She has taught sociology and criminology since 1996, taking the role of Deputy Dean for the Faculty of Social Science in 2016. Jackie has completed research projects for the Home Office, Department of Health and the Royal College of Paediatrics and Child Health using appropriate opportunities to link her data analysis with policy and practice.
She recently obtained collaborative funding for, and supervised, three DA PhD research projects: Domestic violence, the women's sector and the criminal justice system (in collaboration with 'Standing Together') completed in 2018, Predictors of abuse (in collaboration with Essex County Council) completed in 2019, and Police response to domestic violence in Essex (in collaboration with Essex Police) completed in 2020. Jackie's most recent co-authored book, Women and the Criminal Justice System, was published in 2018. Alongside Dr Ruth Weir, Thames Valley and Bedfordshire police forces, she is currently writing 'Policing Domestic Violence'.

Professor Emma Bond is Pro-Vice Chancellor Research and Professor of Socio-Technical Research of Suffolk at the University. She is a Senior Fellow of the Higher Education Academy, with over 20 years teaching experience on social science undergraduate and post-graduate courses, including PhD. Her extensive research experience has focused on online risk and vulnerable groups, image-based abuse (sexting and revenge pornography), online harassment, domestic abuse and sexual abuse. Her recent research includes an extensive body of work on online harassment in UK Universities, including the Catalyst-funded Digital Civility of University Students for the Office for Students which informed the Higher Education Online Safeguarding Self-Review Tool, UUK's Tackling Online Harassment and Promoting Online Welfare Report, as well as Online Harassment and Hate Crime in HEIs.

Meena Kumari is a safeguarding expert and the Founder/director of H.O.P.E Training and Consultancy. As a response to the Covid-19 pandemic, she has developed and currently leads national Domestic Abuse calls within Black, Asian and racially minoritised communities. She founded H.O.P.E in 2008 to share her skills and knowledge around domestic abuse, sexual violence and safeguarding with professionals. In 2015, Meena was shortlisted as a finalist as part of the Iranian & Kurdish Women's Rights organisation IKWRO Awards for her work in combating Honour Abuse and Forced Marriages. She coordinates a series of online knowledge sharing events, providing a national platform for Black, Asian and other racially minoritised communities to discuss sexual and domestic violence and abuse during the pandemic. She is also an Associate for some reputable national organisations: e.g. SafeLives, Safeline, as well as the College of Policing, focusing on delivering a culture shift within policing around domestic abuse and vulnerability. In October 2020, Meena was shortlisted for the Emma Humphreys Memorial Prize.

Scoping Review Summary: Identifying predictors

This scoping review includes 104 articles, reports and dissertations published in the English language between 2000 and 2021. It is designed to give an overview of the literature on predictors of harm for high-risk perpetrators in Black, Asian and other racially minoritised communities, with particular focus on highlighting gaps in the evidence base. It follows the robust methodological framework for scoping reviews outlined by Arksey and O'Malley (2005).

The scoping review refers to intimate partner violence and abuse (IPV) rather than domestic abuse. This is because, while researchers searched the literature using a variety of related key words, including "intimate partner violence", "domestic violence", "domestic abuse" and Boolean strings of these and other relevant terms, articles which met the inclusion criteria almost exclusively focus on sexual or physical violence and/or abuse perpetrated in the context of an existing or previous intimate partner relationship (99 out of 104 included articles). Meanwhile, the Home Office definition of domestic abuse additionally includes violence, abuse and coercive and controlling behaviours which occur within a familial relationship.[11]

This disparity in the literature may reflect underlying differences in the prevalence of IPV and familial domestic abuse, and therefore the perceived urgency of investigating risk factors and predictors of harm. Turner *et al* note that "the bulk of the cases dealt with by the police under [the Home Office domestic abuse] definition are intimate partner violence incidents" (Turner *et al*, 2021: 3). Similarly, when looking a subset of the *highest* harm cases – domestic homicides and suspected victim suicides – recent data suggests that the largest proportion of deaths were associated with IPV rather than familial domestic abuse (Bates *et al,* 2021). Available literature suggests that the gender and relational dynamics and risk factors for familial domestic abuse differ significantly from IPV; for example, "Whilst intimate partner homicide victims and suspected suicide victims were overwhelmingly female (85% and 90% respectively), half the victims of adult family homicide (50%) and nearly half of child death victims (48%) were male" (Bates *et al,* 2021: 8). Therefore, the scoping review findings suggest that there may be a gap in the literature regarding predictors of harm in relation to familial domestic abuse.

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[11] "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" (Home Office, 2013).

KEY FINDINGS

Ethnicity and perpetration (RQ1)

Key message: **Research on IPV perpetration conducted in a criminal justice context points to differences in police recording, patterns of offending, prevalence and risk factors (e.g. hazardous drinking) between different ethnic groups. Further qualitative and participatory research, and greater attention to intersectionality may shed light on underlying reasons for these differences.**

Among the 36 articles which discussed ethnicity in the context of IPV perpetration risk factors, only five were undertaken specifically in a criminal justice-related context. Among these five studies, three took place in the United States (US), one was conducted in Spain, and one was undertaken in Montenegro.

Each of these five articles identified differences regarding IPV police recording, patterns of offending, prevalence and risk factors in relation to ethnicity, including:

- A higher probability of IPV perpetration by non-White respondents, with ethnicity being the only control variable which was found to be predictive of IPV (Eriksson and Mazerolle, 2015). See below for further discussion of this finding. (Study location: US)

- Differences in IPV between interracial and monoracial couples, with interracial couples demonstrating an increased likelihood of mutual assault and injury of the victim relative to monoracial racially minoritised couples. Interracial couples also displayed reduced rates of alcohol or substance use before or during the IPV event relative to White couples (Fusco, 2010). (Study location: US)

- Discrepancies between victim narratives and police recording about IPV perpetrated by individuals from different ethnic groups, which indicates that "severe physical IPV against Black women, or more specifically that perpetrated by Black men, is regarded as less severe if the [Conflict Tactics Scale] coding is considered the "gold standard" against police charges" (Lipsky *et al*, 2012: 2156). (Study location: US)

- A higher likelihood of IPV among interracial than monoracial couples (Radojevic *et al,* 2020). (Study location: Montenegro)
- An association between ethnicity/migration and hazardous drinking behaviour (itself considered a risk factor for IPV) among men accessing a court-mandated batterer programme (Catalá-Miñana *et al,* 2017). (Study location: Spain)

Perhaps due to being overwhelmingly quantitative in design, many of the reviewed studies on IPV victimisation (RQ2) identified ethnic differences without exploring why these exist. Similarly, one of the above studies (Eriksson and Mazerolle, 2015) highlights disparities in perpetration but does not explore the underlying causal mechanisms responsible. This is perhaps a consequence of the quantitative methodological approach, the study's primary focus on gender, and exposure to family-of-origin violence as predictors of IPV perpetration, with ethnicity acting as a control variable. This limitation is seemingly less pronounced in studies looking at how specific risk factors interact with ethnicity (see RQ2 discussion), and speaks to the importance of considering context, within-group diversity and lived experience when seeking to understand trends in perpetration, to design and administer interventions.

Ethnicity and victimisation (RQ2)

Key message: Most of the reviewed literature identified differences between ethnic groups regarding IPV prevalence, patterns of victimisation and risk/protective factors. However, the exact nature of relationship/risk varied across studies, and others found no effect when controlling for other relevant variables.

Most articles (78 out of the 104 which met inclusion criteria) broadly corresponded to RQ2, focusing on ethnicity and intersectionality in the context of IPV victimisation. As with reviewed articles relating to RQ1, the majority (66) employed a quantitative research design, with the remainder utilising a mixed method (4), geodemographic (1) or qualitative (1) approach, or reviewing literature (6).

Analysis of selected articles revealed often contradictory findings, with some studies highlighting a disproportionate risk among certain ethnic groups, such as Bohn *et al,* 2003, while others identify no significant racial/ethnic differences, for example Bassuk *et al*, 2006. This may be a consequence of the complex interactions between ethnicity, other socioeconomic and demographic factors and different risk and protective factors, which problematise claims about relative risk based on differences between "crude rates of IPV across ethnic groups" (Field and Caetano*,* 2004: 307).

In broad terms, 61 articles identified some form of ethnic difference in relation to IPV victimisation, including:

- Increased prevalence of high-harm or fatal forms of IPV, such as abuse during pregnancy (Bohn *et al*, 2003; Elliston, 2004), "severe" physical abuse (Lacey *et al*, 2016), strangulation (Ramos, 2017) and femicide (Petrosky *et al,* 2017) among racially minoritised women

- Choice of protective strategies among victimised women from different ethnicities, with White women adopting more "placating" behaviours than South Asian women (Irving and Liu, 2020)

- Varying correlates of IPV victimisation among men (Nowinski, 2012), women (Cheng *et al,* 2016; Steele *et al,* 2020) and mixed gender people (Ellison *et al,* 2007) from different ethnic groups, which suggest that risk and protective factors interact with/are mediated by ethnicity.

Meanwhile, 11 articles found no significant differences in risk or patterns of IPV when controlling for other relevant interpersonal, socioeconomic and demographic variables, such as age and financial security (Cho, 2012), neighbourhood poverty (Caetano *et al,* 2010), adverse childhood experiences such as sexual abuse, exposure to family-of-origin IPV and female caretaker mental health issues (Bassuk *et al,* 2006). A further six articles looked at prevalence, risk factors or patterns of victimisation within ethnic groups; for example, women of African descent across three US sites (Stockman *et al,* 2014) or examined the association between risk factors such as depressive symptoms, substance use and IPV among diverse women and how these translate to specific support needs (Holden *et al,* 2012).

Ethnicity and recorded patterns of offending (RQ3)

Key message: Reviewed articles identify concerns about the use of charge data in risk modelling, due to the risk of embedding and compounding historic biases in policing. Using only charge data for serious offences reduced the risk of racially biased modelling but also reduced predictive accuracy.

Two reviewed articles (Turner *et al*, 2021; Rovatsos *et al,* 2019) discussed varying notions of fairness in risk modelling, and the potential for algorithmic bias due to disparate criminal justice reporting, recording and outcomes for racially minoritised individuals.

- When developing an IPV risk assessment model, Turner *et al* noted that the most important predictors in their model "pertained to charge data, which is a proxy for the true variables of interest, concerning criminal history" (Turner *et al,* 2021: 20). However, they observe that there are serious concerns about the use of this as a proxy given evidence of biases in UK policing as they impact racially minoritised (and particularly Black) people. Meanwhile, solely using "charge data for crimes known to be less subject to bias" such as serious offences reduced the predictive accuracy of the model (*ibid).*

- Rovatsos *et al* also discuss critiques of the use of historical crime data in predictive policing due to concerns about amplifying existing biases (Rovatsos *et al,* 2019: 50).

Ethnicity, intersectionality and risk forecasting (RQ4)

Key message: Risk assessment tools can yield differential predictions based on 'baked in' assumptions and contextual factors (e.g., historic biases in policing). Tools should be validated with different ethnic groups to promote predictive accuracy.

Three US-based studies discussed the role of ethnicity and intersectionality in risk assessment in a wider criminal justice context (Rembert, 2013; Munoz *et al,* 2021; Waldron, 2012).

- Rembert (2013) found that the PACT-P risk assessment tool differentially predicted some forms of assaultive behaviour in young offenders from different ethnic groups

- Munoz *et al* (2021) identified increased weighting of social/contextual factors for ethnic ingroup versus outgroup members when probation officers used a structured professional judgement risk assessment tool (SAVRY) for young offenders. However, this was not found to result in differences in overall risk classification by ethnicity

- Waldron (2012) examined the Static-99 scores of incarcerated Black, White and Latino men. Static-99 is a tool developed to predict the risk of recidivism among sex offenders. Five out of 10 survey items showed significant differences in scoring patterns based on ethnicity, and Black participants showed an elevated mean score relative to White and Latino participants. This indicates a need to conduct validation studies with different demographics and offending histories to ensure predictive accuracy across ethnic groups and mitigate biases.

Aggregation and ethnic categorisation (RQ5)

Key messages: Few articles covered this topic in depth, but reviewers identified issues around varying levels of specificity and cultural relevance in the ethnic 'categorisations' used across studies, and the exclusion of under-represented groups from statistical analysis

Reviewed articles typically exemplified/acknowledged (rather than predominantly focused on) issues around ethnic aggregation and categorisation. Issues identified included:

- Under-represented ethnic groups within a sample being excluded from statistical analyses for statistical reasons (e.g. Rembert, 2013) or aggregated into an 'Other' category (Eriksson and Mazerolle, 2015; Munoz *et al*, 2021). This has implications for identifying and responding to group-specific risk factors, and how membership of that ethnic group may mediate risk factors

- The cultural specificity/variability of ethnic categorisations e.g. Hispanic or Latino communities in a US context. Such categories may not be straightforwardly ‘transferable’ cross-culturally (for example, when applying the findings to a UK context) and may not correspond to the identity and lived experiences of individuals within these groups

- Reviewed studies employed both ‘blunt’ and fine-grained levels of description regarding ethnicity e.g., Black (Field and Caetano, 2004) versus Igbo, Yoruba or Hausa (Dim, 2020) and Asian (Fusco, 2010) versus Filipino, Chinese and Vietnamese (Cho, 2012). Some studies even employed a dichotomous categorisation of White versus ‘non-White’ participants (Eriksson and Mazerolle, 2015). The level of description employed may impact the accuracy and transferability of findings

- Previous work by Weir (2019) found that another important intersection to consider when analysing domestic abuse are the structural and cultural characteristics of the neighbourhood. Four variables; the income score from the Index of Multiple Deprivation; the rate of Anti-Social Behaviour (ASB); the proportion of ethnic minorities with the population; and the population density – all found to explain 82% of the variation in the area’s Domestic Abuse rate. In the research limitations, Weir suggested further work needed to be done to explore the ethnicity in more depth.

1.1. Key research questions

RQ1 – What is the profile of domestic abuse suspects by ethnicity?
RQ2 – What is the profile of crime harm, overall and by ethnicity?
RQ3 – What is the profile of risk assessment by ethnicity?
RQ4 – What is the profile of investigative outcome by ethnicity?
RQ5 – What is the contribution of different ethnicities to the ‘power few’ most harmful suspects?
RQ6 – Are Black, Asian, and other racially minoritised communities at increased risk of domestic abuse at the population level?
RQ7 – What individual level characteristics are associated with CCHI?

1.2. Report structure

The report structure is as follows: Chapter 1 presents the scoping review summary and outlines how the report contributes to the evidence base. Chapter 2 discusses the methodology and the rationale for selecting the variables in the analysis. It also discusses the analysis strategy beginning with the descriptive analysis, followed by the regression analysis. Chapter 3 presents the key findings from the analysis and concludes with some recommendations and policy implications. For the benefit of other researchers and analysts who may wish to replicate the study or apply our models to other police forces' data, technical details are included in the Appendix.

1.3. Ethics

The research was conducted having been augmented by the University of Suffolk's Research Ethics Committee. Research undertaken at the University of Suffolk complies with the UK Research Integrity Office (UKRIO) Code of Practice for Research (2021)[12].

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[12] https://ukrio.org/publications/code-of-practice-for-research/

2. Methodology

Researchers analysed data from several sources.

Data provided by selected forces

Datasets were supplied from three English police forces: Thames Valley, Sussex, Bedfordshire. A data specification and follow up meeting was provided for each force through the data collection process, ensuring some consistency of format in the datasets received. Although data recording for crimes – and domestic abuse in particular – is subject to national guidelines, at an individual record level there are numerous discrepancies to manage when aggregating data of this nature.

The consistent variables we were able to secure comprised of: (1) Offence ID number, (2) earliest date upon which the crime took place, (3) Home Office Counting Rule code, (4) Crime Classification description, (5) Investigation outcome, (6) Suspect ID number (where applicable), (7) suspect age, (8) suspect ethnicity as defined by themselves, (9) suspect ethnicity as defined by the recording officer, (10) suspect sex and various indicators of suspect's prior criminal history for domestic and non-domestic crimes.

We also collected several variables which were supplied by one or two of the forces but not by the complete set. We retained the following variables because of their potential for particular interest: (1) date of the crime being recorded[13], (2) relationship between suspect and victim, (3) risk assessment grading, (4) alcohol warning, (5) suicide warning, (6) victim ethnicity, (7) victim sex, (8) victim age[14].

Population level data and study area

Point level data was aggregated to Census Lower Super Output Area (LSOA) level[15] in ArcGIS, using the grid reference of the offence location recorded and supplied by each

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[13] Date recorded is different from date crime occurred in crimes of a non-recent nature.

[14] See technical appendix on the aggregation process used in this report.

[15] LSOA was selected as it was the lowest level of granularity at which the independent variables were available.

force[16]. For Bedfordshire there were 18,472 domestic abuse crimes recorded for the period from 23rd May 2017 – 31st December 2020[17]. Of these crimes, 260 (1.4%) did not have a useable grid reference, or the location of the crime was recorded out of force. For TVP there were 85,496 domestic abuse crimes recorded between January 2017 and December 2020. 7,443 (8.7%) did not have a useable grid reference. Unusable records were omitted from the analysis and the count of domestic abuse crimes was calculated for each LSOA in Bedfordshire and TVP. As the data in Bedfordshire was for a shorter time span and there was no date field in the TVP data, an adjusted count was calculated to make the data comparable[18].

Descriptive analysis

This portion of the research is exploratory in nature, dealing with a cross-sectional dataset. Our initial research questions do not venture beyond the descriptive – seeking to establish a 'baseline' profile of the issue of harm and its distribution across ethnicities. It sought to address the following questions:

- RQ1 – What is the profile of domestic abuse suspects by ethnicity?
- RQ2 – What is the profile of crime harm, overall and by ethnicity?
- RQ3 – What is the profile of risk assessment by ethnicity?
- RQ4 – What is the profile of investigative outcome by ethnicity?
- RQ5 – What is the contribution of different ethnicities to the 'power few' most harmful suspects?

These analyses were undertaken in Microsoft Excel.

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[16] Crime location was used rather than victim or perpetrator address as this field is more reliable and complete than the other address fields.

[17] A shorter time span was used when Bedfordshire starting using a new crime recording system on this date and would also have taken too much time to extract data from the previous system.

[18] Using the number of days in each dataset to calculate the adjustment.

CCHI and predictor variables – OLS Regression model

A simple Ordinary Least Square (OLS) Regression model and a correlational analysis were used to identify the predictors significantly associated with CCHI while controlling for other indicators. It sought to address the following question: RQ7 – What individual level characteristics are associated with CCHI?

We have selected potential predictor variables based on the scoping review of the relevant literature, from our conversations with the police forces and practitioners, and the initial regression analysis based on population level variables and bivariate relationships.

Table 3: Bivariate relationships between CCHI and selected variables

Variable	**Categories**	**Statistical results**
Age	Continuous variable	-.023**
Relationship with victim[a]	Acquaintance Boyfriend/girlfriend/partner Child of offender Employer of offender Ex-partner Neighbour Other family member Parent of offender Sibling of offender Stranger Victimless/crime against state Brother	Significant
Sex/Gender*	Female Male Non-Binary Trans female to male Trans male to female	Significant
Alcohol marker	Binary variable (1, Yes, 0, No)	.012
Suicide marker	Binary variable (1, Yes, 0, No)	.034**
DASH score	Continuous variable	.168**

**Significant at $p < 0.01$.

a: Chi square tests were used to examine the relationship for these categorical variables

Our equation can be expressed as a function of the underlying socio-demographic factors and socio-economic factors:

$CCHI_p$ = *f* (set of possible indicators)*

*(Suspect's age, suspect's ethnicity, suspect's sex, suspect's relationship with victim, Alcohol warnings, Suicide warnings, DASH risk score, selected population variables)

Examined hypothesis and selected determinants:
The study's basic expectations, holding all things constant, are that the following will hold:

1. Suspect's ethnicity is positively/negatively associated with CCHI
2. Suspect's age is positively/negatively associated with CCHI
3. Suspect's sex (being a female) is positively associated with harm
4. Suspect's health harming behaviours (alcohol and suicide warnings) are associated with harm
5. The type of relationship with the victim is associated with higher levels of harm
6. Higher levels of risk (DASH score assigned) are associated with CCHI*
7. Higher levels of deprivation are associated with higher levels of harm (IMD and health); alternative proxy: employment)
8. Housing situation is associated with higher levels of harm
9. Having children is associated with higher levels of harm.

OLS Robustness Tests

Simple bivariate relationships and coefficients were estimated to confirm linear dependence amongst the regressors – a very important statistical assumption for linear regression analysis (see technical appendix for the tables). We also examine the changes on R^2 and changes in the coefficients of other explanatory variables to identify the usefulness of including a variable.

The extreme outliers in the dataset created issues with regards to the Normality, Skewness and Kurtosis. From our descriptive analysis, we are aware that the CCHI does not follow a normal distribution. However, while normality is not too problematic with larger datasets (Field, 2018), the impact of the extreme values for the CCHI score needed addressing. Cleaning the data further by using Q-Q plots and trimmed mean analysis provided best estimated for trimming based on N = 18,289, filtering out any cases greater than 5,000 and less than 20.

Based on the residual analysis and examining the plots, the model performed better with a log-linear version of the dependent variable. This involved comparing the untransformed variables with the log-linear and square root forms.

We retained only the variables that had low Variance Inflation Factors (VIFs) to reduce the risk of multicollinearity.

OLS Model specification

Intuitively, we can interpret the model that any increasing or decreasing effects on CCHI scores for suspects are likely to be key determinants of harm. The determinants are on the right side of Equation 2 below, and they feature as the explanatory (independent) variables in the estimation.

Mathematically, this study's simple OLS model can be expressed as follows:

$$\mathbf{LnY_i = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k + e_i} \qquad (1)$$

Where Y is Log of CCHI score, and this study's dependent variable; α, is a constant; $\beta_{1\ \mathrm{to}}\ \beta_k$ are unknown coefficients; and e_i is an error term.

This study's regression specification for the model can be expressed as follows:

$$\mathbf{LnY = \beta_0 + \beta_1\,() + \beta_2() + \beta_{3()} + \gamma\ age + \beta_4\,() + \gamma\ dummies + \gamma\ alcohol\ dummies + \gamma\ suicide\ dummies + \gamma\ Income\ and\ Social\ Class + \varepsilon_i} \qquad (2)$$

Our main objective with the study is to identify individual level characteristics of the offender or victim which can often compound the risk of injury and severity of abuse. Identifying these individual-level predictors on a large-scale will improve the evidence-base for identifying high-risk or high-harm perpetration within minoritised communities.

To capture any potential non-linear effects for the other continuous variable in the model, first we included a new variable, Suspect Age^2 (square of Suspect Age). However, this non-linear derived variable did not significantly improve on the model, so we dropped this variable and included only Suspect Age. Similarly, for log transformed area level variables, all the analysis was undertaken using SPSS v28.

The role of ethnicity and other predictors – using ONS data area-level variables

It sought to address the following question:

> RQ6: Are Black, Asian, and other racially minoritised communities at increased risk of domestic abuse at the population level?

This next section details the data that was used for both models before more specific details about the data and methods are explained for each model.

Social disorganisation theory comprises of three measures: economic disadvantage; ethnic heterogeneity; and population turnover. Economic disadvantage was measured using the income score from the 2019 Index of Multiple Deprivation, and ethnic heterogeneity using data from the 2011[19] census, divided into broad ethnic groups. Population Turnover was calculated by dividing people who migrated into the area from either within the UK or from outside the UK within the year before the census, divided by all usual residents in the LSOA in 2011. Community cohesion was measured using Anti-social Behaviour (ASB) data. 2019 ASB data was downloaded from data.police.uk.

Intersectional characteristics known to impact the amount of abuse at the individual level have been included in their aggregate form at the LSOA level, including the proportion of the population that is female, the median age, as well as ethnicity, which is included as an SDT variable. Population density (persons per square kilometre) was calculated by dividing the population in each LSOA, using 2019 population estimates by the area (which was calculated in ArcGIS).

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[19] Unfortunately, this is the most recent data available.

As the population sizes of the LSOAs are similar (approximately 1,500), the count of domestic abuse was used as the dependent variable in the global model[20]. The data did not follow the normal distribution and was found to be over dispersed, with the conditional variance exceeding the conditional mean. A negative binomial regression model was therefore run in Stata[21]. 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. This might not always be the case, so we ask readers to bear this context in mind.

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[20] If there are varying population sizes this will violate the assumption that the error variance is homogenous.

[21] A test was run in Stata to determine which was the most appropriate method to use with the dataset and the results found negative binomial regression to be the most suitable. This method is a generalisation of Poisson regression as it has the same mean structure as Poisson regression but includes an extra parameter which models the over-dispersion, λ_i(Stata, 2021, Oswood, 2000). The formula for negative binomial regression is:

$$P(Y_i=y_i)=\frac{\Gamma_{yi+\emptyset}}{y_i!\Gamma(\emptyset)}\frac{\emptyset^{\emptyset}\lambda_i^{yi}}{(\emptyset+\lambda_i)^{\emptyset-yi}}$$

Where Γ is the gamma and ∅ is the reciprocal of the residual variance of underlying mean counts α (Gardner *et al,* 1985).

3. Key Findings

RQ1 – What is the proportion of domestic abuse crimes by ethnicity?

A moderate proportion of self-defined ethnicity data are unrecorded, either due to the suspect being unidentified, refusing to answer the question or the police failing to record the answer. As Table 5 shows, this was a substantially greater occurrence in Thames Valley.

Table 44: Proportion of crimes with unrecorded self-defined ethnicity

Bedfordshire	Sussex	Thames Valley
28.2%	10.3%	51.0%

For the purposes of this profiling, these records were excluded but clearly the true answers may skew our findings, even in the most optimistic case. We are unable to decipher if the gaps in recording are systematic or random and so we urge a note of caution in the interpretation of these findings.

Figure 2 shows that there is no distinct or obvious pattern of higher repeat offending rates in Black/Caribbean/African suspects compared with White British suspects. These analyses are based on our overall crime dataset, so repeat offenders of the same recorded ethnicity may skew results. We explored the extent of repeat offending on the offender subset, therefore controlling for high volumes of repeat offenders.

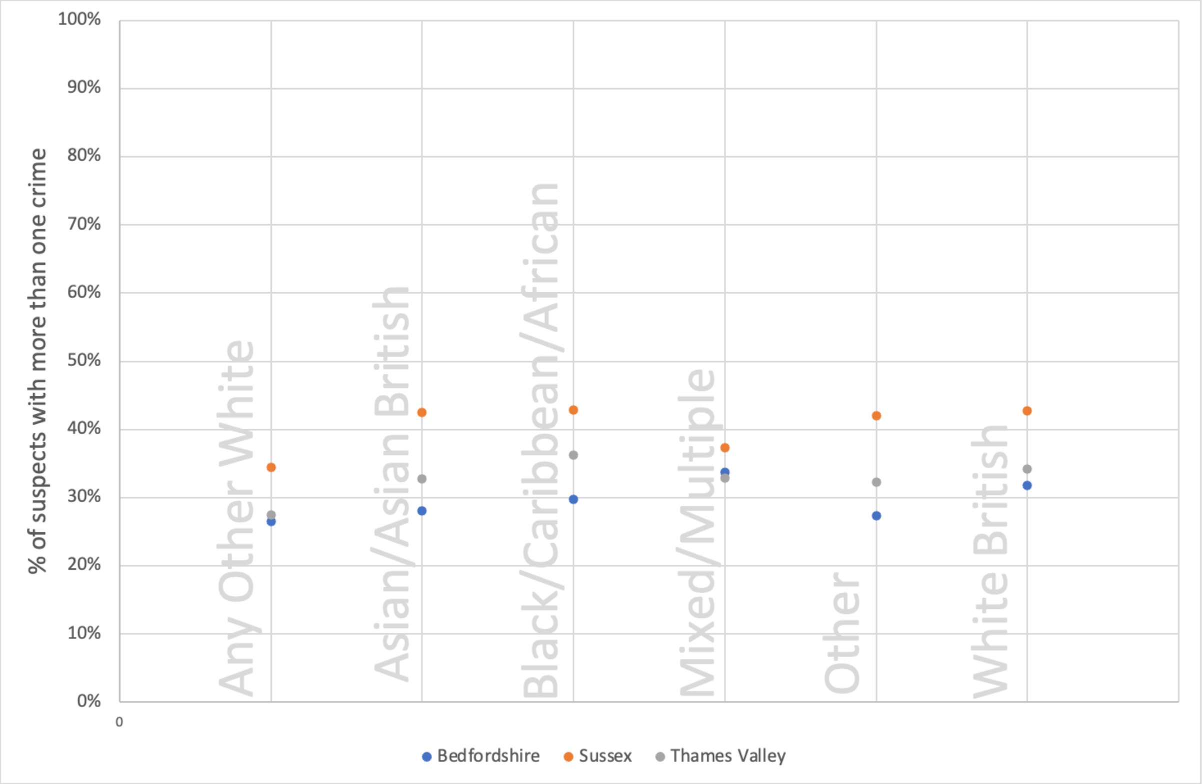

Figure 2: Comparison of repeat suspect rates across ethnicity bands

RQ2 – What is the profile of crime harm, overall and by ethnicity?

Typically, analyses that utilise the CCHI are not normally distributed. This is also the case with our dataset, which represents something approximating a Pareto distribution. As Figure 3 shows, most suspects across the three datasets accumulated CCHI totals equivalent to less than six months in prison. There is not a universal Pareto distribution however – note the peak around 1825 days (five years) which is linked to the minimum sentence for grievous bodily harm offences.

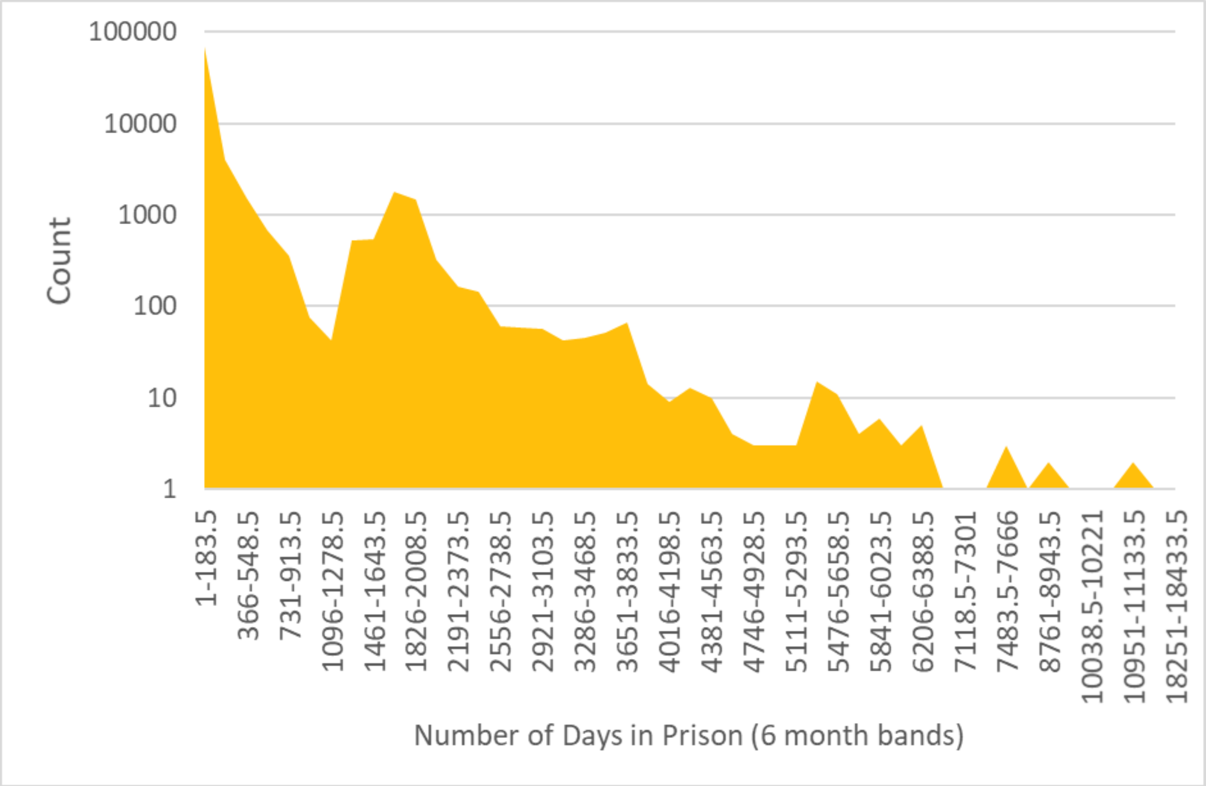

Figure 3: Distribution of CCHI totals among suspects

This distribution mirrors that seen in previous studies in this area (see Bland and Ariel, 2015; 2020; Barnham, Barnes and Sherman, 2016). In simplistic terms, a small proportion of suspects are associated with a greater proportion of harm. In these three datasets combined this trend is that 5% of suspects account for 65% overall harm. This issue is explored in more detail in RQ5.

The measure of central tendency in the data is affected by this distribution, which includes some extreme outliers. The mean number of CCHI days is 177 (SD = 538). The median is a more accurate reflection of the centre of the dataset at 10 days. The central point holds true across different ethnicity bandings within the force jurisdictions, as shown in Table 5.

Table 5: Median CCHI totals for suspects by ethnicity banding

	Bedfordshire	Sussex	Thames Valley
Any Other White	5	10	10
Asian/Asian British	3	10	10
Black/Caribbean/African	3	10	10
Mixed/Multiple	5.5	10	10
Other	5	10	8
White British	5	10	10

The exception is notably Bedfordshire, where median CCHI totals are approximately half of those in Sussex and Thames Valley for every ethnicity banding. In practical terms, we might infer that the 'typical' cumulative harm of domestic abuse offenders does not rise above the level of an actual bodily harm – a violent crime which is to the detriment of the victim but does not cause serious physical injury.

RQ3 – What is the profile of risk assessment by ethnicity?

Bedfordshire were the only force to supply us with DASH risk assessment gradings. In total, 74% of these were at the 'moderate' risk level, 15% at the 'high' risk level and the remaining 10% at 'standard' risk. Almost a third of these records had no recorded suspect ethnicity, so we again emphasise caution in the findings and note that among these 'blank ethnicity' cases, 15% were 'standard' risk. Figure 4 shows the full breakdown.

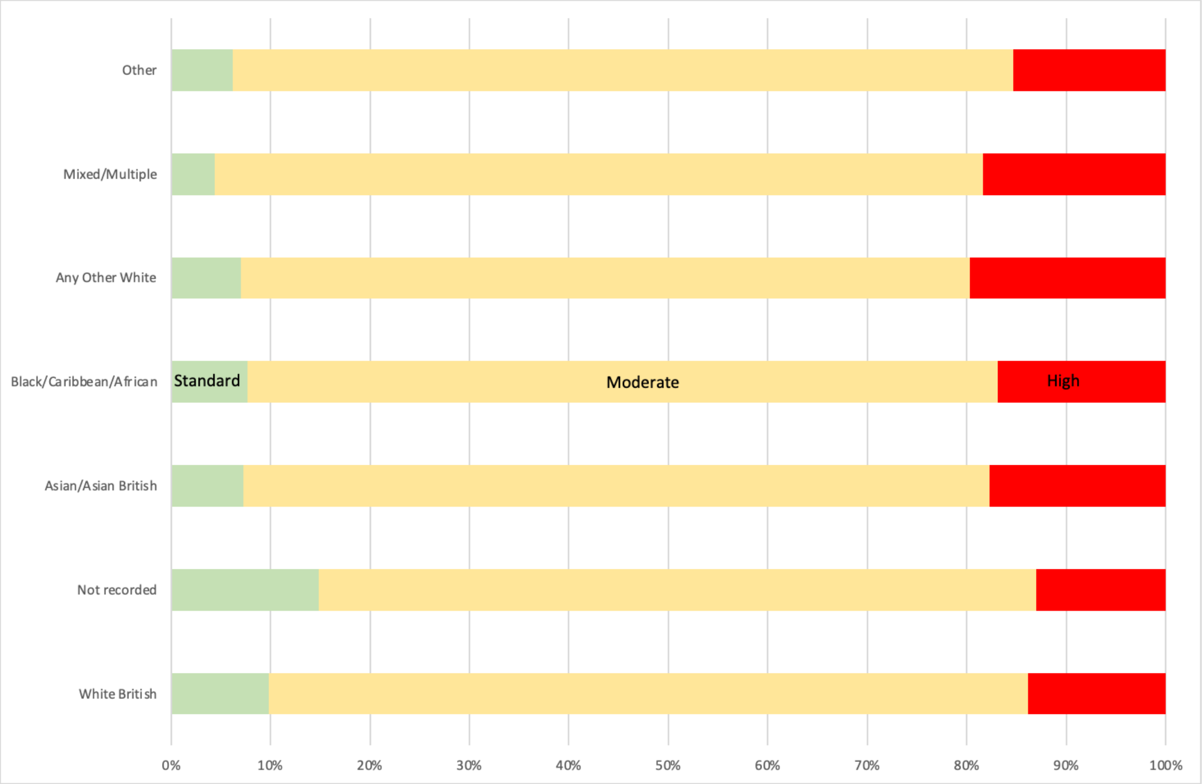

Figure 4: Proportions of risk assessment score by ethnicity banding

It is difficult to draw meaningful conclusions from these data based on the descriptive analysis alone. They relate to just one force, and the smallest dataset among those we received. They do not indicate any stark disproportionate differences in gradings between differing ethnicity groups but there are differences. 13.8% of white British cases are identified as ‘high risk’. Proportionally, all other bandings have higher rates of ‘high risk’ grading, with ‘any other white’ the most different at almost 1.5 times the rate. These statistics offer little more than context, however.

RQ4 – What is the profile of investigative outcome by ethnicity?

All domestic abuse crimes reported to the police are investigated and assigned an ‘outcome code’ based on the results of that investigation. Broadly, the 22 codes are divided into two categories which might be described as ‘solved’ and ‘unsolved’. Solved cases include charging the suspect to court, issuing a caution or community resolution[22]. Unsolved codes are divided into differing reasons for that outcome, such as a different organisation being passed the case or the victim being unwilling to support a prosecution. Police forces are commonly assessed on their ‘solved rates’, the proportion of crimes which they obtain a positive outcome for, as an indicator of their performance.

Table 6: Solved rates across different ethnicity bandings

	Bedfordshire	**Sussex**	**Thames Valley**
Any Other White	15.7%	17.1%	19.9%
Asian/Asian British	11.3%	12.9%	16.2%
Black/Caribbean/African	13.3%	16.2%	18.0%
Mixed/Multiple	14.3%	15.6%	19.9%
Other	8.1%	20.4%	15.8%
White British	13.4%	16.4%	18.9%

Table 7 reports these solved rates in each of the three jurisdictions we gathered data for. The results show little variation which is not attributable to ‘statistical noise’. The low proportion of solved cases in Bedfordshire for the “other” banding pertains to a small sample size (n = 17 solved of 211 total cases) and is not a pattern repeated in Sussex or Thames Valley. One pattern that is repeated however, is that cases involving “Asian/Asian British” suspects are solved at between 0.79 and 0.86 times the rate of “White British” cases. Indeed, the solved rate for cases with “Asian/Asian British” suspects is nearly always lower than all other bandings.

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[22] We note that national police policy dictates that outcomes other than charges should not be issued for domestic abuse cases, but it is widely acknowledged that it happens nonetheless (see Westmarland and Johnson, 2018).

RQ5 – What is the contribution of different ethnicities to the ‘power few’ most harmful suspects?

In RQ2, we identified that the distribution of harm in our datasets broadly mirrors a Pareto distribution mirroring previous work on domestic abuse harm. Specifically, we highlighted that 5% of suspects correlate with 65% of harm. This is consistent with the concept of ‘the power few’ – the few offenders who offer the most powerful opportunities for harm reduction.

When dividing the aggregated data into three datasets, the ‘power’ of the power few in each force is slightly different.

Table 7: ‘Power few’ for Bedfordshire, Sussex and Thames Valley Police forces

	Number of suspects within the top 5% most harmful	Total % of harm this group correlates to
Bedfordshire	544	78%
Sussex	1,413	54%
Thames Valley	2,601	59%

In Sussex and Thames Valley, a total score of 1,825 CCHI days (equivalent to a grievous bodily harm offence) would mean a suspect is included in the ‘power few’. In Bedfordshire, the distribution of harm is more acute. A score of 400 days or above would place a suspect in the top 5%. Nevertheless, we have treated each force as distinct to reflect the patterns within each jurisdiction’s most harmful suspects.

These analyses show that “Asian/Asian British”, “Black/Caribbean/African” and “Mixed/Multiple” bandings are consistently over-represented in the most harmful group of suspects than we might expect if all things were equal. The baseline distribution of the ‘power few’ is that just 5% of suspects are within this category. So our starting hypothesis is that each ethnicity banding will reflect this equally. Figure 5 shows the proportion of each ethnicity banding that are within the ‘power few’.

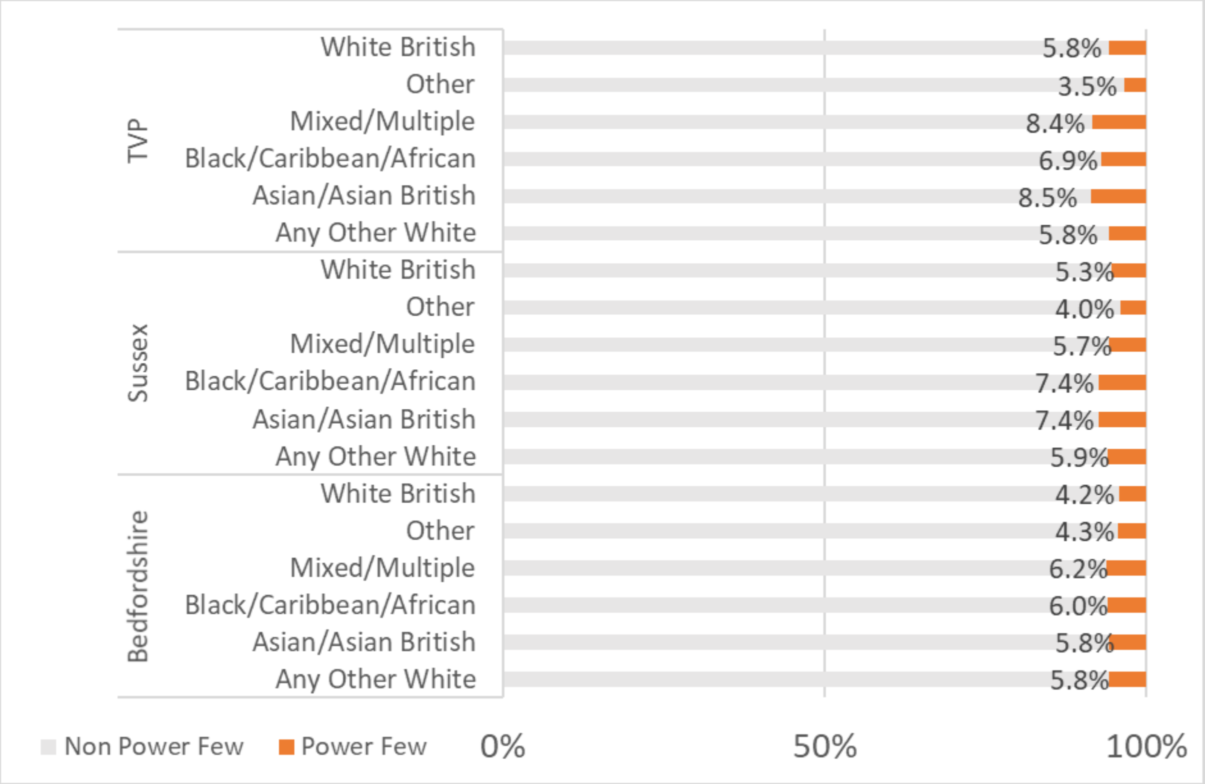


Figure 5: Proportion of suspects within the power few, by ethnicity banding

Proportions as small as these can be difficult to interpret visually. We might notice that "Asian/Asian British" proportions are higher in two forces but how much stock to place in this difference is harder to determine without inferential statistics. We undertook z-tests for two population proportions to test the hypothesis that these proportions were different from each other in a generalisable sense. Table 8 shows these results. From these we may conclude that we may accept that there are real differences between the proportions of "White British" and all three of "Asian/Asian British", "Black/Caribbean/African" and "Mixed/Multiple" suspects in the power few. These differences are universally consistent with a higher proportion of suspects in the latter three categories.

Table 8: Z-test results for comparison of proportions within power few for each ethnicity banding pair

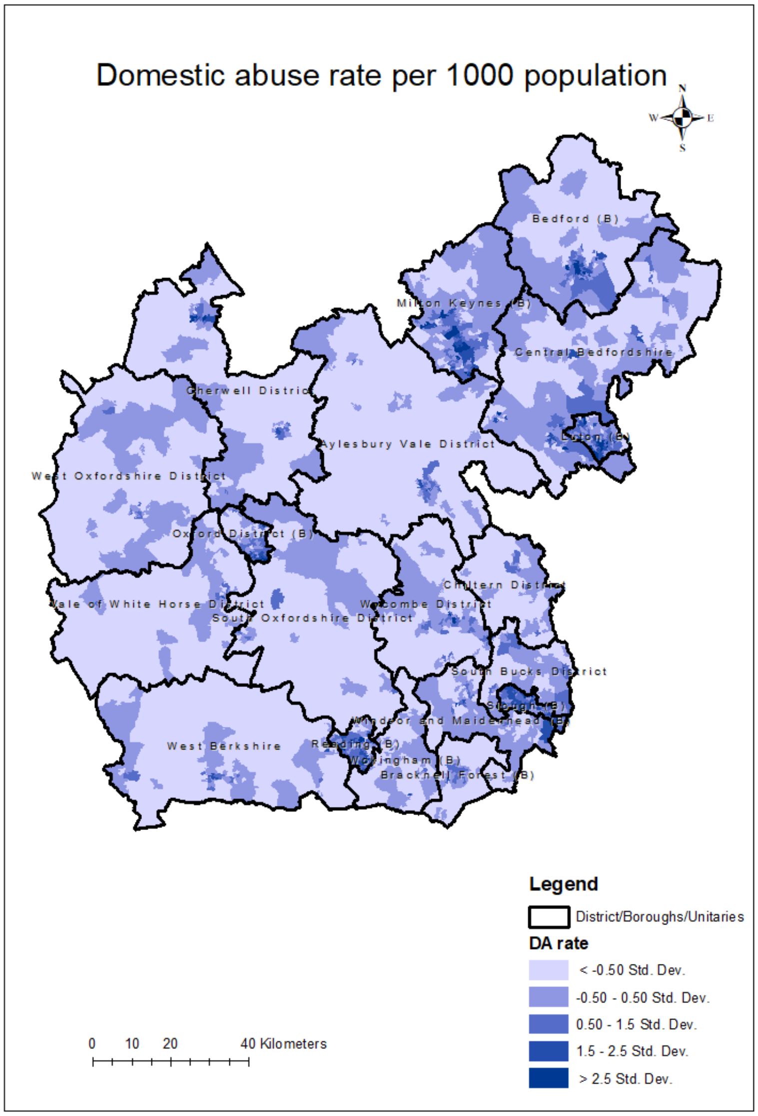
		Any Other White	Asian/Asian British	Black/Caribbean/African	Mixed/Multiple	Other	White British
Beds	Any Other White		0	-1.691	-2.04	0.7085	1.9555*
	Asian/Asian British			0.1924	-0.2133	0.7277	2.4054*
	Black/Caribbean/African				-0.104	0.7972	2.2979*
	Mixed/Multiple					0.7448	1.2904
	Other						0.0578
Sussex	Any Other White		0.7186	-1.4411	0.1421	1.0257	0.9626
	Asian/Asian British			0	1.0425	1.6215	2.5502*
	Black/Caribbean/African				1.0658	1.6371	2.7782*
	Mixed/Multiple					0.7424	0.2357
	Other						0.7671
TVP	Any Other White		-3.2978***	-1.383	-2.016*	1.6503	0
	Asian/Asian British			2.1654*	0.0718	3.115***	5.6272***
	Black/Caribbean/African				-1.1456	2.3026*	2.1171*
	Mixed/Multiple					-2.7412***	2.3479*
	Other						-1.7389

*p<.05, ***p<.0001

RQ6: Are Black, Asian, and other racially minoritised communities at increased risk of domestic abuse at the area level?

Map 1 below shows the rates of domestic abuse across the area, with the higher rates in the darker blue colours. The LSOAs with the highest rates were in Luton, Milton Keynes, Bedford, Reading and Oxford.

Map 1: Domestic abuse rate per 1000 population by LSOA



The amount of domestic abuse in an area was estimated using a range of independent variables based on social disorganisation theory, measures of community cohesion, intersectional characteristics, and population density.

Table 9: Population-level model variables for Bedfordshire and TVP

Variable name	Mean	SD	Minimum	Maximum
Dependent variables				
Domestic abuse count	38.5	30.8	0	471
Domestic abuse rate	22.1	14.9	0	117.0
Independent variables				
% Asian	9.5	12.6	0	93.0
% Black	3.2	4.0	0	30.5
% Mixed heritage	2.5	1.4	0.1	9.8
% Other racial minoritised communities	0.7	0.8	0	5.7
Female population	867.7	271.6	505	5757
Median age	41.3	6.6	18.3	58.4
ASB count	28.3	33.7	0	567
ASB Rate	15.9	14.9	0	158.6
Income score (IMD)	13.5	10.1	0.5	63.5
% single people	48.9	10.1	12.4	93.4
% one person households	26.3	7.7	5.2	62.6
% private rented	15.8	10.9	2.5	76.5
Population turnover	12.0	6.7	3.6	65.0
Population density	1830.6	2201.2	10.2	17412.8

Note: N = 1796

Negative Binomial Regression Model – Results

Table 11 shows the results from a series of models that were run using negative binomial regression. To aid interpretation of the coefficient values, the Incidence Rate Ratios (IRR) were calculated in Stata. Model 1 shows that when just looking at ethnicity, the proportion of Asian, Black and mixed heritage people in the population are all significant predictors of the volume of LSOA level domestic abuse, but the proportion in other racially minoritised communities is not significant. The results show when holding all other variables constant, a one unit increase in the Asian population increases the domestic abuse count by a factor of 1.008, the Black population by 1.067 and the mixed heritage population by 1.094.

Table 10[23]: IRR coefficient ratios

Variable	**Model 1 IRR coefficient (std error)**	**Model 2 IRR coefficient (std error)**	**Model 3 IRR coefficient (std error)**	**Model 4 IRR coefficient (std error)**
% Asian	1.008 (0.001)***	1.0004 (0.001)	1.002 (0.001)*	1.003 (0.001)*
% Black	1.067 (0.006)***	1.007 (0.004)	1.008 (0.004)*	1.008 (0.004)*
% Mixed heritage	1.094 (0.015) ***	0.991 (0.010)	0.986 (0.010)	0.984 (0.010)
% Other racially minoritised communities	1.022 (0.024)	1.034 (0.017)*	1.027 (0.017)	1.030 (0.017)***
Female population		1.006 (0.004)	1.006 (0.004)	1.007 (0.004)
ASB count		1.006 (0.0003)***	1.005 (0.0004)***	1.005 (0.0004)***
Income score (IMD)		250.4 (58.3)***	111.0 (30.8)***	109.71 (30.53)***
Median age		0.970 (0.002)***	0.968 (0.003)***	0.971 (0.002)***
Population density		0.9999 (0.000)*	0.9999 (0.000)**	0.9999 (0.000)***
% single people			1.007 (0.003)**	1.010 (0.002)***
Population turnover			0.991 (0.002)***	0.991 (0.002)***
% one person households			1.005 (0.002)*	
Constant	20.731 (0.62)***	45.47 (10.28)***	36.92 (10.48)***	30.08 (8.09)***
Log-likelihood	-7737.14	-7035.76	-7019.08	-7021.54
AIC	15486.27	14093.52	14066.16	14069.07
BIC	15519.234	14153.95	14143.07	14140.49

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[23] Asterisks indicate the p value: * = 0.05, **=0.01 ***= 0.001

Following the initial modelling of just the ethnicity data, the *nestreg* function was run in Stata to evaluate the significance of blocks of other predictors. Using these results, the log-likelihood of each model was used as a measure of the model fit, with the lower the value the better the model fit. Tables 12-14 below reports the final models from this evaluation. Model 3 had the lowest log-likelihood, but there was found to be multicollinearity[24] between the percentage of single people and the percentage of one person households. The percentage of one person households was therefore removed in model 4.

Interestingly, in model 2, when the other female population, ASB count, income score, median age and population density are added, the proportion of Asian, Black and mixed heritage people in the population are no longer statistically significant, but other racially minoritised communities becomes significant. However, when the proportion of single people and the population turnover are added in model 4, the proportion of Asian, Black and other racially minoritised communities is significant again. Yet, the coefficient values are lower than in model 1, particularly for the proportion of Black people, suggesting that there is a confounding variable/s that has reduced the effect of these variables on the overall model. In model 4, all variables are statistically significant apart from the proportion of mixed heritage and the female population.

Holding all other variables constant, a one-unit increase in the proportion of Asian people increases the domestic abuse count by a factor of 1.003, the proportion of Black people by 1.008, other racially minoritised communities by 1.030, the ASB count by 1.005, the proportion of single people by 1.010, and income score by 109.71 (so in areas that are more income deprived, the count of domestic abuse is higher). For median age, the count gets higher as the median age gets younger, by a factor of 0.971. The count also decreases as population density decreases (by a factor of 0.9999) and where population turnover is lower (by a factor of 0.991).

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[24] With a Variance Inflation Factor (VIF) of 7.32

Overall, the *nestreg* evaluation (see Table 11) found the most significant contribution to the model was the income score, followed by the ASB count, the proportion of Black people in the population, the proportion of Asian people in the population and the median age. The proportion of mixed heritage people, the population turnover, proportion of single people and population density also made significant but smaller contributions to the model.

Table 11: *Nestreg* Wald chi2 results

Variable block	**Wald chi2**
% Asian	294.98***
% Black	435.3***
% Mixed heritage	42.66***
% Other racially minoritised communities	0.86
Female population	1.3
ASB count	437.57***
Income score (IMD)	679.27***
Median age	216.24***
Population density	6.23*
% single people	13.55***
Population turnover	15.12***

Significance levels: * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$.

RQ7: What individual level characteristics are associated with CCHI?

Ethnicity

This was tested with 18 categories of self-defined ethnicity data from the three selected datasets. These categories were entered into the model as dummy variables (with White British as the reference group). Three of the dummy variables were highly correlated with each other (also known as multicollinearity) and so were excluded. There was a significant relationship between ethnicity and CCHI (controlling for other factors), which is in line with the exploratory results using area-level data from the CSEW. In Model 1, 11 categories were statistically significant. When various controls were applied, the most likely categories to be statistically significant (consistent in at least two of the models) were ‘Any other Asian’; ‘Bangladeshi’, and ‘White and Black Caribbean’. Therefore, not all the categories of ethnicity were statistically significant across the models, which supports our argument for the need for further disaggregation of ethnicity categories in modelling work beyond dichotomous categories of ‘White’ and ‘Non-White’ for example.

Age

This was a significant predictor of CCHI which remained consistent across all the models, except for Model 4 suggesting that age variations are likely to matter in relation to risk profiles of suspects.

Sex/Gender

Being male and trans female was significantly associated with CCHI in relation to being female. Men were more likely to be suspects of domestic abuse harm than females (over 80% of suspects were male) and this relationship remained consistent with a full set of controls. It is important to note that the trans female category was relatively small so this finding should be interpreted cautiously. In fact, in Model 2, only the male category remained statistically significantly associated with CCHI.

Relationship with victim

This was tested with 12 categories (with acquaintance as the reference group). In line with research on victimisation, the type of relationship between the suspect and victim was a significant predictor of CCHI. Three relationship categories were excluded from the regression analysis due to multicollinearity.

Income and Social class variables

Five area-level variables from the ONS data (see Table 2) were used in the regression analysis to proxy for income and social class variables. In Model 4 (with the full set of controls) only one out of the five variables were significantly associated with CCHI.

Suicide Warnings

In Model 2, when the alcohol and suicide markers were included, both were not significantly associated with CCHI. It is important to note that while there is a lot of missing data for both the alcohol and suicide markers in the dataset, a bivariate relationship between suicide markers and CCHI provided a strong case for including this as a potential predictor. In Model 4, with the full set of controls, the suicide markers were significantly associated with CCHI.

Excluded variables

DASH Score: As noted in the earlier section, the sample size was too small to enable any reasonable conclusions to be drawn in the regression analysis. However, based on the bivariate analysis, DASH scores were positively correlated with the CCHI suggesting that it could be a significant predictor. With better quality data on DASH risk assessments, this could be a potential area of future research.

Summary of findings

- The descriptive analysis based on ethnicity of suspects have been mapped to six categories outlined by the ONS in their population statistics (White British/Any Other White/Mixed or Multiple Ethnicity/Asian or Asian British/Black, Caribbean or African/Other Ethnicities

- In RQ1, ethnicity profile of suspects: 35% of self-defined ethnicity data are unrecorded, either due to the suspect being unidentified, refusing to answer the question or the police failing to record the answer

- In RQ2, we identified that the distribution of harm in our datasets broadly mirrors a Pareto distribution, mirroring previous work on domestic abuse harm. Particularly, we highlighted that 5% of suspects are involved with 65% of harm

- In RQ3, it was difficult to draw meaningful conclusions from the DASH data based on the descriptive analysis. They relate to just one force, and the smallest dataset among those we received. They do not indicate any stark disproportionate differences in gradings between differing ethnicity groups but there are differences

- In RQ4, we gathered data for solved rates in each of the three jurisdictions. The results show little variation which might not be otherwise accounted for as 'statistical noise'. The low proportion of solved cases in Bedfordshire for the "other" banding pertains to a small sample size (n = 17 solved of 211 total cases) and is not a pattern repeated in Sussex or Thames Valley. One pattern that is repeated however, is that cases involving 'Asian/Asian British' suspects are solved at between 0.79 and 0.86 times the rate of 'White British' cases

- In RQ5, In Sussex and Thames Valley, a total score of 1,825 CCHI days (equivalent to a grievous bodily harm offence) would mean a suspect is included in the 'power few'. In Bedfordshire, the distribution of harm is more acute. A score of 400 days or above would place a suspect in the top 5%. Nevertheless, we have treated each force as distinct to reflect the patterns within each jurisdiction's most harmful suspects. These analyses show that 'Asian/Asian British', 'Black/Caribbean/African' and 'Mixed/Multiple' bandings are consistently over-represented in the most harmful group of suspects than we might expect if all things were equal

- In RQ6: Are Black, Asian, and other racially minoritised communities at increased risk of domestic abuse at the population level? To further explore to what extent ethnicity (and the need for disaggregation) matters, we undertook exploratory tests (negative binominal regression analysis) using population-level data from the ONS. The regression analyses showed that from a series of models that were run just looking at ethnicity and Domestic Abuse Count and Rate. The proportion of Asian, Black and mixed heritage people in the population are all significant predictors of the count of domestic abuse at the LSOA level, but the proportions in other racially minoritised communities are not significant. The results show, when holding all other variables constant, a one unit increase in the Asian population increases the domestic abuse count by a factor of 1.008, the Black population by 1.067 and the mixed heritage population by 1.094

- Following the initial modelling of just the ethnicity data, the *nestreg* function was run in Stata to evaluate the significance of blocks of other predictors. These other predictors have been selected based on previous research (Weir, 2019)

- The proportions of Black, Asian and racially minoritised communities within the population is a statistically significant predictor of the domestic count and rate at the LSOA level along with other structural and community cohesion variables, suggesting that ethnicity matters. However, the ethnicity data in the CSEW is quite old and as such we must exercise some caution in its interpretation

- In RQ7 – we found strong predictors of CCHI to be Suspect’s ethnicity, Suspect’s Age, Sex, Relationship with the victim, and Suicide markers.

4. Key messages and policy implications

This report presents findings that suggest that there are likely to be benefits to using targeted perpetrator programmes administered to suspects or groups within Black, Asian, and other racially minoritised communities who have been identified as high-risk in relation to domestic abuse offending. The risk factors identified in this report may be used when selecting individuals (taking their ethnicity background into account as well as other risk factors) for different interventions. Using the more strongly associated predictors (individual and area-level characteristics) should help identify the individuals most in need of intense support.

As this report's findings show, when it comes to domestic abuse, ethnicity matters. Simply adopting a 'colour blind' or 'one size fits all' approach means that racially minoritised people's specific needs and sensitivities too often go unrecognised and unfulfilled. To ensure equal protection from harm, and equal access to justice, it is incumbent on those designing, commissioning and evaluating programmes to explicitly consider the needs of different groups and make sure that these are embedded at each stage of programme development.

Rather than adopting a 'one-size fits all' model when identifying and engaging with suspects who may pose a risk in relation to domestic abuse offending, an intersectional approach which recognises the interaction of multiple risk factors is merited. Equally, to facilitate more informed interventions and make identifying those most at risk of harm easier, there is a need for more consistent police recording regarding individual-level predictors.

Our primary aim has been to identify predictors of harm from this work which will support the national policy effort and enable commissioners and practitioners to target their resources and services more effectively, enabling earlier identification of perpetrators, encourage communities' capacities to act as 'capable guardians', and reduce the harm for victims and their families. Strength of the predictors varied based on ethnicity, holding all things constant. However, this requires further research into whether this varies consistently across space and to test whether the regression models exhibit the same patterns using data in other police forces.

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6. Technical appendix

Cleaning and aggregating strategy

To achieve a unified dataset, we needed to clean various fields to make the data consistent and ready for analysis. For example, forces use different terminology to describe ethnicities, but have the same underlying structure. Our cleaning process involved recoding investigative outcome, ethnicity, sex, age, and relationship variables accordingly. We also needed to cross reference location information to map crimes to the LSOA in which they occurred. This enabled us to add more than 70 additional demographic predictors taken from ONS datasets in relation to population (deprivation, age, ethnicity, crime rate, etc).

In addition to data cleaning and the amalgamation of geographic variables, we also coded all records with a harm variable, using the Cambridge Crime Harm Index (Sherman, Neyroud and Neyroud, 2016) as the instrument. This index (known as CCHI) weights Home Office Counting Rule codes, which label different types of crime consistently for all English and Welsh police forces. Sentence length, as specified by The Sentencing Council or Crown Court guidelines is the determinant of each weighting. Weights are expressed in days, as in the number of days of custodial sentence one would receive for this offence. The CCHI principle is that the starting point guideline (also the lowest possible sentence, for which a crime has no aggravating factors and an offender has no prior record) be used for consistency. The one exception we applied to this is for the offence of coercive and controlling behaviour, which we considered a score too low in proportion to its gravity (see Stark, 2007) and we adjusted the weighting to the midpoint. All crimes in the dataset were matched to the reference table published by the Cambridge Centre for Evidence Based Policing (https://www.cambridge-ebp.co.uk/the-chi).

Dates

Owing to differing circumstances, each of our three provider forces gave us slightly different reporting periods:

- Bedfordshire: May 2018 – December 2020
- Sussex: April 2017 – March 2020
- Thames Valley: January 2017 – December 2020.

Records Removed

Part of the cleaning process involved removing records we deemed did not meet the eligibility criteria. This subsection summarises the various aspects of these procedures for the purposes of transparency and replication. Records were removed as follows:

1. Victim is 'crown' – crimes against the state are known as 'victim is crown' and cannot be defined as domestic abuse, so were removed
2. Relationship types that did not conform to the standard UK cross-government definition of domestic abuse (intimate partners – current or former, or family members, over age of 16), were removed. We found examples of 'stranger', 'tenant', 'patient' and 'neighbour', among others
3. Duplicated crimes in which the relationship variable was 'unknown'
4. Any record which did not relate to a crime.

The final dataset consisted of 153,209 crime records across all three forces. A second 'subset' dataset in which each offender appears only once was also produced. This involved removing all crimes with no suspect record (n = 15,705) and collating data against each offender's first known crime record (in the period of data available). This second dataset comprised of 80,768 unique offenders.

Variables that were recategorised

Type of relationship

159 different categories were used to capture the type of relationship in the various police datasets. This were recoded into 12 categories during the cleaning process.

Self-defined ethnicity

55 categories were recorded, and this was then recoded into 18 categories.

OLS Tables and estimations

Notes to the tables:

Reference variables used in the models:

- Ethnicity (for both victim and suspect variables) – White British
- Type of relationship – Acquaintance
- Suspect Sex/Gender – Female
- Alcohol Warnings – No
- Suicide Warnings – No

Table 12: Model 1

Coefficients[a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.996	.037		54.105	.000		
	Suspect_Ethnicity_Self_coded=Any Other White Background	-.299	.044	-.033	-6.729	<.001	.975	1.026
	Suspect_Ethnicity_Self_coded=Asian – Pakistani	-.312	.065	-.024	-4.821	<.001	.981	1.019
	Suspect_Ethnicity_Self_coded=Asian – Indian	-.273	.089	-.015	-3.065	.002	.988	1.012
	Suspect_Ethnicity_Self_coded=Any Other Asian Background	-.229	.082	-.014	-2.802	.005	.989	1.011
	Suspect_Ethnicity_Self_coded=Caribbean	-.208	.091	-.011	-2.298	.022	.992	1.008
	Suspect_Ethnicity_Self_coded=African	-.237	.079	-.015	-3.010	.003	.990	1.010
	Suspect_Ethnicity_Self_coded=White and Black Caribbean	-.343	.104	-.016	-3.305	<.001	.993	1.007
	Suspect_Ethnicity_Self_coded=Any Other Black Background	-.314	.091	-.017	-3.448	<.001	.994	1.006
	Suspect_Ethnicity_Self_coded=White Irish	-.348	.114	-.015	-3.049	.002	.996	1.004

	Suspect_Ethnicity_Self_coded=Any Other Mixed Background	-.079	.115	-.003	-.688	.491	.995	1.005
	Suspect_Ethnicity_Self_coded=Any Other Ethnic Group	.069	.124	.003	.557	.578	.996	1.004
	Suspect_Ethnicity_Self_coded=Bangladeshi	-.298	.121	-.012	-2.468	.014	.994	1.006
	Suspect_Ethnicity_Self_coded=White and Black African	.263	.173	.007	1.516	.130	.998	1.002
	Suspect_Ethnicity_Self_coded=Chinese	-.249	.248	-.005	-1.002	.316	.998	1.002
	Suspect_Ethnicity_Self_coded=White and Asian	-.600	.180	-.016	-3.329	<.001	.998	1.002
	Suspect_Ethnicity_Self_coded=Gypsy or Irish Traveller	.083	.413	.001	.201	.841	1.000	1.000
	Suspect_Ethnicity_Self_coded=Arab	.007	.584	.000	.012	.991	1.000	1.000
	Suspect_Age_cleaned	-.006	.001	-.042	-8.527	<.001	.983	1.017
	Suspect_Sex_coded=Male	.923	.026	.170	34.959	<.001	.982	1.018
	Suspect_Sex_coded=Non-Binary	2.409	1.131	.010	2.131	.033	.999	1.001
	Suspect_Sex_coded=Trans female to male	.080	.653	.001	.123	.902	.999	1.001

Suspect_Sex_coded= Trans male to female	2.479	.682	.018	3.637	<.001	.999	1.001
Relationship_recoded= Ex-partner	.473	.026	.097	18.447	<.001	.844	1.185
Relationship_recoded= Neighbour	-.224	.799	-.001	-.280	.780	1.000	1.000
Relationship_recoded= Other family member	-.070	.035	-.011	-2.025	.043	.860	1.163
Relationship_recoded= Parent of offender	-.921	.060	-.076	-15.282	<.001	.950	1.053
Relationship_recoded= Sibling of offender	-.664	.088	-.037	-7.575	<.001	.972	1.028
Relationship_recoded= Stranger	.482	.249	.009	1.940	.052	.997	1.003
Relationship_recoded= Victimless/crime against state	.705	.472	.007	1.495	.135	.999	1.001
Relationship_recoded= Brother	-1.140	.128	-.043	-8.883	<.001	.982	1.018

a. Dependent Variable: LogCCHISuspect

Table 13: Model 2

Coefficients[a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
2	(Constant)	5.423	.053		101.579	.000		
	Suspect_Ethnicity_Self_coded=Any Other White Background	.014	.063	.002	.216	.829	.986	1.014
	Suspect_Ethnicity_Self_coded=Asian - Pakistani	.360	.120	.031	2.997	.003	.992	1.008
	Suspect_Ethnicity_Self_coded=Asian - Indian	.169	.141	.012	1.198	.231	.994	1.006
	Suspect_Ethnicity_Self_coded=Any Other Asian Background	.377	.120	.032	3.152	.002	.992	1.009
	Suspect_Ethnicity_Self_coded=Caribbean	.157	.140	.012	1.121	.262	.994	1.006
	Suspect_Ethnicity_Self_coded=African	.116	.113	.011	1.031	.303	.994	1.006
	Suspect_Ethnicity_Self_coded=White and Black Caribbean	-.149	.149	-.010	-.998	.318	.994	1.006
	Suspect_Ethnicity_Self_coded=Any Other Black Background	-.082	.124	-.007	-.662	.508	.996	1.004

Suspect_Ethnicity_Self_coded=White Irish	-.001	.168	.000	-.008	.994	.995	1.005
Suspect_Ethnicity_Self_coded=Any Other Mixed Background	.197	.149	.014	1.321	.187	.991	1.009
Suspect_Ethnicity_Self_coded=Any Other Ethnic Group	.038	.166	.002	.227	.821	.994	1.006
Suspect_Ethnicity_Self_coded=Bangladeshi	.429	.215	.020	1.993	.046	.996	1.004
Suspect_Ethnicity_Self_coded=White and Black African	.375	.207	.019	1.809	.071	.997	1.003
Suspect_Ethnicity_Self_coded=Chinese	.128	.346	.004	.368	.713	.998	1.002
Suspect_Ethnicity_Self_coded=White and Asian	-.007	.280	.000	-.024	.981	.999	1.001
Suspect_Ethnicity_Self_coded=Gypsy or Irish Traveller	-.288	.447	-.007	-.643	.520	.998	1.002
Suspect_Ethnicity_Self_coded=Arab	-.215	.547	-.004	-.392	.695	.999	1.001
Suspect_Age_cleaned	-.004	.001	-.046	-4.380	<.001	.965	1.036
Suspect_Sex_coded=Male	.464	.041	.117	11.347	<.001	.981	1.019
Suspect_Sex_coded=Non-Binary	.607	.953	.007	.637	.524	.988	1.012

	Suspect_Sex_coded= Trans female to male	.192	1.340	.001	.143	.886	.999	1.001
	Suspect_Sex_coded= Trans male to female	.492	.508	.010	.969	.332	.994	1.006
	Relationship_recoded= Ex-partner	.020	.031	.008	.668	.504	.832	1.202
	Relationship_recoded= Neighbour	1.695	1.340	.013	1.265	.206	1.000	1.000
	Relationship_recoded= Other family member	-.167	.043	-.044	-3.857	<.001	.820	1.220
	Relationship_recoded= Parent of offender	-.693	.147	-.049	-4.703	<.001	.971	1.030
	Relationship_recoded= Sibling of offender	-.556	.229	-.025	-2.431	.015	.983	1.017
	Relationship_recoded= Stranger	.233	.269	.009	.865	.387	.992	1.008
	Relationship_recoded= Victimless/crime against state	-.202	.424	-.005	-.475	.635	.997	1.003
	Alcohol_War0i0g	.055	.186	.003	.299	.765	.987	1.013
	Suicide_War0i0g	.018	.054	.003	.335	.737	.970	1.031

a. Dependent Variable: LogCCHISuspect

Table 14: Model 3

Coefficients[a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
3	(Constant)	4.479	.304		14.736	<.001		
	Suspect_Ethnicity_Self_coded=Any Other White Background	.078	.133	.013	.586	.558	.903	1.107
	Suspect_Ethnicity_Self_coded=Asian – Pakistani	.508	.144	.077	3.539	<.001	.896	1.116
	Suspect_Ethnicity_Self_coded=Asian – Indian	.169	.213	.017	.792	.428	.965	1.037
	Suspect_Ethnicity_Self_coded=Any Other Asian Background	.342	.197	.037	1.736	.083	.960	1.041
	Suspect_Ethnicity_Self_coded=Caribbean	.051	.182	.006	.281	.779	.955	1.047
	Suspect_Ethnicity_Self_coded=African	.445	.189	.050	2.359	.018	.965	1.036
	Suspect_Ethnicity_Self_coded=White and Black Caribbean	-.591	.241	-.051	-2.455	.014	.978	1.022
	Suspect_Ethnicity_Self_coded=Any Other Black Background	-.211	.226	-.020	-.933	.351	.978	1.023

	Suspect_Ethnicity_Self_coded=White Irish	-.077	.296	-.005	-.261	.794	.988	1.012
	Suspect_Ethnicity_Self_coded=Any Other Mixed Background	-.041	.274	-.003	-.149	.882	.981	1.020
	Suspect_Ethnicity_Self_coded=Any Other Ethnic Group	.282	.321	.018	.880	.379	.979	1.021
	Suspect_Ethnicity_Self_coded=Bangladeshi	.660	.256	.055	2.577	.010	.950	1.053
	Suspect_Ethnicity_Self_coded=White and Black African	.501	.493	.021	1.015	.310	.986	1.014
	Suspect_Ethnicity_Self_coded=Chinese	.664	.894	.015	.742	.458	.998	1.002
	Suspect_Ethnicity_Self_coded=White and Asian	.101	.587	.004	.172	.863	.994	1.006
	Suspect_Ethnicity_Self_coded=Gypsy or Irish Traveller	.087	1.099	.002	.079	.937	.990	1.010
	Suspect_Age_cleaned	.000	.002	.001	.056	.956	.961	1.041
	Suspect_Sex_coded=Male	.744	.103	.150	7.196	<.001	.980	1.021
	Relationship_recoded=Ex-partner	-.005	.071	-.001	-.065	.948	.869	1.151
	Relationship_recoded=Neighbour	1.006	1.096	.019	.918	.359	.996	1.004

	Relationship_recoded= Other family member	-.289	.261	-.023	-1.111	.267	.968	1.033
	Relationship_recoded= Parent of offender	-.828	.167	-.107	-4.969	<.001	.928	1.078
	Relationship_recoded= Sibling of offender	-.500	.273	-.039	-1.835	.067	.960	1.042
	Relationship_recoded= Stranger	1.169	1.551	.016	.754	.451	.994	1.006
	Relationship_recoded= Brother	-1.112	.269	-.087	-4.141	<.001	.961	1.040
	IMD score	-.002	.006	-.015	-.311	.755	.183	5.466
	Health Dep score	-.226	.101	-.111	-2.241	.025	.175	5.705
	%single people	.014	.006	.094	2.336	.020	.263	3.802
	%one person household	-.001	.006	-.004	-.125	.900	.439	2.276
	%Private rented	-.003	.003	-.028	-1.014	.311	.579	1.726

a. Dependent Variable: LogCCHISuspect

Table 15: Model 4

Coefficients[a]

		Unstandardised Coefficients		Standardised Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
4	(Constant)	4.810	.506		9.501	<.001		
	Suspect_Ethnicity_Self_coded=Any Other White Background	-.006	.235	-.001	-.027	.978	.948	1.055
	Suspect_Ethnicity_Self_coded=Asian – Pakistani	.309	.222	.042	1.391	.165	.932	1.073
	Suspect_Ethnicity_Self_coded=Asian – Indian	-.141	.322	-.013	-.438	.662	.952	1.051
	Suspect_Ethnicity_Self_coded=Any Other Asian Background	.930	.376	.073	2.470	.014	.966	1.035
	Suspect_Ethnicity_Self_coded=Caribbean	-.027	.291	-.003	-.093	.926	.966	1.035
	Suspect_Ethnicity_Self_coded=African	.297	.288	.031	1.032	.302	.955	1.047
	Suspect_Ethnicity_Self_coded=White and Black Caribbean	-.962	.319	-.089	-3.017	.003	.969	1.032
	Suspect_Ethnicity_Self_coded=Any Other Black Background	.069	.524	.004	.131	.895	.987	1.013

	Suspect_Ethnicity_Self_coded=White Irish	-.154	.529	-.009	-.290	.772	.969	1.033
	Suspect_Ethnicity_Self_coded=Any Other Mixed Background	-.043	.393	-.003	-.109	.913	.981	1.019
	Suspect_Ethnicity_Self_coded=Any Other Ethnic Group	.304	.553	.016	.550	.582	.986	1.014
	Suspect_Ethnicity_Self_coded=Bangladeshi	.966	.587	.048	1.646	.100	.982	1.019
	Suspect_Ethnicity_Self_coded=White and Black African	.742	.958	.023	.775	.439	.978	1.023
	Suspect_Ethnicity_Self_coded=Chinese	.686	1.163	.017	.590	.555	.996	1.004
	Suspect_Ethnicity_Self_coded=White and Asian	-.130	.738	-.005	-.176	.860	.991	1.009
	Suspect_Ethnicity_Self_coded=Gypsy or Irish Traveller	-2.208	1.662	-.039	-1.328	.184	.973	1.027
	Suspect_Age_cleaned	-.007	.004	-.053	-1.722	.085	.904	1.106
	Suspect_Sex_coded=Male	1.135	.175	.192	6.504	<.001	.973	1.028
	Relationship_recoded=Ex-partner	-.062	.109	-.018	-.568	.570	.843	1.186
	Relationship_recoded=Neighbour	1.067	1.645	.019	.649	.517	.994	1.006

	Relationship_recoded= Other family member	-.498	.323	-.046	-1.543	.123	.947	1.056
	Relationship_recoded= Parent of offender	-1.144	.216	-.166	-5.305	<.001	.872	1.147
	Relationship_recoded= Sibling of offender	-.915	.325	-.085	-2.811	.005	.930	1.075
	Relationship_recoded= Stranger	.537	1.649	.010	.326	.745	.989	1.011
	IMD score	.009	.009	.059	.938	.348	.218	4.583
	Health Dep score	-.302	.144	-.137	-2.102	.036	.199	5.019
	%single people	.007	.009	.040	.735	.462	.285	3.506
	%one person household	.003	.009	.015	.375	.708	.535	1.868
	%Private rented	.000	.005	.001	.020	.984	.592	1.688
	Alcohol_War0i0g	-.178	.261	-.020	-.682	.495	.958	1.043
	Suicide_War0i0g	-.318	.142	-.068	-2.248	.025	.937	1.067

a. Dependent Variable: LogCCHISuspect

Table 16: Scoping review: Research questions and corresponding articles selected for inclusion

Name	Description	Number of articles*
IPV and perpetrator ethnicity (RQ1)	A focus on (a) perpetrator ethnicity as a (potential) risk factor for IPV; (b) perpetrator ethnicity and intersection with other risk factors or markers for IPV perpetration; and (c) anything else looking at the relationship between perpetrator ethnicity and IPV risk, particularly with regards to high-risk/high-harm perpetrators	36/104
IPV and victim ethnicity (RQ2)	A focus on (a) ethnicity as a risk factor for IPV victimisation; (b) ethnicity and its intersection with other risk factors associated with a risk of IPV victimisation; and (c) anything else looking at this relationship, including ethnicity as a protective factor	78/104
Ethnicity and recorded patterns of offending (RQ3)	A focus on how ethnicity impacts recorded patterns of offending, with reference to risk modelling	2/104
Ethnicity, intersectionality, and risk forecasting (RQ4)	A focus on integrating ethnicity and/or intersectionality into risk forecasting procedures in law enforcement and, more broadly, criminal justice	3/104
Aggregation problems and risk forecasting (RQ5)	A focus on how problems of aggregation and categorisation, such as ethnic lumping and others, might affect risk forecasting procedures in law enforcement and criminal justice, as well as how these impact research on risk	5/104

**Some articles relevant to more than one RQ*