The Interrelationship between Area Deprivation and Ethnic Disparities in Sentencing Deprivation and Ethnic Disparities in Sentencing

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July 10, 2023

Abstract

In the study of sentencing disparities, class related hypotheses have received considerably less attention than explanations based on offenders’ ethnicity. This is unfortunate since the two mechanisms are likely interrelated, at the very least as a result of their overlap in the population, with ethnic minorities being generally more deprived than the White majority. In this registered report we propose exploring the mediating and moderating effects between offenders’ area deprivation and their ethnic background using a novel administrative dataset capturing all offences processed through the England and Wales Crown Court. Specifically, we seek to test whether the reported ethnic disparities in sentencing are explained away by area deprivation, and whether White offenders from deprived areas are more disadvantaged than the average ethnic minority offender. Results from this empirical analysis will shed new light on the underlying causes of sentencing disparities, but crucially—if deprivation is shown to play a major role in the generation of ethnic disparities—they will also help inform the adequate policy responses to redress this problem.
The Interrelationship between Area Deprivation and Ethnic Disparities in Sentencing

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Keywords Sentencing · disparities · ethnicity · deprivation · Crown Court

Acknowledgements This work was supported by the Secondary Data Analysis Initiative of the Economic and Social Research Council (Grant Ref: ES/W00738X/1).
1 Introduction

The Lammy Review (2017) managed to bring the question of ethnic disparities in the criminal justice system to the forefront of the political debate in England and Wales. The review documents some hard to justify disparities. For example, in relation to the sentencing of drug offences the report highlights how Black offenders are 140% more likely to receive a custodial sentence than White offenders. Importantly, besides highlighting the problem, Lammy (2017) proposed a new vital principle, “explain or reform”, applicable to all criminal justice institutions. More specifically, a series of action points were laid to ensure that such disparities are both documented and redressed. These action points are monitored by the Parliamentary Justice Committee (2019), the Race Disparities Unit at the Cabinet Office, the Ministry of Justice (2020), and all criminal justice agencies involved (see for example The Parole Board, 2018), which illustrates well the influence that the Lammy Review - and consequently the question of ethnic disparities - will continue to play in the years to come.

The impact of the Lammy Review can also be evidenced by ensuing reports on the subject of disparities, which expanded the debate to other policy areas, such as housing, education, or health (Race Disparity Unit, 2019), and emphasised social class as another dimension that ought to be considered alongside ethnicity (Commission on Race and Ethnic Disparities, 2021; House of Commons Education Committee, 2021). The latter became particularly present in the political discourse following the Brexit vote, which was - incorrectly but - widely interpreted as a White working class protest (Antonucci et al., 2017), and heavily capitalised by the subsequent Brexit governments (Centre for Labour and Social Studies, 2016). Regardless of any political motivations, we believe introducing the class dimension in the analysis of sentencing disparities enriches the debate around this subject.

Class disparities have been comparatively less thoroughly explored, and when studied, this has been done as a separate dimension (see for example Chiricos and Bales, 1991; Miethe and Moore, 1985; Skeem et al., 2020), neglecting the intersectional nature of class and ethnicity (Cunningham and Rious, 2014; Diemer et al., 2013). Several sentencing studies from the US have introduced variables capturing defendants/offenders’ level of education, employment, or socio-economic status (Doerner and Demuth, 2014; Ward et al., 2016; Wu and Spohn, 2010), since these are variables often made available by Sentencing Commissions publishing sentencing data. However, for the most part these variables are used as controls, rarely questioning how they interact with offenders’ ethnicity. Some important exceptions are Mitchell (2005), whose meta-analysis of the literature showed ethnic disparities more than halved in studies controlling for socio-economic status, or more recently Donnelly (2021), who found that offender’s area deprivation acts as an amplifier of ethnic disparities in sentencing. This last study can be framed within a growing body of research exploring the extent to which area characteristics explain some of the stark ethnic disparities in criminal justice outcomes documented in the US (Donnelly and Asiedu, 2020). Here, we propose to contribute to this body of literature by testing the potential mediating and moderating effects that underlie the intersectional relationship between ethnicity and deprivation in the context of the England and Wales Crown Court.

There are multiple reasons that make the study of the intersectionality between ethnicity and deprivation particularly informative. For example, we can think of different mechanisms through which deprivation could be mediating the effect of race on sentencing; such as: i) considerations of rehabilitative potential affected by prospects of employment, family structure, or access to rehabilitation programs (Chen et al., 2022); ii) judicial perceptions of offenders’ culpability and dangerousness affected by general perceptions of coldness, incompetence and ‘otherness’ commonly attributed to the poor (Kiebler and Stewart, 2022; Lindqvist et al., 2017); iii) the type of legal defence afforded (Anderson and Heaton, 2012), an inequality exacerbated in England and Wales in the last decade as a result of cuts to legal aid; iv) overpolicing of more deprived areas, which are also the more highly populated by ethnic minorities (Suss and Oliveira, 2022); or vi) even more plainly, exempting the impact of prison to

1 Throughout this report we use the term ‘offender’ to encompass also ‘defendants’.
those perceived as more valuable members of society, which was perfectly exemplified - if anecdotally - in the case of the Oxford student Lavinia Woodward, who was exempted from a custodial sentence following the stabbing of her boyfriend to avoid damaging her promising future career as a surgeon (BBC News, 2017).

Furthermore, in terms of potential moderators, we should consider how some deprivation-related perceptions of unworthiness, incompetence, or dangerousness are not attributed uniformly across ethnic groups (Petty and Wiener, 2019). In the context of England and Wales, we could hypothesise that working class White individuals (derogatorily known as ‘chavs’) are particularly looked down upon (Jones, 2020; Tyler, 2008). It is therefore possible that the ethnic disparities reported in the literature could be, on average, partially explained away after taking into account deprivation, while simultaneously, by breaking down the deprivation effect by ethnicity, we might find starker ethnic disparities between the economically better and worse off groups.

In this study we propose using new sentencing datasets made available by the Ministry of Justice (MoJ) in collaboration with the Office for National Statistics (ONS) and Her Majesty Courts and Tribunal Service (HMCTS). These are case-level administrative datasets capturing all hearings that took place at the Magistrates’ and the Crown Court in England and Wales from as early as 2011 (2013 for the Crown Court data) to 2020. Besides their unique coverage, these two datasets include two key variables that have been so far missing from all previous England and Wales sentencing datasets available to researchers: i) offenders’ ethnicity; and ii) their area of residence, from which we can derive the level of area deprivation. Leveraging the opportunities afforded by this new data, and focusing on the most common offence types sentenced in the Crown Court, we will test the following three hypotheses:

**H1** The probability of being placed in remand and custodial sentence length are each at least 10% higher for ethnic minority than for White offenders, after adjusting for case characteristics.

**H2** Over half of the ethnic disparities estimated in H1 are mediated by area deprivation.

**H3** Ethic disparities are more pronounced for offenders living in average areas compared to offenders living in the top 10% most deprived areas.

Beyond their academic merit, the above hypotheses relate to key questions that need to be explored if we hope to redress the well documented disparities in sentencing in England and Wales. There are no easy options to solve this problem. Reducing judicial discretion not only undermines the principle of individualisation, in some instances it has also been shown to be detrimental to proportionality and even lead to further disparities (Fischman and Schanzenbach, 2012). Similarly, the effectiveness of unconscious bias training or the introduction of reminders in the guidelines is questionable (Forscher et al., 2019; FitzGerald et al., 2019). However, if deprivation appears to play a key role either as mediator or moderator of ethnic disparities, then a potential solution could be envisaged in the form of clearly listing deprivation as a mitigating factor. The need for deprivation to be seen as a mitigating factor has been recurrently discussed (Ashworth, 1994; Tonry, 1995; Von Hirsch and Ashworth, 2005), but so far it has not been made explicit in the sentencing guidelines, probably because it can be seen to undermine the principle of equality before the law. Such argument could however be questioned if deprivation is found to be mediating the observed ethnic disparities. If that was the case, it would follow that by acting on deprivation sentencers would be redressing, rather than undermining, the biggest threat to the principle of equality before the law.

2 Data

The proposed study will be possible thanks to the new sentencing datasets made available by the Data First program. Data First is a research project funded by Administrative Data Research UK, linking datasets from across the justice system and other government departments, and making them available
to accredited researchers via secure platforms. Specifically, we will use the linked version of the first two datasets released by Data First, the Magistrates’ and Crown Court datasets. The former is sourced from extracts of Libra, the latter from XHIBIT, the administrative databases used by the Magistrates’ and Crown Court to manage cases across England and Wales (Jackson et al., 2022).

Our analytical strategy is based on the specification of two sentence outcomes, the probability of being placed in remand, and the duration of custodial sentences. The former is operationalised as a binary variable capturing whether the offender was placed in remand by a Crown Court judge as opposed to granted bail. The latter is operationalised as a count variable measured in days, ranging from zero (the offender was not sentenced to custody) to life imprisonment (capped at 20 years). For the analysis of remand the population is all defendants regardless of their guilt verdict or plea, for the exploration of sentence length the population is restricted to offenders found guilty. Furthermore, given the strong variability in ethnic disparities documented across types of offences (Hopkins et al., 2016), we will estimate separate models for each of the main offence-specific sentencing guidelines. These are: assault, breach, burglary, drugs, fraud, robbery, sex, and theft.

For each of the two sentence outcomes and eight offence groups, we explore the effect of offenders’ ethnicity and area deprivation through a sequence of three regression models, one for each of our hypotheses. Ethnicity and area deprivation is introduced differently in each of those models (explained in Section 2), however the set of controls employed does not change. These include: offender’s age and sex, offence type, whether a guilty plea was introduced, a breach was incurred, and number of previous convictions recorded in the dataset.

Age is a continuous variable, it will be centered around the mean and introduced as a polynomial term of order two to capture the quadratic relationship between age and sentence severity reported in the literature (Ronald and Jacobs, 2002; Steffensmeier et al., 1995). For sex, we will use male as the reference category, and set unknown values as missing. Guilty plea and breach are also binary variables. The former captures whether a guilty plea has been entered prior to the outcome considered being recorded. The latter captures whether a guilty plea has been entered prior to the outcome considered being recorded. The latter captures whether a guilty plea has been entered prior to the outcome considered being recorded. The latter captures whether a guilty plea has been entered prior to the outcome considered being recorded.

In relation to offence type we will use the Home Office offence-specific classification. This helps reduce unobserved heterogeneity compared to the standard approach followed in sentencing research, where only broad categorisations of the offence type (such as violence, drugs, sex offences, etc.) are controlled for (Hopkins et al., 2016; Mitchell, 2005). Using the specific offence type is nonetheless problematic because of how many there are. Based on the pivot tables from the Ministry of Justice (2021) we counted 352 different specific offence types sentenced in the Crown Court according to the Home Office code. For reasons of parsimony, we will only explore the most common offence types processed in the Crown Court. Specifically, to ensure that the sample size for each offence type is large enough, we consider offences for which at least 200 cases were sentenced to immediate custody between 2019 and 2020. This represents 35 offence types (listed in Table 1), covering 67.5% of the cases sentenced in the Crown Court.

After offence type, number of previous convictions is the most consequential case characteristic. Unfortunately previous convictions is not directly recorded in the dataset. Instead we will derive it, for each case, from the number of times an offender appeared before the hearing under consideration, in either the Magistrates’ or the Crown Court datasets, while sentenced to a disposal type different from an ‘absolute discharge’. To be able to follow offenders from the Magistrates’ to the Crown Court we will use the ‘linked datasets’, the version of the sentencing datasets that provides a common unique offender identifier. We will be able to retrace previous convictions from as far back as 2011. Even though the datasets represent a Census of all criminal cases sentenced in England and Wales, limiting the calculation of the number of previous convictions to cases processed from 2011 will create a problem of left-censoring, which will be more pronounced in older cases than in those processed more recently.

The application process to access this data can be found here, https://www.gov.uk/government/publications/data-first-criminal-courts-linked-data.
Table 1: Offence types included in the analysis

<table>
<thead>
<tr>
<th>Sentencing Guideline</th>
<th>Offence type as classified by the Home Office</th>
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<tbody>
<tr>
<td>Assault</td>
<td>‘5A Wounding with intent to cause grievous bodily harm’, ‘8F Wound / inflict grievous bodily harm without intent’, ‘8.01 Assault occasioning actual bodily harm’, ‘8.22 Assault of an emergency worker’</td>
</tr>
<tr>
<td>Burglary</td>
<td>‘28 Burglary in a dwelling’, ‘29 Aggravated burglary in a dwelling’, ‘30A Burglary in a building other than a dwelling’</td>
</tr>
<tr>
<td>Drugs</td>
<td>‘92A.09 Production, supply and possession with intent to supply a controlled drug - Class A’, ‘92A.10 Production, supply and possession with intent to supply a controlled drug - Class B’, ‘92D.01 Possession of a controlled drug - Class A’, ‘92E.01 Possession of a controlled drug - Class B (cannabis)’</td>
</tr>
<tr>
<td>Fraud</td>
<td>‘53.4 Conspiracy to defraud’, ‘53C Fraud by false representation: cheque, plastic card and online bank accounts’, ‘53F Fraud by abuse of position’</td>
</tr>
<tr>
<td>Robbery</td>
<td>‘34 Robbery’</td>
</tr>
<tr>
<td>Theft</td>
<td>‘39 Theft from the person of another’, ‘40 Theft in dwelling not automatic m/c or meter’, ‘41 Theft by an employee’, ‘44 Theft of pedal cycle’, ‘45 Theft from Vehicle’, ‘46 Theft from shops’, ‘48 Theft of a motor vehicle (excl. aggravated vehicle taking)’</td>
</tr>
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</table>

To minimise this problem we will use the full window of observation in the datasets to calculate the number of previous convictions, but restrict our analysis to cases sentenced in 2019 and 2020. This approach will still miss convictions dating from up to six years before the hearing under analysis, which will inevitably introduce a form of negative systematic measurement error in the variable. However, to some extent, such form of measurement error will be indirectly controlled for after including offenders’ age in the same model. As for the case of age, previous convictions will be introduced in our models as an order-two polynomial term (Roberts and Pina-Sánchez, 2014).

In addition to the Magistrates’ and Crown Court offenders data, this study will use open data describing the relative deprivation in local areas across England and Wales (Ministry of Housing, Communities and Local Government, 2022). Specifically, we will use the 2019 index of multiple deprivation (McLennan et al., 2019), which is composed of seven domains of deprivation (income, employment, education, skills and training, health and disability, crime, barriers to housing services, and living environment). This index of deprivation will be matched to the Magistrates’ and Crown Court data using the Lower Layer Super Output Areas (LSOAs), which are geographical hierarchies used to report statistics in small areas, covering one to three thousand residents. The matching process will comply with the principles of the Five Safes (Office for National Statistics, 2022a) and the conditions for matching data in secure settings (Office for National Statistics, 2022b). The index of deprivation is a continuous variable, however to facilitate interpretations we will not use each area’s specific value of deprivation, but rather their percentile. In addition, we will centre this variable around the mean so the reference category will be an offender from the average LSOA.

Lastly, offenders’ ethnicity is operationalised as a binary variable, indicating whether the offender is White, or from any other ethnic group. This involves collapsing three (Asian, Black and Other) of the ethnic categories available into a single ‘Other’ category, which incurs a loss of information. We nonetheless favour this approach for the sake of parsimony, particularly needed when exploring potential moderating effects between area deprivation and social class. The ethnicity variable we will
use captures offenders’ ethnicity as determined by the police. We decided to use this variable rather than a self-reported measure of ethnicity - also available in the dataset - since a police officer’s perception of the offender’s ethnicity will likely overlap more closely with the judge’s perception, which represents the decision-making process that we seek to model (Pina-Sánchez et al., 2022).

As far as we are aware, from the variables to be used only offenders’ sex and ethnicity are subject to missing data. To adjust for this, we will use multiple imputation. Specifically we will use the MICE package in R (Van Buuren, 2018), to estimate five sets of imputations under Bayesian logistic regression, using the function ‘logreg’, and all the variables listed in this section except for the two outcomes considered (remand and sentence length) as auxiliary data, plus another variable capturing the location of the court where the sentence was imposed, and the self-reported measure of ethnicity in its original form. Table 2 lists all the variables that will be used in the analysis classified as outcomes (i.e. dependent variables), exposures (i.e. explanatory variables of interest), controls (i.e. not interpreted in the analysis), and auxiliary data (to be used for the missing data adjustment).

### Table 2: Variables used in the analysis

<table>
<thead>
<tr>
<th>Outcomes</th>
<th>remand, sentence length</th>
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<tr>
<td>Exposures</td>
<td>police recorded ethnicity, index of multiple deprivation</td>
</tr>
<tr>
<td>Controls</td>
<td>age, sex, offence type, guilty plea, breach, previous convictions</td>
</tr>
<tr>
<td>Auxiliary</td>
<td>self-reported ethnicity, court location</td>
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### 3 Modelling Strategy

Our modelling strategy is built sequentially through three sets of nested models, used to test each of the three hypotheses formulated in Section 1. The composition of these three sets of models is shown visually using causal diagrams (Pearl, 2009; VanderWeele and Staudt, 2011) in Figure 1. The direction of the expected causal effects is represented by arrows, with $\text{ethn}$ reflecting offenders’ ethnicity, $\text{case}$ stands for the set of case characteristics used as controls, $\text{imd}$ for the index of multiple deprivation in the area of residence of the offender, and $\text{int}$ for the interaction between offenders’ ethnicity and area deprivation. The direct effects used to test our three hypotheses are depicted as continuous arrows, while dashed arrows are used to represent indirect effects that we expect to be part of the data generating mechanism but will not be explored in this study.

Binary logit models are used to specify the probability of remand, negative binomial models are used to specify custodial sentence length. Each of them is replicated for each of the eight samples derived from the main sentencing guidelines. Random intercept terms are introduced to account for the between court variability that has been reported in the literature (Drápal, 2020; Pina-Sánchez and Linacre, 2013), and will be estimated using the *lme4* package (Bates et al., 2015) in R.

Model 1 serves as the foundation of our analytical plan. This model is used to test the presence of ethnic disparities (H1: *The probability of being placed in remand and custodial sentence length are each at least 10% higher for ethnic minority than for White offenders, after adjusting for case characteristics*). As such, the importance of this model is threefold: i) it will serve to assess whether Hopkins et al. (2016) findings of ethnic disparities in sentence length are replicated using more recent samples and different sets of controls; ii) it will provide the first set of evidence on the presence or absence of ethnic disparities in remand decisions in England and Wales; and iii) it will be used as a benchmark for H2. A 10% cut-off point is chosen to corroborate H1 since lower disparities could be considered negligible (e.g. the result of unobserved confounders). For context, Hopkins et al. (2016) reported twice
Fig. 1: Modelling strategy depicted using causal diagrams. The continuous lines represent the specific effects that will be estimated, the dashed lines represent indirect causal mechanisms expected to be present but not explored in our analysis.

larger odds of incarceration for ethnic minority compared to White offenders, when considering drug offences, but a non-significant odds ratio of 1.2 when considering sexual offences. In this study, however, we will use average marginal effects instead of odds ratios. That is, in relation to H1, the minimum 10% cut-off point will be taken as the average ratio of adjusted probabilities of remand (and durations of custodial sentences) for ethnic minority compared to White offenders, across all the observations considered in each of our samples. To estimate marginal effects we will use the `marginaleffects` package (Arel-Bundock, 2023) in R.

To test H2 (over half of the ethnic disparities estimated in H1 are mediated by area deprivation) we will estimate Model 2, which includes area deprivation as an explanatory variable. We choose the cut-off point ‘over half the effect size’ in ethnic disparities being explained away by area deprivation, to reflect the high confidence that has been placed by commentators and politicians (Commission on Race and Ethnic Disparities, 2021) in this hypothesis. That is, in order to support the view that ethnic disparities are really a result of social class that has been left uncontrolled, we would expect such biasing effect to be strong enough to explain away most of the observed ethnic disparities.

Lastly, to test H3 (Ethnic disparities are more pronounced for offenders living in average areas compared to offenders living in the top 10% most deprived areas) we estimate Model 3, which includes the interaction between ethnicity and area deprivation. To test this hypothesis we will not use average marginal effects, but rather the marginal effects for White and ethnic minority offenders when the index of deprivation associated with their area of residence changes from the ninth to the fifth decile. The difference in such effects will be determined using a test of second differences (Mize, 2019; Mize et al., 2019).

4 Timeline

The analysis will be undertaken within two months of receiving a final Stage 1 acceptance. The reason why such relatively long period is required for a secondary data analysis stems from the need to access this data through ONS approved secure data labs. Such secure data labs apply limiting conditions to researchers in order to avoid a potential data leak. For example, secure rooms need to be booked in advance, while no phones or computers connected to the internet are allowed, which slow down the coding process. Once the analysis has been conducted we will be submit the report within two months.
Hence, under the scenario that this registered report became conditionally accepted subject to some revisions by June 2023, and factoring in one month to undertake some final revisions, the full report would be resubmitted by the end of October 2023, as shown in Figure 2.

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Fig. 2: Gantt Chart describing the duration of the analysis and write-up involved in the development of this article, assuming that the registered report is conditionally accepted by June 2023.
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