Ethnic Diversity and Police Bias in England and Wales

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***Abstract*—The United Kingdom is increasingly becoming a culturally heterogeneous nation because of its global political outlook and the inflow of immigrants and refugees from around the world. We see several communities across The UK transform into multicultural and diverse spaces - encouraging tolerance towards different religions, cultures, and national identities. In this context, this study investigates the relationship between cultural heterogeneity (or diversity) and law enforcement in England and Wales. The study inspects different models of the estimating police bias and explores various socio-political factors that may influence policing in a locality, specifically ethnic diversity in localities and police departments as well as political inclinations of law enforcement institutions and the prevalence of racism in said localities. Ultimately, looking to measure the relationship between these factors and police bias, and estimate optimal social predictor racially biased law enforcement.**

***Index Terms*—Ethnic Diversity, Police Bias, Racism, Stop and Search**

I. Introduction

Changing cultural circumstances can have both an enriching and taxing impact on contemporary societies. With its ever-increasing cultural and ethnic diversity, the UK is a prime example of a social-political space that is attempting to cope with these changes. Currently, the country is home to approximately 15.7 million people of non-British origin and continues to be one of the most sought-after destination countries of immigrants and refugees around the world [1], [15]. As a result, cities, towns, and local communities are gradually becoming more multicultural, tolerant, and global in their social orientation [13]. However, the momentary downsides to these transitions are the challenges in governance, security, and welfare. Catering to the needs and requirements of many intersections of society is a demanding endeavour, leaving very little room for error.

In this context, the study here looks to investigate how well the state and its apparatuses have fared in maintaining an unbiased position while executing their duties. The primary focus of the study will be to measure the level of bias observed in repressive state apparatuses, specifically the police force. For this purpose, the study will first investigate various measurements of police bias and select an optimal model to measure the level of bias observed across the law enforcement (Police) departments in the UK.

The need for such a study takes inspiration from the many studies and news articles that have cited the racial disparity in policing and conviction carried out in The UK. Many studies have posited that Police-forces across the country are far from being efficient and unbiased in their law-enforcement method, specifically pointing out the disproportionate treatment of ethnic minority groups. Therefore, to unravel the causes of these phenomena, this study will attempt to paint an empirical picture of the socio-political and institutional contexts these Police-forces function in and look to understand which/what social factors (if any) impact the level of bias observed in the respective Police-forces. To do so, the study will measure the social and political attributes of each police force area in England and Wales. These are:

· Ethnic Diversity in Police Force Area (PFA)
· Ethnic Diversity in Police Department of each PFA
· Governing Party (i.e., the party affiliation of CPP of PFA)
· Racist Incidence in PFA

Through this analysis, the study endeavours to identify the unique social conditions and/or parameters that may be a significant predictors for the occurrence of biased policing in specific areas.

II. Literature Review

Over the past decade, many studies have endeavoured to identify the factors that affect the level of bias observed in the law-enforcement agencies, citing factors that vary from, 'effectiveness of police recruitment and training method' to the impact of psychological well-being of police officers. However, this study will look to explore factors concerning the social and political setting of an area, such diversity, racism, etc. But before moving further it is essential to provide an outline of how these are conceptualized and operationalized for the purpose of this study. Hence, the following section will be dictated to the same.

A. Key Terms

- Bias: The idea of Bias in the most general sense is 'an inclination of temperament or outlook', i.e., it entails a variation in the action/process of an agent away from an established standard of action or procedure. In this study, the preliminary form of bias examined is the measure of prejudice in policing. That said, there are other conceptions of bias that are relevant to this investigation, which will be elaborated on in the subsequent sections.

- Prejudice: The first type of bias the study will investigate is the idea of prejudice. This refers to the '...set of negative attitudes, beliefs, and judgments about whole categories of people, and about individual members of those categories, because of their perceived race and/or ethnicity.' [18] In this study, a subset of this concept, i.e., racism (and its prevalence) is used to measure the police bias. Here, the categories of race or ethnicity are defined as per the 'ONS 5+1 2011' categories which specify five broad ethnic groups - 'White', 'Mixed/Multiple ethnic groups, 'Asian/Asian British', 'Black/ African/Caribbean/Black British' and 'Other ethnic group'. [11] Hence, the disproportionate treatment of people based on their membership to the above categories of ethnicities will be the parameter for assessing police bias. The mechanism of how disproportionate treatment is measured will be elaborated in the section on 'Police Bias' and 'Methodology' in more depth.
- Police Bias: One of the most debated issues amongst researchers concerning the phenomenon of police bias is how to conceive of a method to measure it. Although there is a consensus amongst scholars on utilizing stop and search data as a starting point to make said estimations, the debate typically arises from the question of which demographic data the stop and search data ought to be compared against to ensure reliable results. Bowling and Phillips (2009), suggest four criterion - (i) resident population data, (ii) available population data, (ii) Crime rates, and (iv) stop and search 'hit rate' [7]. Based on their comparison of the above criterion, they further suggest 'available population' data as a good estimator for measuring police bias. Hence, this study conceives bias as the level of variance that is observed in stop and search rates (weighted by 'available population' data) , i.e., the higher the variance in the stop and search rates between racial groups in a specific locality, the higher the level of bias. Though in the interest of thoroughness a calculation of bias was performed based on each criterion as a part of the initial investigation. For further information refer to this link.
- Algorithmic Bias: With the exponential strides science has taken in the realm of computation and technology over the past few decades, it is no surprise that technology has become a major part of our everyday life, taking on a supplementary role to enable people to carry out their everyday responsibilities in a more efficient manner. This is the same assumption made by states when incorporating new technologies and algorithms into governing and policing institutions. That said, although these technologies are mathematically and scientifically grounded, they are not beyond fault. For instance, taking the example of the predictive policing algorithm 'Predpol' (which began suggesting racially biased dispatch messages to on-the-job officers) it is clear that even algorithms are susceptible to making biased recommendations, if not developed appropriately.

  Hence, this section will explore the concept of algorithmic bias and its various forms, to mitigate possible drawbacks in the methods used in this study. The most common origin for algorithmic bias cited by scholars is incomplete or unrepresented data, however, this is only half the story as there are many other reasons an algorithm may under-perform and make skewed predictions. As Babuta and Oswald (2019) suggest, algorithmic biases arise due to inadequacies at different stages of the project cycle [5]. First, a bias may arise because of an inadequate conception of a crime or offence; for instance, it is imperative to define and differentiate the severity of different offences, if not, the algorithm is susceptible to giving petty crimes and severe offences the same weightage, thus yielding inaccurate predictions. This study has ensured to maintain a clear definition of what it looks to measure and how (this will be further elaborated in the method section).

  Second, bias may arise because of choosing the wrong criteria of reference for contextualising the data. As highlighted in the previous section, if one were to analyse stop and search data of different localities, without contextualising it based on the ethnic makeup of those areas, the data would show that the individuals categorized as 'white' are at a high risk of the being stopped by a police officer than other ethnicities. However, when this data is contextualised based on the 'available population' criteria, 'Black' and 'Asian' individuals are observed to be at a much higher risk than then 'white' individuals. Hence, to avoid misrepresentation or over-representation, it is crucial to understand and interpret data based on its origin's social and political context. The third potential origin of bias comes through inadequate model selection, in the scenario where a too simple or too complex model is chosen for making predictions and estimations, the model may fall prey to underfitting or over-fitting the training data, respectively. Hence, it is imperative to choose models taking into consideration the nature and structure of the training data (eg: cross-sectional or longitudinal, balanced or unbalanced, etc.). Taking such precautions will help reduce the effect of extraneous factors, and avoid statistical biases such as omitted-variable bias, recall bias, among others. The final origin of bias arises at the final stage of the project cycle: deployment. A significant risk factor at the stage of deployment comes from deploying an algorithm without clarity on the extent of its utility in the concerned procedure. This may lead to the risk of automation bias, wherein there is an over-reliance on the algorithm and unwarranted discounting of relevant information. Hence, at deployment, there must be clarity on the functions and limitations of the model to strike the right balance between the reliance on the algorithm and user intuition.
- Ethnic Diversity: In its broadest sense, ethnicity is defined as a shared culture (i.e., practices, values, and beliefs) of a group (cite). However, as Kolo (2012) points out,

there is no clear cut definition or right or wrong answer in the question of ethnicity - every state or international organisation has their specific official interpretation of the idea [14]. Hence, for this study, as stated earlier, ethnicity is operationalized in terms of 'ONS 5+1 2011' ethnic categories. In this context, the next question concerns the question measuring the diversity or dispersion of various ethnic groups in a locality. The study on methods undertaken by Kolo (2012) suggests that it is imperative to choose the right index of measurement based on the context of analysis. After careful consideration of various indexes of measuring diversity, the study chose ethnolinguistic fractionalization index (EFL), as it best describes diversity in terms of the needs of this study.

- Act of Racism: An 'act of racism' or a 'racist incident' as per the UK Government is conceptualized as, "... any incident, including any crime, which is perceived by the victim or any other person to be motivated by a hostility or prejudice based on a person's race or perceived race.." [19] This study will utilise the racist incident data published by the government to calculate the racist incidence rate by equating the ratio between the racist incidents and total crimes committed.

III. Methodology

A. Data Sourcing

Data Sourcing The study used the https://www.gov.uk data archives to source all the required datasets. All the datasets used for this study are from the year 2011; the study chose this specific year to maintain consistency in data estimations, as most estimations and calculations involve the use of 2011 UK census data. The datasets utilised for the study are:

·Police Powers and Procedures
·Police Service Strength
·Racist incidents
·Crime (Dataset)

Note: the police force area of 'City of, London' was excluded from all datasets due to missing values.

B. Data Management and Pre-processing

A Google Collaboratory python environment was used to carry out data management and pre-processing, with the use of the following libraries:

- Pandas: Pandas is a software library written in python used for data manipulation and analysis. In this study, the library's primary utility was for data cleaning, merging and wrangling. It also aided in reading and fetching the .csv and .xlsx files. [17]
- Tabula: Tabula is a python environment library that is used for extracting tables from a pdf file. In this study, this library was used to extract dataset tables from UK government-issued statistical documents that were formatted in pdf. [3]
- NumPy: NumPy is an open-source library used to carry out numerical computing with Python. The library was used to perform mathematical calculations, such as matrix multiplication, variance calculation, among others, for this study. [16]
- Sci-kit Learn: Sci-kit Learn or 'sklearn' is a machine learning library that enables users to perform a variety of machine learning and statistically modelling computations. The library was used to perform tasks such as features scaling and feature selection at different stages of the study. The library was used to import the 'SelectKBest' model in the regression analysis section of the study to estimate the best socio-political predictor for police bias in the UK. [2]

C. Data Visualisation

The libraries used purpose of the data visualisation were:

- ggplot: Imported using the plotnine library, ggplot was used to carry out basic bar plots, specifically to show the significant variation that was observed in the law enforcement behaviour. [12]
- Matplotlib + Geopandas: The combination of matplotlib and geopandas was used in the study to plot geographical plots to highlight the difference in the observation concerning police bias, cultural diversity and racist incidents in different police force areas in England and Wales.

D. Diversity Calculation

As stated in the literature review section, the estimation of diversity within a police force, and ethnic diversity in a police force area, can be measured using the ethnolinguistic fractionalization index.

$$ELF = 1 - \sum_{i=1}^{K} p_i^2, \qquad i = 1, ...K$$

The 'EFL' is an offshoot of the Herfindahl-Hirschman concentration index, here K is the number of ethnic groups *i* and *p* represents the relative size of the ethnic groups. The diversity values move between zero and one, with higher values showing higher ethnic diversity in the locality or PFA under consideration. [14]

E. Bias Calculation

As per the findings of Bowling and Phillips (2009), the study calculated the level of police bias in a police force area by equating the variance of stop and search rates across ethnic groups. The stop and search rate used for the equation, is the weighted value equated by taking the ratio between the number of stop and search incidents of a specific ethnic category and the respective total population of the same ethnic category. This yields a proportionate estimate of the likelihood of being stopped and searched based on the ethnic category a person belongs to. Taking the level of variance between these likelihoods is a good estimator of the level of implicit racial bias (concerning the propensity towards committing an offence) among police forces. Based on this, the study assumes a direct relation between the variance in stop and search rates (SS rates) and policing bias, i.e., The higher the

variance observed in SS rates, the higher level of the bias vis-à-vis disproportional treatment of the based on the ethnic backgrounds.

The above calculations were carried out in google colab notebook, first, using the pandas library to merge population and SS dataset using the 'police force area' as primary. And second, using numpy to carry out the matrix calculations to estimate SS rate and to equate the variance of SS rate for each locality.

F. Regression Analysis

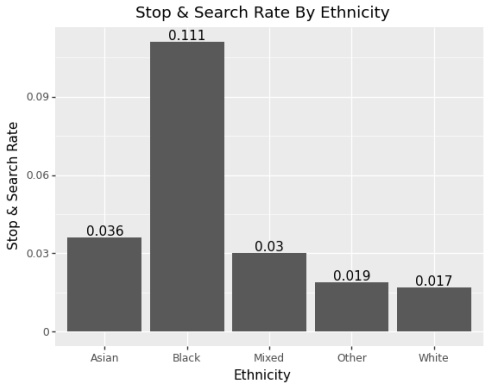
A regression analysis was carried out to estimate the optimal social-political predictors for police bias. For this, the dataset on stop and search rates, ethnic diversity, police department diversity, racist incident rates and bias were merged using pandas using PFA as a primary key. The dataset was then split into independent variable feature space (X1,...,Xn) and the dependent variable (bias). Following this, the 'SelectKBest' model was imported using sklearn library to estimate the best feature among the independent variables, the score parameter for the model was set to *f_regression()* and 'k' set to all. Finally, the model was fitted to the dataset and the scores and p-values for each of the features were recorded.

IV. Result

A. Data Exploration and Initial findings

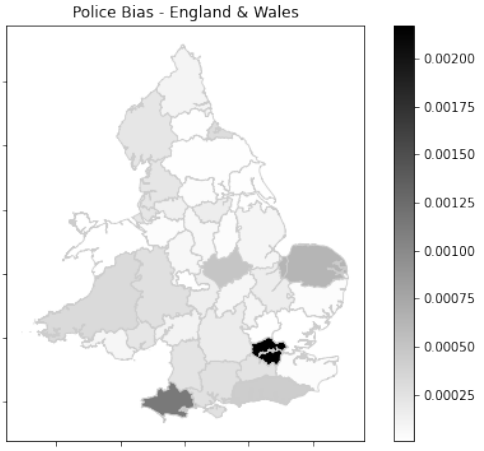
In the exploration stage of the study, the fowling data set were analysed:

- PFA Population Data: Using this dataset, the study estimated the police force areas with the highest ethnic diversity using the ELF index. The analysis found that areas under the jurisdiction of Metropolitan Police (0.59), West Midlands (0.47) and Bedfordshire (0.37) show the highest levels of diversity, while area such as Cumbria (0.03), Dyfed-Powys (0.03) and Durham (0.04) shows least levels of diversity.
- Police Service Strength: Using this data, the study looked to estimate the diversity within police departments in England and Wales. This task, like the previous one, also used the ELF index to estimate the level of diversity in the police department. These were the results observed for the same, the Met (0.19), West Midlands Police (0.15) and Leicestershire (0.13) showed the highest ethnic diversity, while Humberside (0.018), North Wales (0.013) and Dyfed-Powys (0.013) showed the least level of diversity in their police departments.
- Crimes Data: The crimes and arrests dataset was used to estimate stop and search rate in different police force areas and find the ethnic group that is at disproportionate risk of being stopped and search. From the analysis done using the 'available population' criterion as a weighting factor - it was observed that in 40 out of 42 police force areas the 'Black' ethnic category is at the highest risk of being stopped and searched, and by extension bias policing. The other two PFAs North Yorkshire and Northumbria saw a bias towards 'Asians' and 'White' ethnicities respectively. Taking into consideration the overall SS rate trend in England and Wales, these observation are consistent with the larger context of police bias in the nation. The bar chart below shows the overall stop and search risk by ethnicity.



- Racist Incidents: The racists incident data set was used to estimate the areas where race-related crimes are most probable in England and Wales. Using the ratio between racist incidents and total crimes committed, the following observations were made; South Wales, South Yorkshire and Staffordshire show the highest probability for race-related incidents, while Lincolnshire, Wiltshire and North Yorkshire show the least probability.

B. Bias Estimation



The stop and search rate dataset created in this analysis was further used to estimate the levels of bias in each PFA based on the variance between observed SS rate by ethnicity. The estimates show that The Met (0.002), Dorset (0.001) and Norfolk (0.0006) show the highest levels of ethnic or racial bias in policing while Hertfordshire (0.000016), North Wales (0.000015) and Essex (0.000007) showed the least level of bias. The above visualisation shows the bias in the various police force areas in the UK.

C. Best Predictor and Regression Analysis

In this stage of analysis, the study firstly ran the 'SelectKBest' algorithm to determine which of the parameters stated

in the study is a better predictor of bias. The analysis found the Ethnic Diversity (p-value: 0.006816) and police department (p-value: 0.014288) were optimal predictors for Police Bias, while the ruling party and racist incidents rates were observed to be statistically insignificant.

Features	Score	P-value
Ethnic Diversity	8.189350	0.006816
Police Dept. Diversity	6.594149	0.014288
Labour (CPC Party)	1.795469	0.188219
Conservative (CPC Party)	0.498299	0.484554
Independent (CPC Party)	0.368376	0.547501
Racist Incident Rate	0.064115	0.801471

To further investigate the nature of the relation between the bias and the two predictors, the slopes of their individual regression was recorded. From the slope values, it was observed that there is a positive correlation between the levels of bias and the predictors. Hence, there is a higher propensity for police bias in the ethnically diverse localities as opposed to the more ethnically homogeneous spaces.

Discussion

From the analyses performed in this study, it is clear that police bias is present across England and Wales, however, in varying levels. An important insight to note here is that, in almost all instances the individuals who are at highest risk of being victims of police bias are the 'Black' ethnic group. The study has also noted that the ethnic diversity of a specific region can be a good predictor for bias policing, a suitable example for the same is the Metropolitan Police Region, which was observed to have high levels of policing bias and ethnic diversity.

In addition, counter-intuitively, it was also observed that areas that have a diverse police departments also show high levels of bias in policing. Hence, raising a question regarding the impact of an ethnically diverse working environment on the social outlook of police officers . For instance, Bhugowandeen (2013) speaks about the internal racial tension in police departments that come about as a result of preferential recruitment to ethnic minorities police officers. Hence, the diversity in the police departments may not necessarily lead to unbiased policing.

Finally, although the study has established a statistical relation between diversity (ethnic or institutional) and police bias, the study would assert that there are many more factors at play in the relationship between society, culture and law enforcement. Hence, this study can be seen as a starting point for further investigation into this area of study.

Conclusion

In conclusion, this study explored many aspects of law enforcement practices and their social outcomes in England and Wales, highlighting manifestations of institutional racism and the victims of the same. The study also investigated the relationship between the socio-political setting of a locality and law enforcement practices, bringing to light some interesting insights regarding cultural diversity and stop and search rates. However, for a bigger research endeavour, the study would look to perform a panel analysis of the crime data through the years to identify the causal relations between ethnic diversity/polarity and police bias.

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