The Interrelationship between Area Deprivation and Ethnic Disparities in Sentencing

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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 two key hypotheses: i) the reported ethnic disparities in sentencing are mediated and explained away by area deprivation; and ii) ethnic disparities are moderated by area deprivation, with ethnic disparities being narrower in the more deprived areas. 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.

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 on 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. Several sentencing studies from the US have introduced variables capturing 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, with some studies documenting and interpreting their association with sentence severity, but rarely questioning its correlation and interaction with defendants' race (see important exceptions in Mitchell, 2005; Steffensmeier and Demuth, 2000). Here we propose to test the potential mediating and moderating effects that underlie the intersectional relationship between ethnicity and deprivation.

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 potentially affected by prospects of employment, family structure, or access to rehabilitation programs (University of Hertfordshire, 2022); ii) judicial perceptions of offenders' culpability and dangerousness affected by general perceptions of coldness, incompetence and 'otherness' commonly attributed to the poor (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; v) 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 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).

In terms of potential moderators we should consider how some deprivation related perceptions of unworthiness, incompetence, or dangerousness are not uniform across ethnic groups. Specifically, 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 way after taking into account deprivation, while simultaneously, by breaking down the deprivation effect by ethnicity, we might find starker disparities between the 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 any previous England and Wales datasets available to sentencing researchers. One being defendants' ethnicity, the second being 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 29 most common offence types sentenced in the Crown Court, we will test the following three hypotheses:

- **H1** The odds of incarceration and bail are at least 10% higher for ethnic minority offenders than for White British offenders after adjusting for case characteristics.
- **H2** Over half of the ethnic disparities estimated in H1 are mediated by area deprivation.
- **H3** Ethnic disparities are lower in the 20% most deprived areas than in more affluent areas.

Beyond their academic merit, the above hypotheses relate to key questions that need to be explored if we hope to redress the problem of disparities in sentencing. There are no easy options to solve this problem. Reducing judicial autonomy 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). 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, seeking to link administrative datasets from across the justice system and other government departments, and make them available to accredited researchers via secure platforms.[1] 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).

The variables included in these datasets can be grouped in four categories: i) procedural information such as the dates of hearings, and the initiation of proceedings; ii) case characteristics, such as the

[1] The application process to access this data can be found here, https://www.gov.uk/government/publications/data-first-criminal-courts-linked-data.

type of offence, whether a guilty plea was entered, or the offender incur in a breach; iii) defendant characteristics such as age, gender or area of residence; and iv) judicial decisions, such as whether given bail or remand, or the sentence outcome.

Our analytical strategy is based on the specification of two sentence outcomes, the probability of being sentenced to immediate custody, and the duration of such custodial sentences. The specific variables to be used are named *'disposal_ho_group_desc'* and *'duration1'* in the dataset. The former will be reduced to a binary variable capturing whether an immediate custodial sentence is imposed and the reference category will be all other possible disposal types. The latter is measured on different units (years, months and days), defined in the variable *'units1'*. We will transform this variable so custodial sentence length is expressed just in months.

For each of the two sentence outcomes we explore the effect of offenders' ethnicity and area deprivation through a sequence of three regression models, one for each of our hypothesis. 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: defendant's age and gender, offence type, whether a guilty plea was introduced, a breach was incurred, and number of previous convictions recorded in the dataset.

Offenders' age and gender are named *'age_at_committal'* and *'sex'*. The former is a continuous variable that will be demeaned and introduced as 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). The latter is a categorical variable taking one of three values *'male'*, *'female'* or *'unknown'*. We will set the last category as missing values and introduce gender as a dummy variable with *'male'* taken as the reference category. To control for guilty plea we will use *'plea_rank_desc_dc'*, introduced as a dummy variable with *'guilty'* taken as the reference category. We will use *'breach_marker'* to control for whether the offender was recorded as having a breach proceeding at any point in their case, also introduced as a dummy variable.

In relation to offence type, we use *'offence_ho_code_desc'*, which captures the specific offence type as defined by the Home Office. This helps reduce unobserved heterogeneity importantly 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 their large number. Using the pivot tables from the Ministry of Justice (2019) 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 500 cases were sentenced to immediate custody in 2018. This represents 29 offence types, 21.3% of the cases sentenced in the Crown Court.[2] These offence types are listed in Table 1, which provides the descriptive statistics that can be derived from the metadata for each of the variables to be used in our analysis.

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 a defendant appeared before the hearing on 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 defendant 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

[2] Some of these offences are distinguished in the dataset according to whether they are considered *indictable* or *triable either way*. These are: 28. Burglary in a dwelling, 30A. Burglary in a building other than a dwelling, 66.9. Other offence against the State or public order, 807. Driving licence related offences (excluding fraud and forgery). To eliminate such unnecessary distinction we will regroup them into a single category that does not distinguish whether the offence is triable either way or indictable.

Cases that went to trial ($N = XXXX$)		
	mean	(min, max)
Custody	XX	(0, 1)
Age	XX	(18, XX)
Gender (ref: male)	XX	(0, 1)
Ethnicity (ref: White)	XX	(0, 1)
Area deprivation	XX	(1, 100)
Previous convictions	XX	(0, XX)
Guilty plea (ref: not introduced)	XX	(0, 1)
5A. Wounding with intent to cause grievous bodily harm	XX	(0, 1)
8F. Wound / inflict grievous bodily harm without intent	XX	(0, 1)
8.01. Assault occasioning actual bodily harm	XX	(0, 1)
8.10. Breach of a restraining order	XX	(0, 1)
10C. Possession of other weapons	XX	(0, 1)
10D. Possession of article with blade or point	XX	(0, 1)
28. Burglary in a dwelling	XX	(0, 1)
30A. Burglary in a building other than a dwelling	XX	(0, 1)
34. Robbery	XX	(0, 1)
39. Theft from the person of another	XX	(0, 1)
45. Theft from vehicle	XX	(0, 1)
46. Theft from shops	XX	(0, 1)
49. Other theft	XX	(0, 1)
53C. Fraud by false representation	XX	(0, 1)
54. Handling stolen goods	XX	(0, 1)
66.1. Affray	XX	(0, 1)
66.7. Breach of a criminal behaviour order	XX	(0, 1)
66.9. Other offence against the State or public order	XX	(0, 1)
802. Dangerous driving (MOT)	XX	(0, 1)
807. Driving licence related offences	XX	(0, 1)
83.2. Failing to surrender to bail	XX	(0, 1)
86.1. Taking, distributing or publishing indecent photographs of children	XX	(0, 1)
104. Assaulting, resisting or obstructing a constable	XX	(0, 1)
105. Common assault and battery	XX	(0, 1)
92A.09. Production, supply and possession with intent to supply a controlled drug - Class A	XX	(0, 1)
92A.10. Production, supply and possession with intent to supply a controlled drug - Class B	XX	(0, 1)
803A. Driving a motor vehicle under the influence of drink or drugs	XX	(0, 1)
149. Criminal damage offence	XX	(0, 1)
66.2. Breach of sexual offences prevention order	XX	(0, 1)

Cases sentenced to custody ($N = XXXX$)		
	mean	(min, max)
Sentence length (months)	XX	(0, 1)
Age	XX	(18, XX)
Gender (ref: male)	XX	(0, 1)
Ethnicity (ref: White)	XX	(0, 1)
Area deprivation	XX	(1, 100)
Previous convictions	XX	(0, XX)
Guilty plea (ref: not introduced)	XX	(0, 1)
5A. Wounding with intent to cause grievous bodily harm	XX	(0, 1)
8F. Wound / inflict grievous bodily harm without intent	XX	(0, 1)
8.01. Assault occasioning actual bodily harm	XX	(0, 1)
8.10. Breach of a restraining order	XX	(0, 1)
10C. Possession of other weapons	XX	(0, 1)
10D. Possession of article with blade or point	XX	(0, 1)
28. Burglary in a dwelling	XX	(0, 1)
30A. Burglary in a building other than a dwelling	XX	(0, 1)
34. Robbery	XX	(0, 1)
39. Theft from the person of another	XX	(0, 1)
45. Theft from vehicle	XX	(0, 1)
46. Theft from shops	XX	(0, 1)
49. Other theft	XX	(0, 1)
53C. Fraud by false representation	XX	(0, 1)
54. Handling stolen goods	XX	(0, 1)
66.1. Affray	XX	(0, 1)
66.7. Breach of a criminal behaviour order	XX	(0, 1)
66.9. Other offence against the State or public order	XX	(0, 1)
802. Dangerous driving (MOT)	XX	(0, 1)
807. Driving licence related offences	XX	(0, 1)
83.2. Failing to surrender to bail	XX	(0, 1)
86.1. Taking, distributing or publishing indecent photographs of children	XX	(0, 1)
104. Assaulting, resisting or obstructing a constable	XX	(0, 1)
105. Common assault and battery	XX	(0, 1)
92A.09. Production, supply and possession with intent to supply a controlled drug - Class A	XX	(0, 1)
92A.10. Production, supply and possession with intent to supply a controlled drug - Class B	XX	(0, 1)
803A. Driving a motor vehicle under the influence of drink or drugs	XX	(0, 1)
149. Criminal damage offence	XX	(0, 1)
66.2. Breach of sexual offences prevention order	XX	(0, 1)

Table 1 Descriptive statistics of the two samples used: Principal offences sentenced in the Crown Court in 2019 and 2020 (only values that could be derived from the datasets' codebooks are reported at this point).

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. 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 defendants' age in the same model. As for the case of age, and following the quadratic relationships between previous convictions and sentence severity reported in the literature (Roberts and Pina-Sánchez, 2014), previous convictions will be introduced in our models as an order-two polynomial term.

In addition to the Magistrates' and Crown Court defendants 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 by 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 data using the Lower Layer Super Output Areas (LSOAs), which are geographical hierarchies used to report statistics in small areas, covering one to three thousands 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 demean this variables so the reference category in our models 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. Specifically, for the confirmatory part of our analysis (i.e. to test our three hypotheses) we will use *'ethnicity_police_defined_group'*, which captures offenders' ethnicity as determined by the police. We decide to use this variable rather than self-reported measure of ethnicity (*'ethnic_assessment'*) since a police officer's perception of the offender's ethnicity will likely overlap more closely with the judge's perception, which ultimately is the decision-making process that we seek to model (Pina-Sánchez et al., 2022). For the exploratory part of our analysis we will change this choice and employ *'ethnic_assessment'*, as that breaks down ethnicity into seventeen different groups, which will allow us to undertake more fine-grained explorations, even if accepting that they will be less robust than the alternative of seeing ethnicity as a binary variable.

As far as we are aware of, from the variables to be used, only offenders' gender 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 Table 1 except for the sentence outcome as auxiliary data, plus another variable capturing the location of the court where the sentence was imposed ('*court_name*'), and the self-reported measure of ethnicity *'ethnic_assessment'* in its original form.

3 Modelling Strategy

Our modelling strategy is built sequentially through three nested binary logit models, used to test each of the hypotheses set out in Section 1. The composition of these three 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 *ethn* reflecting offenders' ethnicity, *case* stands for the set of case characteristics used as controls (i.e. guilty plea, breach, previous convictions, offence type, and offenders' age and gender), *imd* for the index of multiple deprivation percentile of the offenders' area of residence, and *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 causal effects that we expect to be part of the data generating mechanism but will not be explored in this study.

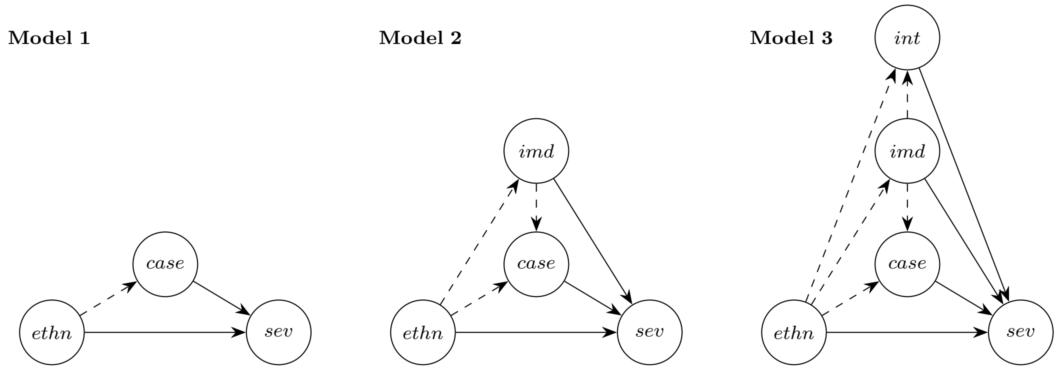

Fig. 1 Modelling strategy depicted using causal diagrams. The continuous lines represent the specific effects that will be estimated, the dashed lines represent indirect causal mechanisms expected to be present but not explored in our analysis.

Model 1 serves as the foundation of our analytical plan. This model is used to test the presence of ethnic disparities (H1: *the odds of incarceration and bail are at least 10% higher for ethnic minority offenders than for White British offenders after adjusting for case characteristics*). The importance of this model, is not so much in terms of originality, since it tests a hypothesis that has been corroborated in past studies of the Crown Court (Hopkins et al., 2016; Isaac, 2020) - albeit based on older samples and different sets of controls - but rather to be used as a benchmark for the testing of H2 and H3. Formally, Model 1 can be expressed as follows,

$$logit(Y_{ij}) = \beta_{0j} + \beta_{1k} case_{ijk} + \beta_2 ethn_{ij} \tag{1}$$

where the subindex k is used to list the thirty-three controls included in the model, i lists the offenders - and their respective principal offence - being sentenced, and j captures the Crown Court location. The last of those subindexes is used in β_{0j} to reflect a random intercept term (Goldstein, 1987). This is introduced to account for the between court variability that has been reported in the literature (Drápal, 2020; Pina-Sánchez and Linacre, 2013), which could otherwise bias the models' measures of uncertainty. Formally, Models 1 to 3 can be defined as binary logit multilevel models, and will be estimated using the *lme4* package (Bates et al., 2015) in R.

If the effect of ethnicity on the probability of receiving a custodial sentence, expressed as an odds ratio (β_2 in eq. 1) is higher than 1.1, then H1 will be corroborated. Such cut-off point is chosen since odds ratio below 1.1 could be considered negligible, but also to avoid relying on statistical significance, which is particularly meaningless given the size of the datasets to be used, which represent a Census of the population of interest. For context, (Hopkins et al., 2016) reported 1.53 odds ratio of incarceration for Black offenders compared to White offenders, but this was only 1.06 when considering Mixed background offenders.

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, and after then calculate the ratio of the two β_2 obtained from eq. 1 and eq. 2,

$$logit(Y_{ij}) = \beta_{0j} + \beta_{1k} case_{ijk} + \beta_2 ethn_{ij} + \beta_3 imd_{ij} \tag{2}$$

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 for, we would expect such biasing effect to be strong enough to explain away most of the observed ethnic disparities.

Lastly, to test H3 (*White British offenders from the 20% most deprived areas are sentenced more harshly than the average ethnic minority offender*) we estimate Model 3, which includes the interaction between ethnicity and area deprivation,

$$logit(Y_{ij}) = \beta_{0j} + \beta_{1k} case_{ijk} + \beta_2 ethn_{ij} + \beta_3 imd_{ij} + \beta_4 int_{ij} \tag{3}$$

The cut-off point set at decile eight of the distribution of area deprivation responds to our interest in focusing on White offenders from the most deprived areas of the country. However, we keep the cut-off point at decile eight, rather than nine or higher, so we could still get a reasonable spread of LSOAs across England and Wales. Since the index of multiple deprivation will be introduced as a continuous variable after being demeaned, the odds of incarceration for White offenders from the 20% most deprived areas will be estimated as $\beta_3 \cdot 30$, while those from the average ethnic minority offender will be estimated as $\beta_2 + \beta_4$.

As explained in Section 1, missing values for gender and ethnicity will be imputed in each of the three models listed above. In addition, we will also undertake some further exploratory analyses that will serve as robustness checks from two key assumptions invoked in our modelling strategy, but also to potentially uncover new insights in the relationship between ethnic and deprivation disparities. Specifically, we will i) discard the White vs non-White divide to explore disparities across the seventeen ethnic groups in the self-reported measure of ethnicity (*'ethnic_assessment'*), and ii) explore potential non-linear interactions between ethnicity and area deprivation. To do the latter we will estimate generalised additive models using the *GAM* (Hastie, 2022) package in R. The equations to be specified will take the following form,

$$logit(Y_i) = \beta_0 + \beta_{1k} case_{ijk} + s_\lambda(imd_{ij}) \tag{4}$$

where $s_\lambda(imd_{ij})$ is some smooth function with λ smoothness parameter, to be defined while conducting the analysis. To explore different forms of area deprivation disparities across ethnic groups we will estimate the same model using samples of each of the seventeen ethnic groups available in *ethnic_assessment*. Given the exploratory nature of these models, adjustments for missing data and between court variability based on multiple imputation and multilevel modelling, will not be included in this part of the analysis.

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 (Office of National Statistics) 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 conducted the analysis we will be able to submit the full report two months after that.

Hence, under the scenario that this registered report became conditionally accepted subject to some revisions by March 2023, and considering the Christmas break, the full report would be resubmitted by the end of August 2023, as shown in Figure 2.

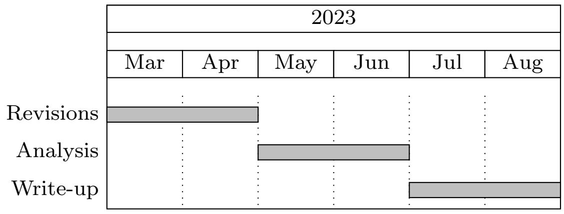

Fig. 2 Gantt Chart describing the duration of the revisions, analysis and write-up involved in the development of this article, assuming that the registered report is conditionally accepted by March 2023.

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