Judicial Decision-Making: An Analysis of Sentencing Decisions in England and Wales

Caroline Dority

Department of Economics

University of California, Berkeley

Undergraduate Honors Thesis

Advised by Professor Aaron Edlin

April 2023

Abstract

Racial and gender disparities are prevalent in nearly all criminal justice systems, but the sources perpetuating these disparities remain unknown. Although evolving literature has been studying racial disparities in the incarcerated population, few scholars break down the type of sentence issued and its severity. Using evidence from the United Kingdom Ministry of Justice, this paper compares the differences in sentences issued and their lengths in various Magistrate Courts within England and Wales to investigate whether or not internal case-specific factors, such as race and gender, contribute to disparities seen in sentencing decisions. By investigating case specific factors behind sentencing decisions, it becomes apparent that there are significant racial and gender disparities in both the type and length of sentences issued.

1 Acknowledgements

I would like to sincerely thank my advisor, Professor Aaron Edlin, for his guidance and support throughout the composition of this paper. I would also like to take the opportunity to express gratitude to Professor Ryan Edwards for the advice he provided at the onset of this paper and for teaching me the foundations of Econometrics. This paper would not have been possible without either of their tremendous support. All remaining shortcomings are my own.

2 Introduction

Judicial decision-making is the process by which judges interpret and apply the law to cases to determine an outcome. The decision-making process involves analyzing both the legality of the issue at hand and the facts surrounding the case that comes before the court. Based on the factors associated with a case, an outcome is produced in the form of a sentence. In the United Kingdom, there are various types of sentences an individual may receive, ranging from a small fine to multiple years in prison. Despite the frequent publication of offender statistics, there is very little research breaking down cases at the microlevel. Prior studies do not analyze factors that influence the type of sentence an individual receives or the sentence's severity. Examining trends in sentencing decisions provides insight into whether or not courts operate fairly and justly, which may help explain the racial disparities seen in the incarcerated population.

People of color are drastically overrepresented in the prison population of the United Kingdom. In 2017, over 26% of offenders identified as a non-white ethnic group, compared to 13% of the general population. Of the non-white prison population, those identifying as Black are the most overrepresented (Sturge, 2018). They comprised 11% of the prison population in 2017, nearly three times the size of their general population in England and Wales (Sturge, 2018). Furthermore, males are incarcerated at a much higher rate than females. In 2017, there were 348 male prisoners for every 100,000 males in the general population, while there were 16 female prisoners per every 100,000 individuals of the female population (Sturge, 2018). These discrepancies might be explained by the fact that fewer females come before the courts for sentencing. The majority of cases the magistrate courts dealt with in 2017 involved males; only 16.67% of the total population that came before the magistrate court were females. 13% of those receiving a prison sentence were female (Ministry of Justice, 2017).

This paper seeks to explain the disparities in the sentencing decisions that may, in turn, contribute to the large disparities in incarceration rates by investigating the factors related to the outcomes. I hypothesize that internal, case-specific factors influence the type and severity of the sentence that an individual receives.

To investigate this question, I used criminal justice statistics produced by the Ministry of Justice (MOJ) in 2017 to obtain information on various cases that came before the magistrate courts. I limited my research to 2017 to ensure my research was immune from effects created by the COVID-19 pandemic. In 2015, the MOJ changed the way in which they recorded offender data, and the data pulled from 2017 contains more offender specific information than the data collected before the change was imposed. My analysis of the data showed that there are visible disparities in both the type and severity of the sentence issued. To further bolster my findings, I utilized a variety of different controls in order to verify the results. I also utilized additional models to investigate the severity of the sentencing decision. This additional regression analysis was designed to show how internal factors may have contributed to the length of imprisonment or the monetary amount of a fine an offender was sentenced to by the court. Across all models, I find that males receive both harsher and more severe sentences than their female counterparts. In terms of race, Black and Mixed individuals are less likely to receive a fine than White individuals, but the former groups are more likely to receive a community sentence. In addition to being overrepresented relative to their share of the general population in England and Wales, among those who receive a prison sentence, Black individuals are sentenced to longer sentences than their White counterparts.

The paper will proceed as follows. Section III summarizes current literature and research detailing the effects that both internal, case specific factors and external factors have on sentencing outcomes. Section IV provides relevant background about the magistrate courts and the population in England and Wales. Section V outlines the data that is being examined. The data was collected by the Ministry of Justice in 2017. Section VI details the specific empirical strategy that was used to determine the causal effect of race on sentencing decisions. Section VII contains the results of the multivariate regression analysis, along with discussions of the coefficients that were produced. In Section VIII, I expand on the future directions that I hope to take in order to extend my findings and the general body of research regarding decision-making. Lastly, Section VIX concludes the paper and is followed by the Section X at the end, which includes tables and figures.

3 Literature Review

In “Temperature and Decisions: Evidence from 207,000 Court Cases,” Heyes and Saberian examine temperature as an influence on decision-making in US Federal Immigration Courthouses spanning 43 US cities (2019). By examining US asylum applicant data at the case level between January 2000 and September 2004, they compile a dataset including 206,924 decisions made by all 266 immigration judges across this three year and nine month period. Because the exact date and location of each case was known, they were able to assign environmental measures, like weather, to each case to assess the relationship between temperature and the hearing outcome. They computed temperature averages from 6am-4pm each day to account for exposure to outdoor temperature while decision-makers were out and about, whether that be traveling to work, stopping for coffee, etc. Their study found that asylum hearing outcomes in US immigration courts are sensitive to outdoor temperature despite the temperature controlled climate in the courtroom. More specifically, they found that a 10 degree increase in temperature reduces the likelihood of a grant decision by 1.075%, which is equivalent to a 6.55% decrease in the grant rate. Their findings are consistent with findings in other studies that reveal decision-making is affected by outside influences, such as hunger and poverty, which also negatively impair cognitive function, and other established findings linking temperature to mood and risk appetite.

Similarly, judicial decision-making is also affected by ethnic bias. In “Ethnic Bias in Judicial Decision Making: Evidence from Criminal Appeals in Kenya,” Choi, Harris, and Shen-Bayh examine judicial bias in Kenya (2022). Like Heyes and Saberian, Choi, Harris, and Shen-Bayh utilized public court data and ran a regression to examine their variables of interest on the decision. They compiled a dataset of 10,000 criminal appeals between 2003 to 2017 from stations of the Kenyan High Court. Their data included information detailing the nature of the alleged crime, ruling date, the location in which the case was heard, and the original sentence issued. By collecting data on the ethnicity of both appellants and judges, they found that judges are 3-5 percentage points “more likely to grant coethnic appeals than non-coethnic appeals,” exhibiting in-group favoritism (Choi et al, 2022). Their findings are consistent with other studies that examine the link between ethnicity and sentencing decision, revealing that judges who identify as a part of a politically dominant ethnic group deliver more favorable outcomes to appellants who are of the same ethnicity.

In addition, there are also studies which examine disparities on the extensive margin. In “Prosecutors, judges and sentencing disparities: Evidence from traffic offenses in France,” Melcarne, Monnery, and Wolff use a regression analysis to examine differences in sentencing decisions across courts located in South-East France (2022). They examine 280,000 cases from 2018 centering around traffic offenses that led to convictions. Despite being appointed civil servants working under the “constitutional principle of equal justice for all,” in relatively homogeneous cases regarding traffic offenses, Melcarne, Monnery, and Wolff find sizable differences in sentencing between neighboring courts (2022). Their findings are consistent with evidence from North Carolina revealing that judges adopt local norms, causing cross-court disparities to remain prevalent overtime (Melcarne et al, 2022). Overall, prior research reveals disparities in court issued sentences, showcasing how influences, such as ethnicity and temperature, impact on decision-making.

My research will build on the wealth of past literature that seeks to analyze judicial decision-making to determine what factors, if any, influence the sentencing decisions issued by judges. Courts are meant to be fully impartial decision-makers, applying the law equally to everyone, but research revealed that judicial decisions are influenced by both internal and external factors. Examining trends in sentencing decisions provides insight into whether or not courts operate fairly and justly, and these findings serve as the groundwork for the implementation of initiatives ensuring equal protection to all individuals. By analyzing sentencing decisions in the United Kingdom, I am able to further our understanding of this topic.

4 Background

This paper aims to study the racial disparities in sentencing decisions using data gathered in 2017 by the United Kingdom's Ministry of Justice (MOJ). The data tracks offender demographics and case level specifics, providing a comprehensive depiction of the sentencing process.

4.1 Institutional Background

The UK has three criminal justice systems— England and Wales, Scotland, and Northern Ireland. This paper will focus solely on the criminal justice system in England and Wales. The criminal justice system in England and Wales is comprised of the Crown Court and the Magistrate Courts (Institute of Race Relations, 2023). This paper analyzes sentencing decisions made in the magistrate courts. The police force is the first governmental body an offender comes into contact with when they commit a crime, and then, the offenders interact with the magistrate courts' judges. There are 42 police forces throughout England and Wales (Ministry of Justice, 2017).

In order to charge a person with an offense, there has to be enough evidence against the suspect, and it has to be in public interest to prosecute the individual. Once an offender passes this two-stage legal test, their case goes to court where they are asked to plead "guilty" or "not guilty." If the offender pleads "not guilty," the case goes to trial (Crown Prosecution Services, 2022). All criminal cases come before one of the 156 magistrate courts located throughout England and Wales for trial or for referral to the higher Crown Court (Ministry of Justice, 2017). The magistrate courts deal with less serious cases, but if the case is serious enough, the justices then raise the case to the Crown Court for a sentencing decision. Indictable only offences, such as rape or murder, are tried in the Crown Court. Summary only offenses, such as motoring offences or public order offenses, are tried at the magistrate court level (Crown Prosecution Services, 2022). In magistrate courts, decisions are made by a panel of magistrates or by a District Judge. The main difference between the Crown Court and the magistrate courts is that at the Crown Court level, cases are heard by both a judge and a jury while the cases heard by the magistrate courts do not face a jury. Upon being found guilty, offenders receive a sentence determined by the magistrates. For the various offense types, there are minimum and maximum sentencing guidelines that the magistrates use when determining the offenders' sentences. Until March 2015, the largest fee that could be imposed on offenders was 5,000 Great British Pounds (GBP) (Ministry of Justice, 2017). However, there is no longer any upper limit on the fine the magistrate(s) can impose. Typically, magistrates cannot sentence offenders to prison time greater than six months or twelve months for consecutive sentences, but there are some instances where magistrates can sentence offenders to prison sentences of up to two years (Ministry of Justice, 2017).

This analysis solely includes the cases where a sentence was issued by a Magistrate Court and does not include the cases given to the Crown Court. Magistrate Courts do not have a jury, so decisions are made solely by the judges hearing the case and thus are immune to influences from other individuals.

4.2 Population Background

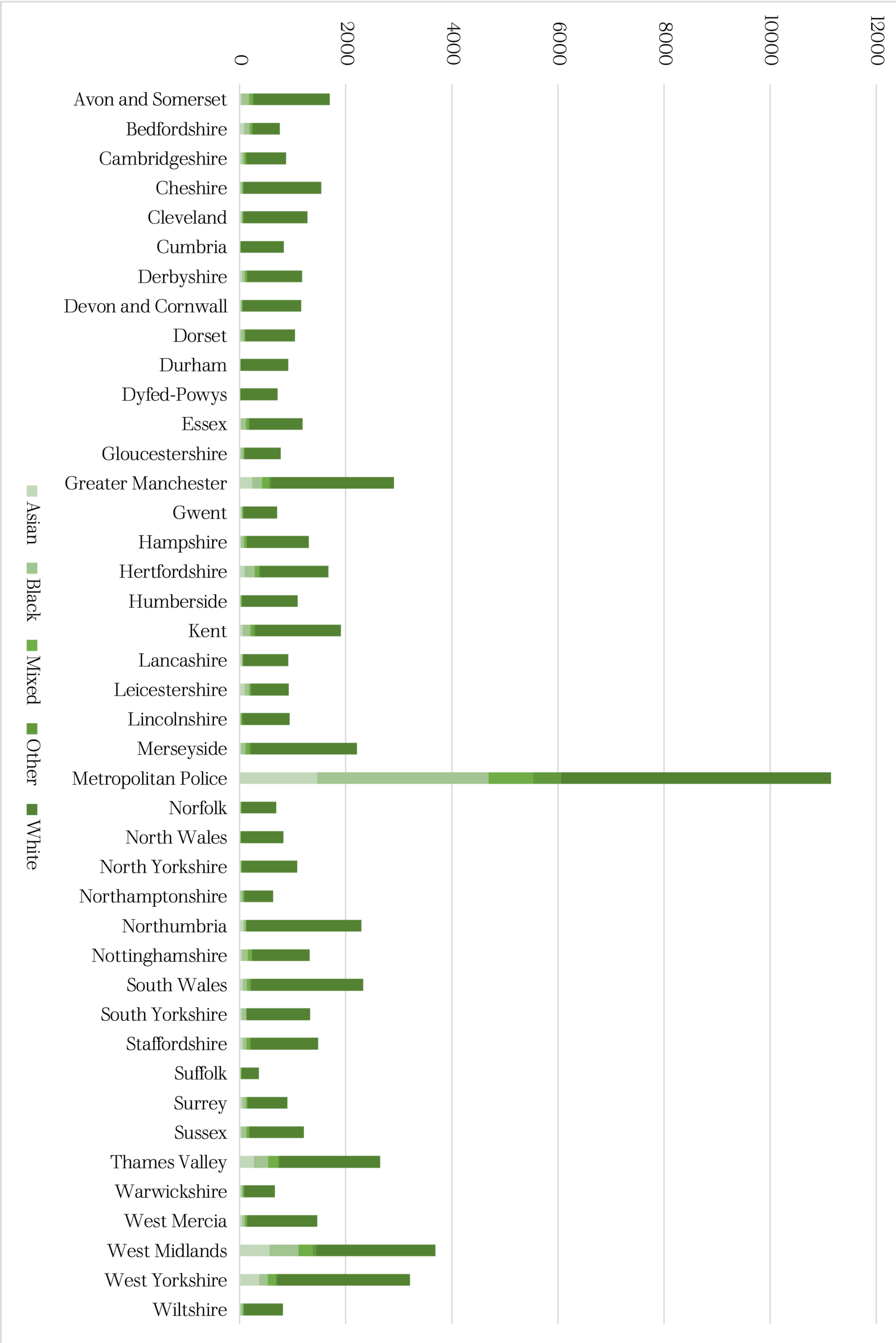
Similarly to how the census is undertaken in the United States, the Office for National Statistics in the United Kingdom undertakes the census every ten years to gather information on the individuals and households that make up the population in England and Wales (Office for National Statistics, 2023). According to the 2021 Census, which captured the closest representation of the population of the United Kingdom in 2017, the population in England and Wales was 59.6 million. Of those 59.6 million, 81.7% of them were white. The second largest percentage of population were those from Asian ethnic groups, comprising 9.3% of the population (Office for National Statistics, 2023). Following this group are those who identified as Black, making up 4.0% of the total population in England and Wales combined. Following this group are those identifying as Mixed (2.9%) and Other (2.1%) ethnic groups (Office for National Statistics, 2023). The way the census defines ethnicity is consistent with the data collected by the Ministry of Justice on race. This allows for a comparison between general population statistics in the United Kingdom with the offender demographics collected by the MOJ to determine if certain racial groups are overrepresented or underrepresented in the Criminal Justice System.

5 Data

5.1 Overview

These sentences are issued by 156 different Magistrate Courts in England and Wales. The Magistrate Courts deal with the majority of adult criminal cases revolving around summary offenses such as motoring offenses, drug offenses, and minor robberies. During 2017, the Magistrate Courts dealt with over 72,433 sentences. All cases have a criminal charge and include case specifics and demographic information specific to the offender. Included in each case is a description of the offender broken down by factors of race, gender, and crime. Gender is a binary variable that is recorded as either male or female. Race is recorded as White, Black, Asian, Mixed, and Other. This data includes cases of those who were immediately discharged. Because there is no further information detailing the length or nature of these sentences, they will not be analyzed in this paper. Instead, I will focus on community sentences, fines, and incarceration, which all have numeric values associated with their length. This allows me to examine the severity of these sentences and to conduct a proper analysis of sentencing decisions across the magistrate courts. Of those remaining cases, a small number of cases were filtered out due to missing information, leaving a sample size of 66,647 individual cases. Based on the case specifics relative to these 66,647 individuals, there are ten different categories of offense. Each crime is categorized as one of the following: 1) violence against the person, 2) sexual offenses, 3) robbery, 4) theft offenses, 5) criminal damage and arson, 6) drug offenses, 7) possession of weapons, 8) public order offenses, 9) miscellaneous crimes against society (misc. crimes), and 10) fraud offenses. There are 42 police forces associated with cases in this data set. On the following page, Figure 1 breaks down the offenders' race by the police force that made the initial charge.

Figure 1: Race Distribution by Force



Each force has a designated region in which they patrol, which provides greater insight into the area the crime was committed and the corresponding judge(s) who make decisions about the case. The majority of those being arrested by the police forces are White individuals, which is consistent with the initial dataset where White individuals represent the majority of the caseload. The majority of the arrests were made by the Metropolitan police force, located in London, the most populated city in the United Kingdom. Following the Metropolitan police force is the West Midlands police force. The police force that made the fewest arrests was the Suffolk police force.

In the initial dataset, for those being sentenced to a fine, each case is recorded with a minimum and maximum amount in Great British Pounds (GBP). The exact amount of the fine that an individual is sentenced to is included. Similarly, for offenders who are sentenced to time in prison, their cases are recorded in a bracketed time frame denoting the lowest and the highest time in prison an offender receives. Table 1 and 2 illustrate how these variables were recoded via the midpoint. The length of the prison sentence was also converted from months into days. It is important to note that the exact monetary amount and length of time in prison that an individual was sentenced to may be higher or lower than the midpoint value used in my analysis.

Table 1: Fine Amount: Recoded Variables

Initial Amount	*Midpoint (GBP)*
Up to and inc £25	12.5
over £25 up to £50	37.5
over £50 up to £100	75
over £100 up to £150	125
over £150 up to £200	175
over £200 up to £250	225
over £250 up to £300	275
over £300 up to £500	400
over £500 up to £750	625
over £750 up to £1000	875
over £1000 up to £2500	1750
over £2500 up to £5000	3750

Table 2: Incarceration Length: Recoded Variables

Initial Length	*Midpoint*	*Midpoint (days)*
Up to and including 1 month	0.5 months	15.21 days
More than 1 month and up to 2 months	1.5 months	45.63 days
More than 2 months and up to 3 months	2.5 months	76.04 days
6 months	6 months	182.5 days
More than 6 months and up to 9 months	7.5 months	228.13 days
More than 9 months and under 12 months	10.5 months	319.38 days
12 months	12 months	365 days
More than 12 months and up to 18 months	15 months	456.25 days

5.2 Demographic Information

Figure 2 illustrates the gender distribution in the data. Gender is recorded as a binary variable: female and male. The majority of offenders are male. Across racial groups, offenders identifying as male represented the majority of the offender population. 81.7% of White offenders are male, 92.6% of Asian offenders are male, 88.3% of Black offenders are male, 84% of Mixed offenders are male, and 86.4% of those identifying as Other are male.

Figure 2: Gender Count by Race

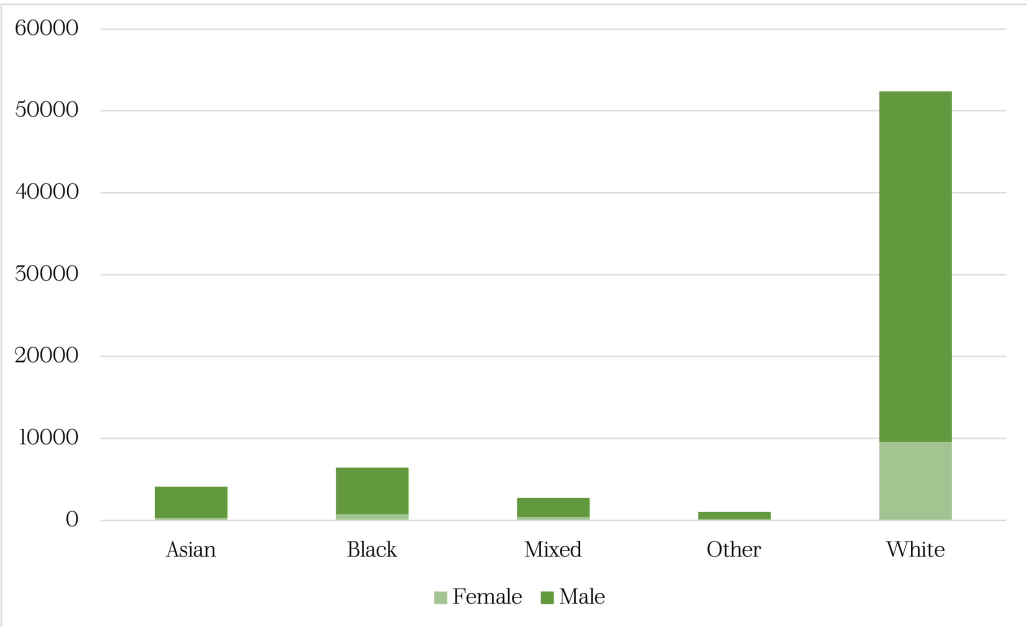
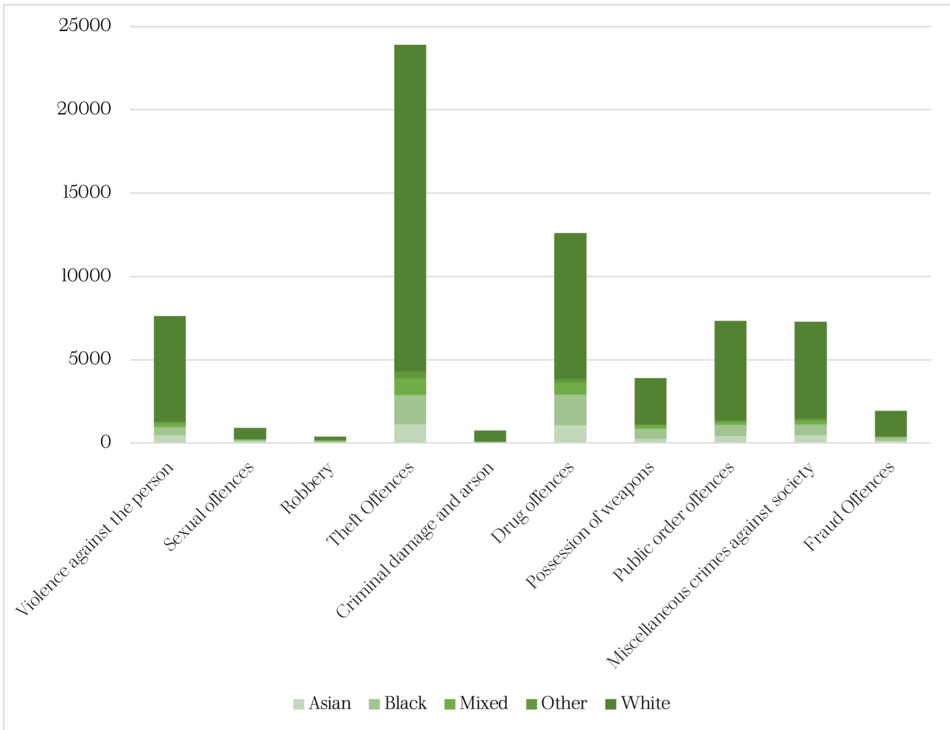


Figure 3 breaks down the type of offense committed by race at the case level. Out of the ten different crime categories, the most frequent crime that came before the magistrates for sentencing in 2017 was theft offenses. The type of crime that least frequently came before the magistrates for sentencing were those categorized as robberies.

Figure 3: Offense Type by Race



On the following page, Figures 4 and 5 break down the gender and race demographics, as well as the type of crime committed, of those sentenced to time in prison. In this subset of the data, there were 15,403 offenders who were sentenced to time in prison, 86.1% of those being male, and the other 13.9% identifying as female. The majority of those sentenced to time in prison identified as male. Of those offenders who are sentenced to time in prison, 95% of Asian offenders were male, 88.8% of Black offenders were male, 83.1% of Mixed offenders were male, 88.5% of those identifying as Other were male, and 85.1% of White offenders were male. Within the subset of those sentenced to incarceration, the majority of offenders committed a crime that fell into the theft offense category. Of those sentenced to incarceration, the least frequent crime that came before the magistrates for sentencing in 2017 was a robbery.

Figure 4: Custodial Sentences by Race and Gender

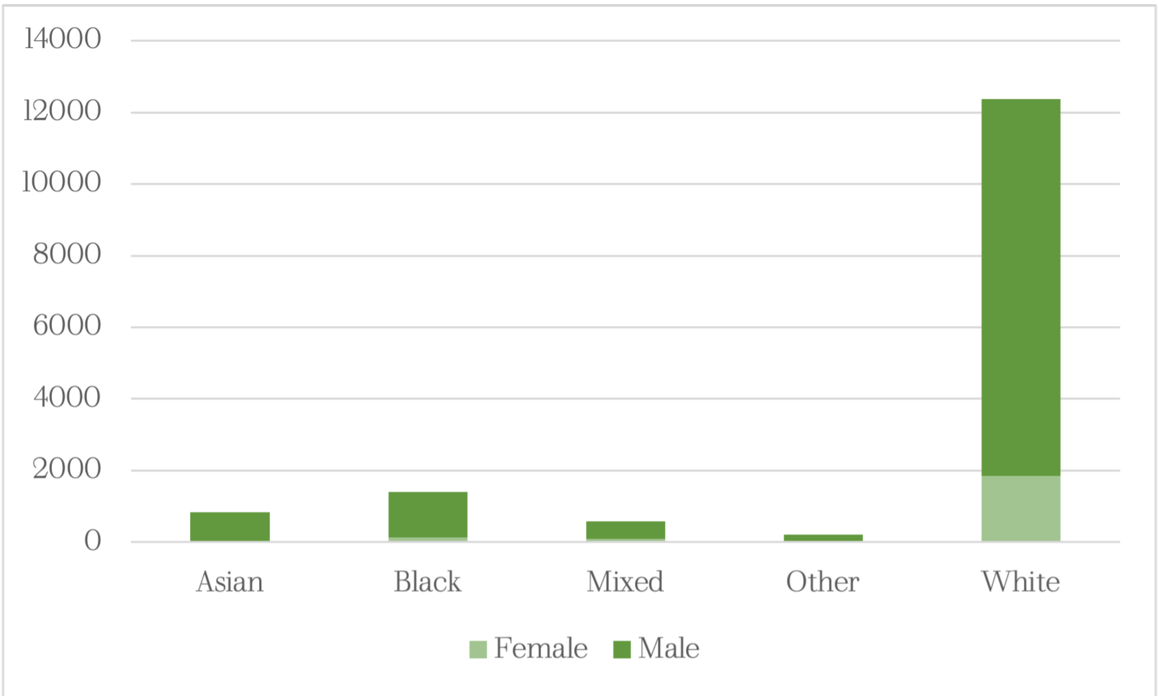
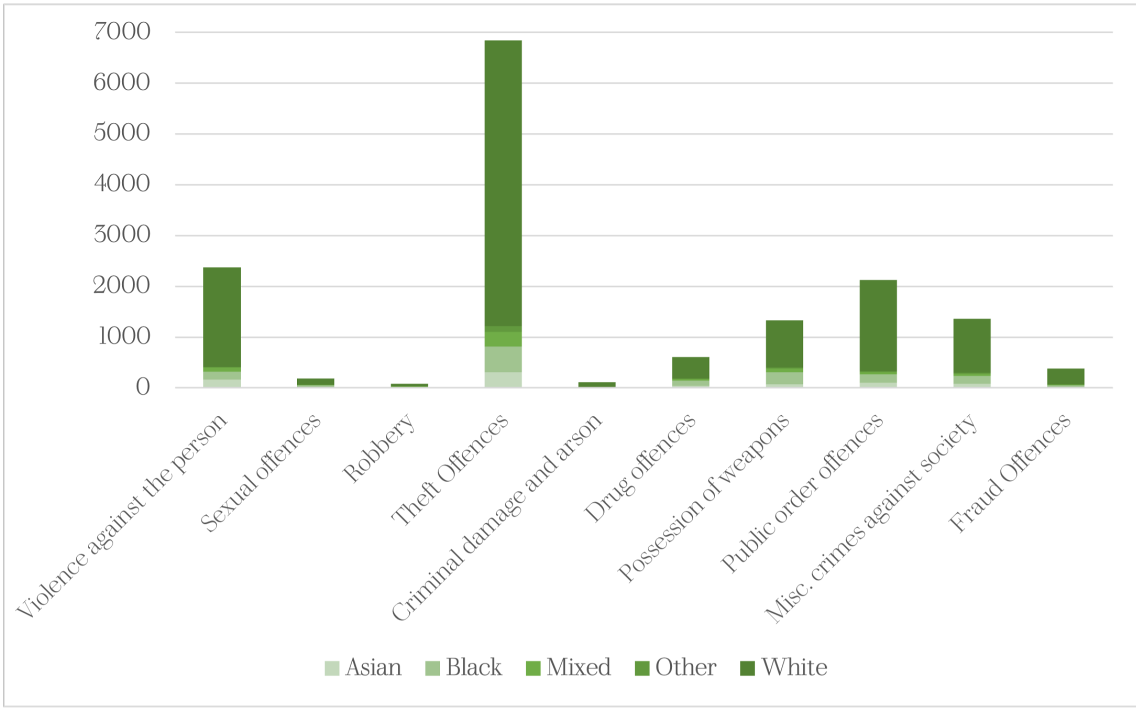


Figure 5: Custodial Sentence by Race and Offence



6 Empirical Strategy

This analysis investigates the racial disparities in sentencing by examining the different types of sentences, specifically community sentences, fines, and imprisonments, and the severity of the sentence issued. By utilizing multivariate regressions, I am able to control for both demographic and case specific factors to determine if there are disparities in the type of sentence issued to people of color and the corresponding severity of the sentence relative to white individuals.

Differences in the type of sentence issued and the severity may reflect differences in the nature of the individual case, the offender's criminal history, or other circumstantial factors. Although the data from the Ministry of Justice permits the incorporation of offender specific and case specific factors into the analysis, there are many factors that are not recorded in the data that may influence the type and severity of sentence issued by the Magistrate Court judges. If these factors are correlated with race, gender, or any other variable included in my analysis, the estimates produced by these regression equations will reflect the impact race has on the sentence issued and also these unobserved factors. Although the data breaks down the different crimes, there are case specific factors that might influence the type and length of the sentence issued. By analyzing the type and severity of the sentence issued to people of color relative to white individuals, the baseline group in all models, racial disparities in sentencing decisions become apparent.

When controlling for other factors in the regression equation, it is important to note that witnessing a change, either a decrease or an increase, in raw disparities does not imply that the disparities in sentencing are justified and/or not driven by demographic factors, like gender or race. Because of the enduring legacy of institutionalized racism, it is nearly impossible to extricate the part race plays in sentencing outcomes from other factors, so measuring the effects that race has on decision-making proves to be challenging. The analysis below is descriptive and provides insights into racially disparate sentencing outcomes, pointing to where they are largest. Examining how race interacts with other factors, such as gender and the type of crime committed, to impact the sentencing decision the court makes, helps identify where and when racial disparities arise in the courts.

There are three overarching sentence types an offender can receive: a fine, a community sentence, or time in prison. All three vary in length and amount. The main outcome of interest is whether or not race plays a role in the court's decision to sentence an offender to prison, a community sentence, or a fine. To determine whether individuals identifying as a certain race are more apt to get a fine, community sentence, or time in prison, I conduct various regression analyzes using variations of the equation below:

$$outcome_i = \beta_0 + \beta_1 Black_i + \beta_2 Asian_i + \beta_3 Mixed_i + \beta_4 Other_i + \beta_5 X_i + \epsilon_i,$$

where $outcome_i$ is the sentence outcome for $individual_i$. Black, Asian, Mixed, and Other are mutually exclusive race factors for $individual_i$. X_i is the additional circumstantial factors like gender, type of crime, and location, and ϵ_{it} is the error term. In this equation, white offenders are the baseline, so there are no indicator variables for white offenders.

I account for the differences in sentencing due to the nature of the offense by controlling for the type of crime committed. I also control for the police force that makes the initial arrest to account for both regional differences and disparities in police forces' behavior that may contribute to sentencing behavior. I then break down the data into two subsets 1) of those who are sentenced to a fine and 2) of those who are sentenced to time in prison to determine if there are racial disparities in the severity of the sentence.

7 Results and Discussion

The following section is broken into three parts. The first subsection details the likelihood of an individual receiving a community sentence. The second subsection considers both the likelihood an individual receives a fine and further analyzes the severity of the sentence. The final subsection delineates the likelihood that an individual is sentenced to time in prison and accounts for the severity of the sentence issued. The tables contained in each section include summary statistics of sentencing outcomes and the control variables considered in my analysis. The significance codes are denoted by asterisks in each table. The codes are as follows: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

7.1 Community Sentence

Table 3 shows the coefficients from a regression model analyzing the correlation between race and receiving a community sentence.

Table 3: Regression Results: Community Sentence

	(1)	(2)	(3)	(4)	(5)
White	0.28041***	0.27401***	0.35916***	0.34320***	0.42158***
	(0.001)	(0.004)	(0.006)	(0.011)	(0.012)
Black	0.00840	0.00789	0.01061 .	0.01822**	0.02252***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Asian	0.02925***	0.02839***	0.02899***	0.03285***	0.03550***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Mixed	0.04458***	0.04440***	0.04960***	0.04948***	0.05614***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Other	0.01482	0.00145	0.01472	0.02589 .	0.02772 .
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Male		0.00783 .	0.00070	0.00647	-0.00060
		(0.005)	(0.004)	(0.004)	(0.004)
Gender	No	Yes	Yes	Yes	Yes
Crime	No	No	Yes	No	Yes
Force	No	No	No	Yes	Yes
N	66647	66647	66647	66647	66647
Adjusted R^2	0.000539	0.000566	0.04304	0.00603	0.04766

Notes: Standard errors are shown in parentheses

White defendants are the baseline group in this model, and each coefficient provides an estimate of the increased (or decreased) likelihood of receiving a community sentence that an individual identifying as a certain race could expect to receive after controlling for additional factors. For example, the second row of the fifth column reveals that those identifying as Black females are 2.25 percentage points more likely to receive a community sentence than who identify as White females. Furthermore, the positive coefficients in the third row shows that Asian females are more likely to receive community sentences than their white counterparts. By focusing on Model 5, which controls for demographic factors, the police force that made the arrest, and the type of crime committed, it becomes apparent that gender does not have a significant effect on the sentencing outcome issued by the courts. The positive and statistically significant coefficients associated with the race variables indicate that there are racial disparities in sentencing decisions. For example, the likelihood that a Black female receives a community sentence is 2.3 percentage points higher than White individuals who commit the same crime and were arrested by the same police force. On average, the output of this regression analysis displays that Black, Asian, and Mixed individuals are more likely to recieve a community sentence than their white counterparts. The coefficients on these variables are both positive and highly statistically significant. Community sentences do not vary significantly in length, and data on the length of the sentence is not recorded by the Ministry of Justice, so no further analysis was conducted (Ministry of Justice, 2017).

7.2 Fine

Table 4 reveals the regression results from those sentenced to fines. The baseline in these models are White females, with the exception of Model 1, where the baseline group is White individuals. As seen in the table below, the coefficients on the race variables

Table 4: Regression Results: Fine

	(1)	(2)	(3)	(4)	(5)
White	0.28956***	0.2711***	0.20926***	0.23728***	0.18889***
	(0.002)	(0.004)	(0.006)	(0.002)	(0.0121)
Black	0.02296***	0.02145***	-0.0070	0.0045	-0.02283***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Asian	0.03503***	0.03257***	0.01168	0.02283**	0.0041
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Mixed	-0.00164	-0.00217	-0.02084	-0.0164 .	-0.03247***
	(0.009)	(0.009)	(0.007)	(0.009)	(0.008)
Other	-0.00218	-0.00324	-0.00589*	-0.0221	-0.01883
	(0.015)	(0.015)	(0.014)	(0.015)	(0.013)
Male		0.02250***	-0.0037	0.0253 ***	-0.00124
		(0.005)	(0.008)	(0.004)	(0.004)
Gender	No	Yes	Yes	Yes	Yes
Crime	No	No	Yes	No	Yes
Force	No	No	No	Yes	Yes
N	66647	66647	66647	66647	66647
Adjusted R^2	0.00046	0.00862	0.08136	0.01694	0.09462

Notes: Standard errors are shown in parentheses differ in amount and sign. The significance level associated with the coefficients changes as more variables are incorporated into the model.

In Models 1 and 2, the majority of the coefficients on the race variables are statistically significant. For example, in Model 2, males are 2.25 percentage points more likely to receive a fine than females, on average. Furthermore, Model 2 reveals that Black and Asian individuals are more likely to receive fines than their White counterparts. The coefficients on those identifying as Mixed and Other are not statistically significant. However, the explanatory power of Models 1 and 2 is much lower than the explanatory power of Model 5, as indicated by the values for R^2. The value of Model 5's R^2 is nearly 205 times larger than those of Model 1 and 2. Model 5 controls for gender, the police force that made the arrest, and the crime committed by the offender. On average, Black females are less likely to receive a fine than their White counterparts, indicated by the negative coefficient on the Black variable. Those identifying as Mixed are also less likely to receive a fine than their White counterparts who commit the same crime and are arrested by the same police force. The coefficients on the variables Black, White, and Mixed are all statistically significant while the coefficients on the variables Asian, Other, and Male are not. Model 5 reveals that on average, Black and Mixed individuals are less likely to receive fines than the baseline group of White individuals.

On the following page, Table 5 details the sentence severity of those receiving fines. The numbers shown in the table are recorded in Great British Pounds (GBP). Across all five models, the coefficients on Black and Mixed are all highly statistically significant, indicating that there are racial disparities in the amount of a fine an individual is sentenced to. However, the sign on each coefficient changes depending on the model's design, which points to the need for further analysis to determine the true effects. When gender is controlled for in Models 2, 3, 4, and 5, the coefficient on the male variable is both positive and statistically significant, indicating that on average, when sentenced to a fine, males receive a higher amount than their female counterparts. To illustrate, in Model 5, when both the police force and type of crime committed are controlled for, males tend to receive a fine that is 39.54 GBP higher than females who commit the same crime and are dealt with by the same police force.

Table 5: Regression Results: Fine Amount in GBP

	(1)	(2)	(3)	(4)	(5)
White	147.46***	108.17***	175.79***	141.32***	207.05***
	(1.45)	(3.24)	(5.32)	(8.97)	(9.73)
Black	-20.42***	24.37***	-20.55***	39.28***	-33.09***
	(4.23)	(4.23)	(4.17)	(4.47)	(4.40)
Asian	3.48	-1.72	1.692	-12.62*	-7.16
	(5.10)	(5.09)	(5.00)	(5.25)	(5.16)
Mixed	-30.34***	-31.70***	-22.08***	-41.42.***	-30.16***
	(6.55)	(6.52)	(6.40)	(6.58)	(6.47)
Other	0.25	-2.29	8.05	-17.54.	-4.64
	(10.60)	(10.55)	(10.35)	(10.65)	(10.45)
Male		47.58***	39.137***	47.59***	39.54***
		(3.51)	(0.008)	(3.51)	(3.50)
Gender	No	Yes	Yes	Yes	Yes
Crime	No	No	Yes	No	Yes
Force	No	No	No	Yes	Yes
N	19578	19578	19578	19578	19578
Adjusted R^2	0.00202	0.01123	0.05233	0.02216	0.05931

Notes: Standard errors are shown in parentheses

Model 1 is a regression run solely on to analyze the effects of race on the amount of the fine issued. No control variables are included in this regression. In the absence of controls, on average, those identifying as Black can expect to receive a fine that is 20.42 GBP less than the fine that those those identifying as white can expect to receive. Similarly, on average, Mixed individuals receive a smaller fine than both Black and White individuals. The coefficients on White, Mixed, and Black offenders are highly statistically significant. The coefficients on Asian and Other are small and positive, but they are not statistically significant.

In the following models, the baseline is white females. As I move across models, other factors, such as crime and/or police force, are incorporated into the baseline group. In Model 2, gender is controlled for, and the baseline is white females. On average, Model 2 reveals that males are more likely to receive a fine that is 47.58 GBP higher than their female counterparts. Controlling for gender increases the model's explanatory power as

R^2 increases from 0.002 to 0.01 and reverses the outcomes of the regression analysis pertaining to Black individuals that were seen in Model 1. In this model, on average, of those sentenced to fines, Black individuals can expect to receive a fine that is 24.37 GBP higher than the fine White individuals are likely to receive. The coefficient on Mixed became slightly more negative, indicating that Mixed individuals are more likely to receive a fine that is less than what White and Black individuals would expect to receive. The coefficients on these variables remain highly statistically significant, and the significance levels for Asian and Other individuals did not change. The additional information included about gender gives greater insight into the racial disparities seen in the amount of the fines individuals are sentenced to, but this model still fails to explain the entire picture.

Model 3 controls for the crime committed, which controls for case specific factors that may influence the type and severity of the sentence issued. Controlling for crime provides greater explanatory power. R^2 increases from 0.01 to 0.05. The baseline in this model is white females, who commit a drug offense. Those committing a sexual offense are most likely to receive the highest monetary amount of a fine, while those committing a theft offense are most likely to receive the lowest. The coefficients on all offense types, located in Section X, Table 9, are all highly statistically significant, indicating that the nature of the crime committed plays a role in the amount of the fine an offender is sentenced to by the courts. There is no coefficient associated with the Robbery variable as no individuals who committed a robbery were sentenced to a fine. Robbery is defined as a more severe crime, indicating a harsher punishment than a fine, such as time in prison. When controlling for the type of crime an individual commits, the coefficients on Black, Mixed, White, and Male all remain statistically significant. There is no change in the significance of the variables Other and Asian. The coefficient on male becomes slightly smaller than what was observed in Model 2; on average, males are likely to receive a fine that is 39.1 GBP higher than females who commit the same crime. The coefficient on Mixed becomes slightly less negative. Incorporating the type of crime committing into this model reverses the trends seen in Model 2. On average, Black individuals are more likely to receive a fine that is lower in its amount than their White counterparts. In this model, Mixed individuals are more likely to receive a fine that is smaller it its monetary amount than both Black and White individuals.

In Model 4, the police force that first deals with the offender is included in the regression equation. This accounts for a small degree of regional disparities that might influence sentencing outcomes and also for the disparities that may arise prior to the sentencing decision. The baseline in this model is white females, who were arrested by the Avon and Somerset police force. Compared to Model 3, which controls for crime committed, the explanatory power of Model 4 drops from 0.05 to 0.02. The coefficients on Black, White, Male, and Mixed remain statistically significant. Additionally, the coefficient on Asian is statistically significant but at a lower significance level. For Black individuals, the trend observed in Model 3 is reversed. On average, Blacks are likely to receive a fine that is 39.28 GBP higher than their white counterparts who come into contact with the same police force. Similarly to the past 3 models, the coefficient on Mixed is negative. In this model, it is slightly more negative, indicating that on average, Mixed individuals are more likely to receive a fine that is lower in its monetary amount than both White and Black individuals. The coefficient on Asian is negative, indicating that on average, Asian individuals are also more likely to receive a fine that is lower than what their White and Black counterparts may expect to receive. The majority of the coefficients on the the force variables, located in Section X, Table 9, are statistically significant, indicating that the region and police force may have an impact on the monetary amount of the fine an individual receives.

In Model 5, all demographic factors are controlled for, in addition to the police force and type of crime the offender commits. In this model, the baseline is white individuals who commit a drug offense and were dealt with by the Avon and Somerset police force. The explanatory power of this model is slightly higher than the explanatory power of the other models. The coefficients on Black, Mixed, male, and White remain highly statistically significant. Unlike Model 4, where the coefficient on Asian was statistically significant, it is no longer statistically significant in Model 5. In this model, it becomes apparent that both Black and Mixed individuals are likely to receive a lower fine than their white counterparts. On average, males receive fines that are higher in monetary amount than their female counterparts. The coefficients on the type of offense remain statistically significant, indicating that their is a causal relationship between the type of crime committed and the amount of the fine issued to the individual. In addition, the coefficients on the majority of the force factors also remain statistically significant, indicating that there may be regional disparities that explain differences in the amount of the fine an individual receives.

As seen in this analysis, depending on what variables are incorporated, Black offenders may be sentenced to fines that are lower or higher in their monetary amount than their White counterparts. Across the board and independent of one another, those identifying as Mixed and female receive fines that are lower in amount than their counterparts. In conclusion, we see varying levels in the monetary amount of the fines offenders are sentenced to by the courts. It is necessary to conduct further research and incorporate other variables to be able to determine if race truly influences the amount of the fine an individual is sentenced to.

7.3 Incarceration

Table 6, located at the top of page 23, reveals the regression results from those sentenced to prison. In all models expect Model 1, the baseline is White females.

In Model 1, the baseline group is White individuals. In Models 1 and 2, the coefficients on the race variables, with the exception of the Other variable, are statistically significant. For example, in Model 2, on average, males are 5.08 percentage points more likely to receive a prison sentence than females. In addition, in Model 2, Black, Asian, and Mixed individuals are less likely to receive time in prison than their White counterparts. The explanatory power of Models 1 and 2 is much lower than the explanatory power of Model 5, as indicated by the values for R^2. In Model 5, gender, the police force, and the crime committed are controlled for. In this model, it becomes apparent that on average, males are 7.02 percentage points more likely to receive a prison sentence than their white

Table 6: Regression Results: Incarceration

	(1)	(2)	(3)	(4)	(5)
White	0.02363***	0.19476***	0.25067***	0.16244***	0.2091***
	(0.001)	(0.004)	(0.005)	(0.010)	(0.014)
Black	-0.01843***	-0.02180***	0.00512	-0.0311***	-0.0082
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Asian	-0.03342***	-0.03897***	-0.01816**	-0.05174***	-0.0322***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
Mixed	-0.02539**	-0.02658**	-0.00811	-0.03461***	-0.0180*
	(0..008)	(0.008)	(0.008)	(0.008)	(0.008)
Other	-0.01959	-0.02198	0.01401	-0.03551**	-0.0328*
	(0.013)	(0.013)	(0.013)	(0.014)	(0.001)
Male		0.05082***	0.07267***	0.04896***	0.0722***
		(0.004)	(0.004)	(0.004)	(0.004)
Gender	No	Yes	Yes	Yes	Yes
Crime	No	No	Yes	No	Yes
Force	No	No	No	Yes	Yes
N	66647	66647	66647	66647	66647
Adjusted R^2	0.00054	0.00255	0.05784	0.01369	0.0687

Notes: Standard errors are shown in parentheses

female counterparts who are arrested by the same police force and commit the same crime. In this model, the coefficient on Black is not statistically significant. On average, both Asian and Other individuals are 3.2 percentage points less likely to receive a prison sentence than their White counterparts, and Mixed individuals are 1.8 percentage points less likely to be incarcerated than their White counterparts. The coefficients Asian and White are statistically significant in addition to the coefficients on Mixed and Other, but the coefficients on the former two are at a higher significance level.

The models in Table 7, located on page 24, are created using a subset of the 2017 data, which includes individuals who are sentenced to time in prison and omits those who are sentenced to a community sentence or fine. The longest amount of time that an offender can be sentenced to by the Magistrate Courts is up to two years (Ministry of Justice, 2017). Table 7 illustrates the coefficients associated with regressing race on the length of the custodial sentence. White defendants are the baseline group in this model, and each coefficient provides the estimate of an increased (or decreased) length

Table 7: Regression Results: Incarceration Length in Days

	(1)	(2)	(3)	(4)	(5)
White	82.75***	63.44***	82.34***	61.87***	80.52***
	(0.63)	(1.52)	(1.99)	(4.04)	(4.05)
Black	10.89***	9.65***	4.24*	6.92**	3.03
	(1.97)	(1.96)	(1.86)	(2.12)	(1.99)
Asian	2.41	0.14	-2.59	-1.80	-3.54
	(2.51)	(2.50)	(2.35)	(2.56)	(2.41)
Mixed	-2.54	-2.08	-4.70 .	-3.25	-5.08 .
	(2.99)	(2.98)	(2.80)	(3.00)	(2.83)
Other	-10.65*	-11.43*	-12.29**	-14.36**	-13.70**
	(4.79)	(4.76)	(4.49)	(4.81)	(4.53)
Male		22.81	17.00***	22.28***	16.69***
		(1.63)	(1.56)	(1.63)	(1.56)
Samples	IC	IC	IC	IC	IC
Gender	No	Yes	Yes	Yes	Yes
Crime	No	No	Yes	No	Yes
Force	No	No	No	Yes	Yes
N	15403	15403	15403	15403	15403
Adjusted R^2	0.002219	0.01474	0.1281	0.02338	0.1347

Notes: Standard errors are shown in parentheses

of a prison sentence that an offender identifying as a certain race expects to receive after controlling for other factors. For example, the second row of table 4, illustrates that on average, black offenders receive longer sentences than white individuals.

When gender is controlled for, the baseline becomes white females. In Models 2, 3, 4, and 5, which include gender, the coefficients on the male variable are extremely statistically significant, indicating that on average, males receive longer prison sentences than females. For example, when controlling for both police force and type of crime in Model 5, on average, males tend to receive a sentence that is 16.69 days longer than the sentence received by females who commit the same crime and are arrested by the same police force.

Model 1 is a regression run solely on to indicate the effects on race on incarceration length. No controls are included in this regression. In the absence of controls, on average, those identifying as black receive longer sentences than those identifying as white.

The coefficients on white and black offenders are highly statistically significant. The negative coefficient on those identifying as other is statistically significant but at a lower significance level.

In Model 2, controlling for gender increases the model's explanatory power as R^2 increases from 0.002 to 0.01. The coefficients on the white and black variables are slightly lower, but they are still highly statistically significant. Including information about gender gives some insight as to why racial disparities in sentencing decisions are observed, but it does not explain the whole picture.

Model 3 controls for the crime committed. Including information on the crime committed allows for control of case severity. Although there are varying degrees of severity within a crime type, controlling for crime provides greater explanatory power. R^2 increases from 0.01 to 0.1. When accounting for differences in initial crime committed, it becomes apparent that Black offenders receive longer sentences. On average, Black offenders receive sentences that are 4.24 days longer than their White counterparts.

The coefficients on the type of crime committed, located in Section X, Table 12, provides insight into which crimes are associated with longer sentences. The baseline here is white females, whose crime is categorized as violence against a person. Those committing a drug offense are sentenced to the lowest length of time in prison, while those committing a robbery are sentenced to the longest length of time in prison. Those who commit a robbery are sentenced to 223.02 days more in prison, while those committing a drug offense are sentenced to 37.13 days less in prison than those whose crime is categorized as violence against a person. To further illustrate this, on average, those committing a robbery are sentenced to 305.41 days in prison, and those committing a drug offense are sentenced to 45.27 days in prison. The coefficients on all offense types are highly statistically significant, indicating that there is a correlation between offense committed and the length of incarceration an individual is sentenced to. Even when controlling for crime, on average, Black individuals receive longer prison sentences than their White counterparts. The significance level drops slightly, but the coefficients on those identifying as White and those identifying as Black are still statistically significant.

When controlling for offense type, the significance level on the Other variable raises. Those identifying as Other, on average, receive shorter sentences than those identifying as White or Black.

Model 4 controls for the police force that makes an arrest. The baseline in this model is White females, who are arrested by the Avon and Somerset police force. Controlling for the police force that makes the initial arrest allows for inclusion of the region in which the crime was committed and potential neighborhood effects. Compared to Model 3, which controls for crime committed, the explanatory power of Model 4 drops from 0.1 to 0.02. The coefficients on those identifying as Black, those identifying as White, and those identifying as Other remain statistically significant. On average, those identifying as Black are sentenced to longer time in prison, while those identifying as Other are sentenced to less time in prison than both Black individuals and White individuals. Most of the coefficients, located in Section X, Table 12, with the exception of Dorset (-27.29 days), Greater Manchester (12.92 days), and Humberside (23.43 days), are not statistically significant indicating that there is no significant correlation between the police force that initially takes the offender into custody and the length of time in prison the offender is sentenced to.

Model 5 controls for all demographic factors, the police force, and the type of crime that was committed and helps explain some of the racial disparities seen in the length of imprisonment. The baseline in this model is White females who commit a drug offense and are arrested by the Avon and Somerset police force. The explanatory power of this model is the highest as the value of R^2 is 0.13, which is much higher than the value for the other models. This model reverses the trends seen in the first four models. In Model 5, which includes all factors, the estimate for Black offenders is positive but no longer statistically significant. The coefficient on offenders identifying as Other remains statistically significant and is the lowest coefficient of the race categories. When controlling for demographic factors, type of crime committed, and the arresting police force, those identifying as Other receive sentences that are about 14 days shorter than White individuals who commit the same crime and are arrested by the same police force.

Most of the coefficients on the different police forces, with the exception of Dorset (24.28 days less), Greater Manchester (12.38 days more), and Humberside (23.15 days more), are not statistically significant indicating that the police force that initially takes the offender into custody is not associated with the length of time in prison an offender is sentenced to. These coefficients are slightly lower than they were when only controlling for police force. The coefficients are slightly lower on the type of crime, but they remain highly statistically significant. Those committing robberies receive a prison sentence that is 221.29 days longer than the baseline group on average, and those committing drug offenses receive a sentence that is 37.01 days shorter on average than the baseline group.

The factors included are not exhaustive and may point to racial disparities elsewhere in the legal system or throughout society. Including these additional factors is necessary for a full understanding of racial disparities that arise in both the likelihood of recieveing a prison sentence and the corresponding length of incarceration.

8 Future Directions

My research has established the groundwork for analyzing the sentencing decisions in the United Kingdom magistrate courts. However, this is only the beginning. One of the main issues with the data used in this analysis is that the court actually issuing the sentence is not recorded. Controlling for location of the court could help account for regional disparities or neighborhood differences in ways controlling for the police force could not. Furthermore, the sentencing decisions may have differed due to regional differences or institutionalized racism within each court. With the addition of this information, differences in sentencing decisions across courts can be examined. My research could be taken further by analyzing group fixed effects of the courts and analyzing sentencing decisions on a more extensive margin. Certain regions in the England and Wales, like London, are significantly more diverse than the others. Examining the differences in the severity of the sentence issued across courts could point to regional disparities and other inequalities within the legal system. Lastly, in regards to the nature of the dataset used in this analysis, I would want to gather more precise information on the length and amount of the sentence issued by the courts instead of using the midpoint value. Some of the brackets for both time in prison and amount of the fine issued are larger than others. The way these variables were recoded may have impacted the results seen in the regresion analysis, but based on the information provided in the dataset, there was no better way to go about it. In the future, if there is more precise information detailing the exact length and amount that an offender was sentenced to, I would like to rerun the regression equations to see if the statistical significance or the coefficients' value varied with a more precise sentence.

Additionally, I would want to use a dataset that is more complete and granular to examine racial disparities across time. The Ministry of Justice changed the way they recorded offender data in 2015, but drawing from a larger sample size, other than just in 2017, would allow for greater analysis of whether or not these racial disparities are perpetuated in sentencing decisions overtime. Furthermore, it would be beneficial to expand and include sentencing data from Crown Court or conduct regression analysis independently at the Crown Court level. This would allow for incorporation of more experienced judges to see if racial disparities in sentencing decisions are unique to magistrate courts or if they plague the United Kingdom as a whole. Magistrates are not subject to the same training as Crown Court judges, so the lack of more rigorous training might explain the disparities seen in both gender and race in my analysis. The Crown Court also deals with more severe crimes that result in more severe punishments, so it would be beneficial to analyze incarceration length at the Crown Court level. Additionally, in efforts to protect offender privacy, the date in which the initial arrest takes place or the date of the hearing is not recorded. Although this data may be hard to obtain, it would be beneficial to obtain in order to analyze external variables, like Heyes and Saberian, to see if those variables help explain the disparities seen here.

9 Conclusion

My research finds significant disparities in judicial decision-making and contributes to the wealth of economic literature that seeks to understand how decisions are made in the courts. The majority of research conducted has found a link between both external factors and internal factors relevant to the case and the decision the courts make, exposing disparities within the judicial system. Racism's institutionalized legacy runs rampant in a system that is supposed to provide equal protection for all. It is imperative to take steps to conduct further research in order to improve a system that is ill-founded on principles of equality and equity.

10 Tables and Figures

Table 8: Regression Results – Model 5: Fine

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.1889	0.0121	15.57	0.0000
Black	-0.0228	0.0062	-3.71	0.0002
Asian	0.0041	0.0073	0.56	0.5751
Other	-0.0188	0.0140	-1.35	0.1784
Mixed	-0.0325	0.0087	-3.74	0.0002
Male	-0.0012	0.0046	-0.27	0.7871
Force_factorBedfordshire	0.0889	0.0189	4.69	0.0000
Force_factorCambridgeshire	-0.0150	0.0181	-0.83	0.4059
Force_factorCheshire	0.0230	0.0153	1.50	0.1327
Force_factorCleveland	-0.0096	0.0160	-0.60	0.5477
Force_factorCumbria	0.1172	0.0184	6.39	0.0000
Force_factorDerbyshire	-0.0246	0.0165	-1.50	0.1342
Force_factorDevon and Cornwall	-0.0319	0.0165	-1.93	0.0535
Force_factorDorset	0.0121	0.0171	0.71	0.4775
Force_factorDurham	-0.0438	0.0178	-2.46	0.0138
Force_factorDyfed-Powys	0.0810	0.0193	4.19	0.0000
Force_factorEssex	0.0228	0.0164	1.39	0.1643
Force_factorGloucestershire	0.0129	0.0188	0.69	0.4930
Force_factorGreater Manchester	-0.0792	0.0132	-5.98	0.0000
Force_factorGwent	0.0086	0.0194	0.44	0.6595
Force_factorHampshire	0.0220	0.0160	1.38	0.1688
Force_factorHertfordshire	0.1895	0.0149	12.69	0.0000
Force_factorHumberside	-0.0802	0.0168	-4.77	0.0000
Force_factorKent	0.0036	0.0145	0.25	0.8032

Continued on next page

Table 8 – continued from previous page

	Estimate	Std. Error	t value	Pr(>|t|)
Force_factorLancashire	-0.0134	0.0178	-0.75	0.4518
Force_factorLeicestershire	-0.0955	0.0177	-5.39	0.0000
Force_factorLincolnshire	0.0499	0.0176	2.83	0.0047
Force_factorMerseyside	0.0237	0.0140	1.69	0.0907
Force_factorMetropolitan Police	0.0464	0.0114	4.05	0.0001
Force_factorNorfolk	0.0160	0.0196	0.82	0.4150
Force_factorNorth Wales	0.0406	0.0184	2.20	0.0276
Force_factorNorth Yorkshire	-0.0246	0.0168	-1.46	0.1440
Force_factorNorthamptonshire	0.0471	0.0202	2.33	0.0196
Force_factorNorthumbria	0.0336	0.0139	2.42	0.0154
Force_factorNottinghamshire	-0.0318	0.0159	-2.00	0.0455
Force_factorSouth Wales	0.0704	0.0138	5.09	0.0000
Force_factorSouth Yorkshire	-0.0984	0.0159	-6.20	0.0000
Force_factorStaffordshire	0.0625	0.0154	4.06	0.0001
Force_factorSuffolk	0.0491	0.0251	1.96	0.0502
Force_factorSurrey	0.0992	0.0179	5.55	0.0000
Force_factorSussex	0.0522	0.0163	3.20	0.0014
Force_factorThames Valley	0.0811	0.0135	6.01	0.0000
Force_factorWarwickshire	0.0853	0.0199	4.30	0.0000
Force_factorWest Mercia	0.0434	0.0155	2.81	0.0050
Force_factorWest Midlands	0.0339	0.0128	2.65	0.0080
Force_factorWest Yorkshire	-0.0147	0.0130	-1.13	0.2602
Force_factorWiltshire	0.0552	0.0185	2.98	0.0029
OffenceType_factor02: Sexual offences	-0.1428	0.0151	-9.43	0.0000
OffenceType_factor03: Robbery	-0.2044	0.0226	-9.05	0.0000

Continued on next page

Table 8 – continued from previous page

	Estimate	Std. Error	t value	Pr(>|t|)
OffenceType_factor04: Theft Offences	0.0155	0.0057	2.70	0.0070
OffenceType_factor05: Criminal damage/arson	-0.0513	0.0166	-3.08	0.0020
OffenceType_factor06: Drug offences	0.3162	0.0063	49.88	0.0000
OffenceType_factor07: Possession of weapons	-0.0679	0.0086	-7.93	0.0000
OffenceType_factor08: Public order offences	0.0943	0.0071	13.28	0.0000
OffenceType_factor09: Mis. crimes	0.1664	0.0071	23.40	0.0000
OffenceType_factor10: Fraud Offences	-0.0097	0.0111	-0.88	0.3806
N				66647

Table 9: Regression Results – Model 5: Fine Amount in GBP

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	207.0479	9.7334	21.27	0.0000
Black	-33.0861	4.4032	-7.51	0.0000
Asian	-7.1620	5.1583	-1.39	0.1650
Mixed	-30.1578	6.4708	-4.66	0.0000
Other	-4.6407	10.4470	-0.44	0.6569
Male	39.5415	3.5000	11.30	0.0000
Force_factorBedfordshire	-24.5880	13.5902	-1.81	0.0704
Force_factorCambridgeshire	-41.3749	14.6066	-2.83	0.0046
Force_factorCheshire	-21.5498	11.5833	-1.86	0.0628
Force_factorCleveland	-66.2552	12.5986	-5.26	0.0000
Force_factorCumbria	-42.0917	12.7842	-3.29	0.0010
Force_factorDerbyshire	-27.7858	13.3345	-2.08	0.0372
Force_factorDevon and Cornwall	-27.1458	13.1924	-2.06	0.0396
Force_factorDorset	-55.5495	12.8651	-4.32	0.0000
Force_factorDurham	-30.2313	15.3649	-1.97	0.0491
Force_factorDyfed-Powys	-28.3484	13.3611	-2.12	0.0339
Force_factorEssex	-24.0539	12.5583	-1.92	0.0555
Force_factorGloucestershire	-54.2294	14.4262	-3.76	0.0002
Force_factorGreater Manchester	-28.3038	11.1770	-2.53	0.0113
Force_factorGwent	-44.2758	14.9105	-2.97	0.0030
Force_factorHampshire	-38.5672	12.2555	-3.15	0.0017
Force_factorHertfordshire	-9.9584	10.3952	-0.96	0.3381
Force_factorHumberside	-68.0593	14.9899	-4.54	0.0000
Force_factorKent	-40.3091	11.2638	-3.58	0.0003
Force_factorLancashire	-56.8492	14.3601	-3.96	0.0001

Continued on next page

	Estimate	Std. Error	t value	Pr(>|t|)
Force_factorLeicestershire	16.1865	16.8570	0.96	0.3370
Force_factorLincolnshire	-25.2745	13.1011	-1.93	0.0537
Force_factorMerseyside	-49.0007	10.6096	-4.62	0.0000
Force_factorMetropolitan Police	-5.6121	8.8656	-0.63	0.5267
Force_factorNorfolk	-34.1447	14.5877	-2.34	0.0193
Force_factorNorth Wales	-40.4554	13.6687	-2.96	0.0031
Force_factorNorth Yorkshire	-19.4498	13.4508	-1.45	0.1482
Force_factorNorthamptonshire	-32.5071	14.9728	-2.17	0.0299
Force_factorNorthumbria	-24.4607	10.6307	-2.30	0.0214
Force_factorNottinghamshire	-31.3406	12.8629	-2.44	0.0148
Force_factorSouth Wales	-48.0903	10.2902	-4.67	0.0000
Force_factorSouth Yorkshire	-57.7019	14.4021	-4.01	0.0001
Force_factorStaffordshire	-26.4892	11.4036	-2.32	0.0202
Force_factorSuffolk	-28.8268	18.1761	-1.59	0.1128
Force_factorSurrey	-30.5018	12.5516	-2.43	0.0151
Force_factorSussex	-14.4869	12.0557	-1.20	0.2295
Force_factorThames Valley	-18.5251	10.0540	-1.84	0.0654
Force_factorWarwickshire	-24.7975	14.0666	-1.76	0.0779
Force_factorWest Mercia	-51.8990	11.5872	-4.48	0.0000
Force_factorWest Midlands	-39.2455	9.8184	-4.00	0.0001
Force_factorWest Yorkshire	-40.4081	10.3138	-3.92	0.0001
Force_factorWiltshire	-44.2343	13.6289	-3.25	0.0012
OffenceType_factor02: Sexual offences	219.4343	23.2313	9.45	0.0000
OffenceType_factor04: Theft Offences	-89.8145	5.0241	-17.88	0.0000

Continued on next page

Table 9 – continued from previous page

	Estimate	Std. Error	t value	Pr(>|t|)
OffenceType_factor05: Criminal damage/arson	-45.8473	17.1344	-2.68	0.0075
OffenceType_factor06: Drug offences	-77.2563	4.9237	-15.69	0.0000
OffenceType_factor07: Possession of weapons	22.5943	8.6535	2.61	0.0090
OffenceType_factor08: Public order offences	-15.9078	5.7553	-2.76	0.0057
OffenceType_factor09: Misc.	-74.1837	5.5273	-13.42	0.0000
OffenceType_factor10: Fraud Offences	-44.6477	9.8293	-4.54	0.0000
N				19578

Table 10: Regression Results – Model 5: Community Sentence

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.4216	0.0123	34.18	0.0000
Black	0.0225	0.0063	3.60	0.0003
Asian	0.0355	0.0074	4.79	0.0000
Other	0.0277	0.0142	1.95	0.0513
Mixed	0.0561	0.0088	6.36	0.0000
Male	-0.0006	0.0047	-0.13	0.8990
Force_factorBedfordshire	-0.0319	0.0193	-1.66	0.0978
Force_factorCambridgeshire	-0.0878	0.0184	-4.78	0.0000
Force_factorCheshire	-0.0868	0.0155	-5.59	0.0000
Force_factorCleveland	-0.0500	0.0163	-3.06	0.0022
Force_factorCumbria	-0.0491	0.0187	-2.63	0.0085
Force_factorDerbyshire	-0.0924	0.0167	-5.53	0.0000
Force_factorDevon and Cornwall	-0.0777	0.0168	-4.62	0.0000
Force_factorDorset	-0.1159	0.0173	-6.68	0.0000
Force_factorDurham	-0.0279	0.0181	-1.54	0.1228
Force_factorDyfed-Powys	-0.0627	0.0196	-3.19	0.0014
Force_factorEssex	-0.0220	0.0167	-1.32	0.1870
Force_factorGloucestershire	-0.0413	0.0191	-2.16	0.0306
Force_factorGreater Manchester	-0.0101	0.0135	-0.75	0.4548
Force_factorGwent	-0.0786	0.0197	-3.98	0.0001
Force_factorHampshire	-0.0631	0.0162	-3.89	0.0001
Force_factorHertfordshire	-0.1176	0.0152	-7.75	0.0000
Force_factorHumberside	-0.0559	0.0171	-3.27	0.0011
Force_factorKent	-0.0392	0.0147	-2.67	0.0076
Force_factorLancashire	-0.0299	0.0180	-1.66	0.0978

Continued on next page

Table 10 – continued from previous page

	Estimate	Std. Error	t value	Pr(>|t|)
Force_factorLeicestershire	0.0019	0.0180	0.10	0.9164
Force_factorLincolnshire	-0.1124	0.0179	-6.27	0.0000
Force_factorMerseyside	-0.0408	0.0142	-2.87	0.0041
Force_factorMetropolitan Police	-0.0901	0.0116	-7.75	0.0000
Force_factorNorfolk	-0.1020	0.0199	-5.12	0.0000
Force_factorNorth Wales	-0.0604	0.0187	-3.22	0.0013
Force_factorNorth Yorkshire	-0.0116	0.0171	-0.68	0.4983
Force_factorNorthamptonshire	-0.0581	0.0205	-2.83	0.0046
Force_factorNorthumbria	-0.0847	0.0141	-6.00	0.0000
Force_factorNottinghamshire	-0.0991	0.0162	-6.13	0.0000
Force_factorSouth Wales	-0.1178	0.0141	-8.37	0.0000
Force_factorSouth Yorkshire	-0.0287	0.0161	-1.78	0.0750
Force_factorStaffordshire	-0.0707	0.0157	-4.52	0.0000
Force_factorSuffolk	-0.0632	0.0255	-2.48	0.0133
Force_factorSurrey	-0.0577	0.0182	-3.18	0.0015
Force_factorSussex	-0.0474	0.0166	-2.86	0.0043
Force_factorThames Valley	-0.0639	0.0137	-4.66	0.0000
Force_factorWarwickshire	-0.1002	0.0202	-4.97	0.0000
Force_factorWest Mercia	-0.0812	0.0157	-5.16	0.0000
Force_factorWest Midlands	-0.0830	0.0130	-6.40	0.0000
Force_factorWest Yorkshire	-0.0386	0.0132	-2.91	0.0036
Force_factorWiltshire	0.0075	0.0188	0.40	0.6894
OffenceType_factor02: Sexual offences	0.3018	0.0154	19.61	0.0000

Continued on next page

Table 10 – continued from previous page

	Estimate	Std. Error	t value	Pr(>|t|)
OffenceType_factor03: Robbery	0.3998	0.0230	17.42	0.0000
OffenceType_factor04: Theft Offences	-0.1006	0.0058	-17.25	0.0000
OffenceType_factor05: Criminal damage/arson	0.0876	0.0169	5.18	0.0000
OffenceType_factor06: Drug offences	-0.1778	0.0064	-27.59	0.0000
OffenceType_factor07: Possession of weapons	0.0910	0.0087	10.45	0.0000
OffenceType_factor08: Public order offences	-0.0789	0.0072	-10.92	0.0000
OffenceType_factor09: Misc. crimes	-0.1197	0.0072	-16.56	0.0000
OffenceType_factor10: Fraud Offences	0.0209	0.0113	1.85	0.0639
N				66647

Table 11: Regression Results – Model 5: Incarceration

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.2091	0.0114	18.36	0.0000
Black	-0.0082	0.0058	-1.41	0.1580
Asian	-0.0322	0.0068	-4.71	0.0000
Mixed	-0.0180	0.0081	-2.21	0.0269
Other	-0.0328	0.0131	-2.50	0.0126
Sex_factor02: Male	0.0722	0.0043	16.79	0.0000
Force_factorBedfordshire	0.0209	0.0178	1.18	0.2388
Force_factorCambridgeshire	0.1398	0.0170	8.25	0.0000
Force_factorCheshire	0.0838	0.0143	5.84	0.0000
Force_factorCleveland	0.0082	0.0151	0.54	0.5866
Force_factorCumbria	0.0396	0.0172	2.30	0.0214
Force_factorDerbyshire	0.1580	0.0154	10.23	0.0000
Force_factorDevon and Cornwall	0.0626	0.0155	4.03	0.0001
Force_factorDorset	-0.0246	0.0160	-1.54	0.1242
Force_factorDurham	-0.0314	0.0167	-1.88	0.0595
Force_factorDyfed-Powys	0.0039	0.0181	0.21	0.8308
Force_factorEssex	0.0437	0.0154	2.84	0.0046
Force_factorGloucestershire	-0.0086	0.0177	-0.49	0.6257
Force_factorGreater Manchester	0.0972	0.0124	7.82	0.0000
Force_factorGwent	0.0851	0.0182	4.67	0.0000
Force_factorHampshire	0.0392	0.0150	2.62	0.0089
Force_factorHertfordshire	-0.0237	0.0140	-1.69	0.0907
Force_factorHumberside	0.0001	0.0158	0.01	0.9956
Force_factorKent	0.0440	0.0136	3.24	0.0012
Force_factorLancashire	0.0026	0.0167	0.16	0.8755

Continued on next page

Table 11 – continued from previous page

	Estimate	Std. Error	t value	Pr(>|t|)
Force_factorLeicestershire	0.0666	0.0166	4.01	0.0001
Force_factorLincolnshire	-0.0094	0.0166	-0.57	0.5681
Force_factorMerseyside	0.0518	0.0131	3.94	0.0001
Force_factorMetropolitan Police	0.0660	0.0107	6.15	0.0000
Force_factorNorfolk	-0.0245	0.0184	-1.33	0.1822
Force_factorNorth Wales	0.0759	0.0173	4.38	0.0000
Force_factorNorth Yorkshire	0.0013	0.0158	0.08	0.9348
Force_factorNorthamptonshire	0.0612	0.0189	3.23	0.0012
Force_factorNorthumbria	-0.0344	0.0130	-2.64	0.0082
Force_factorNottinghamshire	0.0923	0.0149	6.18	0.0000
Force_factorSouth Wales	0.1206	0.0130	9.29	0.0000
Force_factorSouth Yorkshire	0.0757	0.0149	5.09	0.0000
Force_factorStaffordshire	0.0139	0.0145	0.96	0.3362
Force_factorSuffolk	-0.0404	0.0236	-1.71	0.0865
Force_factorSurrey	-0.0023	0.0168	-0.14	0.8906
Force_factorSussex	0.0184	0.0153	1.20	0.2303
Force_factorThames Valley	-0.0092	0.0127	-0.73	0.4672
Force_factorWarwickshire	0.0006	0.0186	0.03	0.9722
Force_factorWest Mercia	0.0008	0.0145	0.05	0.9587
Force_factorWest Midlands	0.0764	0.0120	6.37	0.0000
Force_factorWest Yorkshire	0.0498	0.0122	4.08	0.0000
Force_factorWiltshire	-0.0156	0.0174	-0.90	0.3677
OffenceType_factor02: Sexual offences	-0.1181	0.0142	-8.31	0.0000

Continued on next page

Table 11 – continued from previous page

	Estimate	Std. Error	t value	Pr(>|t|)
OffenceType_factor03: Robbery	-0.1157	0.0212	-5.46	0.0000
OffenceType_factor04: Theft Offences	-0.0137	0.0054	-2.55	0.0107
OffenceType_factor05: Criminal damage/arson	-0.1581	0.0156	-10.12	0.0000
OffenceType_factor06: Drug offences	-0.2648	0.0060	-44.50	0.0000
OffenceType_factor07: Possession of weapons	0.0260	0.0080	3.24	0.0012
OffenceType_factor08: Public order offences	-0.0264	0.0067	-3.95	0.0001
OffenceType_factor09: Misc.crimes	-0.1236	0.0067	-18.51	0.0000
OffenceType_factor10: Fraud Offences	-0.0973	0.0104	-9.36	0.0000
N				66647

Table 12: Regression Results – Model 5: Incarceration Length

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	6345.0822	319.0468	19.89	0.0000
Black	238.8744	156.8773	1.52	0.1279
Asian	-276.2887	189.9450	-1.45	0.1458
Mixed	-400.9835	223.0422	-1.80	0.0722
Other	-1079.6470	357.1553	-3.02	0.0025
Male	1314.9402	122.5691	10.73	0.0000
Force_factorBedfordshire	494.1665	487.4856	1.01	0.3107
Force_factorCambridgeshire	-171.4877	408.8098	-0.42	0.6749
Force_factorCheshire	-107.2508	377.0117	-0.28	0.7760
Force_factorCleveland	-779.9135	425.7396	-1.83	0.0670
Force_factorCumbria	-42.0761	464.0518	-0.09	0.9278
Force_factorDerbyshire	836.5284	376.3559	2.22	0.0263
Force_factorDevon and Cornwall	-81.1549	413.4570	-0.20	0.8444
Force_factorDorset	-1913.9107	489.1578	-3.91	0.0001
Force_factorDurham	-664.9808	482.5879	-1.38	0.1682
Force_factorDyfed-Powys	178.8348	545.7232	0.33	0.7431
Force_factorEssex	390.3042	414.7419	0.94	0.3467
Force_factorGloucestershire	32.5250	515.0807	0.06	0.9497
Force_factorGreater Manchester	975.0552	331.7330	2.94	0.0033
Force_factorGwent	633.5851	462.0136	1.37	0.1703
Force_factorHampshire	273.1044	402.2658	0.68	0.4972
Force_factorHertfordshire	-959.3786	418.7834	-2.29	0.0220
Force_factorHumberside	1832.8178	446.4423	4.11	0.0000
Force_factorKent	390.1898	371.0091	1.05	0.2930
Force_factorLancashire	-77.5414	464.1724	-0.17	0.8673

Continued on next page

Table 12 – continued from previous page

	Estimate	Std. Error	t value	Pr(>|t|)
Force_factorLeicestershire	-147.8863	428.9484	-0.34	0.7303
Force_factorLincolnshire	54.5185	475.4028	0.11	0.9087
Force_factorMerseyside	-237.4467	362.3013	-0.66	0.5122
Force_factorMetropolitan Police	443.9192	302.7752	1.47	0.1426
Force_factorNorfolk	-346.3373	575.6751	-0.60	0.5474
Force_factorNorth Wales	223.6476	442.9537	0.50	0.6136
Force_factorNorth Yorkshire	-71.5582	454.1456	-0.16	0.8748
Force_factorNorthamptonshire	-711.9113	486.1280	-1.46	0.1431
Force_factorNorthumbria	737.7807	387.2436	1.91	0.0568
Force_factorNottinghamshire	104.5742	386.9054	0.27	0.7869
Force_factorSouth Wales	374.1949	341.1443	1.10	0.2727
Force_factorSouth Yorkshire	186.4916	389.9612	0.48	0.6325
Force_factorStaffordshire	-156.8428	406.5463	-0.39	0.6997
Force_factorSuffolk	-712.6059	760.1698	-0.94	0.3486
Force_factorSurrey	340.8610	485.4697	0.70	0.4826
Force_factorSussex	-36.7589	429.2550	-0.09	0.9318
Force_factorThames Valley	-85.6463	371.4042	-0.23	0.8176
Force_factorWarwickshire	-463.4190	530.0686	-0.87	0.3820
Force_factorWest Mercia	-309.8957	414.8470	-0.75	0.4551
Force_factorWest Midlands	-293.4859	327.4985	-0.90	0.3702
Force_factorWest Yorkshire	615.9005	336.0686	1.83	0.0669
Force_factorWiltshire	394.9913	508.8345	0.78	0.4376
OffenceType_factor02: Sexual offences	3162.3260	388.9453	8.13	0.0000

Continued on next page

Table 12 – continued from previous page

	Estimate	Std. Error	t value	Pr(>|t|)
OffenceType_factor03: Robbery	17436.4562	589.2509	29.59	0.0000
OffenceType_factor04: Theft Offences	-1738.9293	124.3561	-13.98	0.0000
OffenceType_factor05: Criminal damage/arson	-1759.4659	495.7096	-3.55	0.0004
OffenceType_factor06: Drug offences	-2916.8623	235.9432	-12.36	0.0000
OffenceType_factor07: Possession of weapons	2069.7317	177.6012	11.65	0.0000
OffenceType_factor08: Public order offences	-1794.0236	154.1725	-11.64	0.0000
OffenceType_factor09: Misc. crimes	-1871.6476	175.3612	-10.67	0.0000
OffenceType_factor10: Fraud Offences	-1141.3635	284.5109	-4.01	0.0001
N				15403

Notes: In this table, time in prison was converted to GBP, using the average wage (28,759 GBP) England and Wales in 2017 to reflect the opportunity cost of lost wages. To convert back to recoded midpoint in days, divided the coefficient value by 28759 and multiply by 365.

References

[1] Choi, D., Harris, J., and Shen-Bayh, F. (2022). "Ethnic Bias in Judicial Decision Making: Evidence from Criminal Appeals in Kenya." *American Political Science Review,* 116 (3), 1067-1080.

[2] The Crown Prosecution Service. (n.d.). *Sentencing.* Retrieved November 12, 2022, from https://www.cps.gov.uk/cps-page/sentencing.

[3] Community sentences. (n.d.). *Sentencing.* Retrieved November 10, 2022, from https://www.sentencingcouncil.org.uk/sentencing-and-the-council/types-of-sentence/community-sentences/.

[4] Criminal Justice System Statistics. (2023, March 21). *Institute of Race Relations.* Retrieved April 21, 2023, from https://irr.org.uk/research/statistics/criminal-justice/.

[5] Crown Prosecution Service. (2022, November 24). How a Criminal Case Works. *CPS.* Retrieved April 21, 2023, from https://www.cps.gov.uk/about-cps/how-a-criminal-case-works.

[6] Disposals. (n.d.). *Youth Justice Board Reparation Order.* Retrieved November 10, 2022, from

https://web.archive.org/web/20110723114612/http://www.yjb.gov.uk/en-gb/practitioners/CourtsAndOrders/Disposals/ReparationOrder/.

[7] Judicial Office. (2022, September 26). Magistrates. *Courts and Tribunals Judiciary.* Retrieved April 21, 2023, from https://www.judiciary.uk/about-the-judiciary/who-are-the-judiciary/magistrates/.

[8] Heyes, Anthony, and Soodeh Saberian. (2019). "Temperature and Decisions: Evidence from 207,000 Court Cases." *American Economic Journal: Applied Economics* 11 (2): 238–65.

[9] Melcarne, A., Monnery, B., Wolff, F. (2022). "Prosecutors, judges and sentencing disparities: Evidence from traffic offenses in France." *International Review of Law and Economics,* 71.

[10] Ministry of Justice. (2017). Criminal Justice Statistics. *GOV.UK*. Retrieved April 21, 2023, from

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachmentdata/file/707621/criminal-justice-statistics-infographic.pdf.

[11] Office for National Statistics. (2023, April 4). Population of England and Wales. *GOV.UK Ethnicity facts and figures.* Retrieved April 21, 2023, from https://www.ethnicity-facts-figures.service.gov.uk/uk-population-by-ethnicity/national-and-regional-populations/population-of-england-and-wales/latest.

[12] PFHelpline. (n.d.). Magistrates Court. *Prisoners' Families Helpline.* Retrieved April 21, 2023, from https://www.prisonersfamilies.org/magistrates-court.

[13] Service, G. D. (2015, January 27). Being arrested: Your rights. *GOV.UK.* Retrieved November 10, 2022, from https://www.gov.uk/arrested-your-rights/how-long-you-can-be-held-in-custody.

[14] Service, G. D. (2015, May 27). Criminal courts. *GOV.UK.* Retrieved November 17, 2022, from https://www.gov.uk/courts. Service, G. D. (2020, August 19). Types of prison sentence. GOV.UK. Retrieved November 17, 2022, from https://www.gov.uk/types-of-prison-sentence/suspended-prison-sentences.

[15] Sturge, Georgina (2018, July 23). UK Prison Population Statistics. *House of Commons Library,* CP04334. Retrieved April 21, 2023, from https://solitarywatch.org/wp-content/uploads/2019/04/UK-Prison-Population-Statistics.pdf.