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The Price of Policing: Uncovering Local Economic Divides in Stop and Search – A Study of London and Merseyside

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Abstract

This study examines the spatial concentration of stop and search (S&S) practices through a comparative analysis of the 2022 Merseyside and Greater London policing data. While existing research extensively explores the ethnic dynamics of S&S, this study expands upon it by considering how differing social compositions between these two regions influence the economic dynamics of policing. Specifically, London's highly diverse, multicultural population contrasting with Merseyside's relatively more homogenous demographic. Departing from a purely demographic focus, this investigation examines the geographical distribution of policing practices and the relationship between S&S incidences and localised economic inequality. By assessing these policing encounters at the local level, the findings reveal statistically significant correlations between S&S incidence and economic inequality. By comparing these regions, this study offers new insights into how differing social make-ups shape the relationship between spatial justice, economic disparity and policing strategies.

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1 Introduction

1.1 Background and Context

Stop and search is a widely used policing tactic that allows officers to stop individuals in public spaces and search them for illegal items such as drugs, weapons or stolen property. While intended to enhance public safety and deter crime, the practice has long been controversial in the UK. Critics argue that it disproportionately targets certain communities, particularly ethnic minorities, raising concerns about racial discrimination and the erosion of public trust in law enforcement. Despite policy reforms aimed at improving transparency and accountability, stop and search remains heavily debated in terms of its effectiveness, fairness and social impact. This dissertation examines the spatial and economic dimensions of stop and search practices, focusing on the relationship between local economic disparities and the geographic distribution of these incidents in two regions: Merseyside and Greater London. By exploring how economic inequality and social composition influence policing strategies, this study contributes to a growing body of work on spatial and structural inequalities in law enforcement.

1.2 Research Problem and Motivation

The central issue addressed by this research is how the spatial patterns of stop and search correlate with localised economic disparities. While a significant body of research has explored the racial and social dynamics of stop and search, far less attention has been paid to the role of economic inequality in shaping its implementation. Understanding how policing practices reflect and reinforce socioeconomic divides is essential for developing a more grounded and critical view of their impact in diverse urban environments. By focusing on two contrasting regions—Merseyside and Greater London—this study responds to a gap in the literature that tends to overlook the intersection between economic conditions and policing. Existing research often treats race, geography and class as separate factors; this project aims to explore how these elements combine to produce differentiated policing outcomes across space.

1.3 Research Aim and Objectives

The primary aim of this research is to explore how the spatial distribution of stop and search practices in Merseyside and Greater London correlates with local economic disparities at the Lower Super Output Area (LSOA) level. The specific research objectives are:

- To analyse the spatial distribution of stop and search incidents in Merseyside and Greater London.
- To assess the relationship between economic inequality and the frequency of stop and search incidents.
- To evaluate the impact of social composition (e.g., ethnicity, income levels) on stop and search practices.

1.4 Research Questions

The research question guiding this study is:

> **To what extent do the spatial patterns of stop and search in Merseyside and Greater London, reflecting their differing social compositions, correlate with localised economic disparities at the Lower Super Output Area (LSOA) level?**

1.5 Methodological Approach

This study will employ a quantitative research design, using publicly available data on stop and search incidents from local police authorities in Merseyside and Greater London. Key variables—including stop and search rates, socioeconomic indicators (such as income levels and deprivation indices) and demographic data (e.g., ethnicity, age)—will be analysed at the LSOA level. Analytical techniques will include spatial mapping to identify policing hotspots, as well as statistical modelling to assess the relationship between economic inequality and stop and search frequency. This approach allows for a detailed examination of both geographic and structural dimensions of contemporary policing.

1.6 Significance and Contribution

This research is significant for several reasons. Academically, it contributes to the underexplored intersection of economic inequality and policing practices in England and Wales, particularly within the context of stop and search. It offers a more integrated understanding of how social and economic factors jointly influence the deployment of police powers across space. From a policy perspective, the findings could inform more equitable approaches to policing by highlighting the socioeconomic biases that underpin current practices. Societally, this study aims to improve public awareness of how stop and search disproportionately affects marginalised communities, particularly in areas marked by economic deprivation and racial inequality.

2 Literature Review

2.1 Theoretical Foundations of Stop and Search

A critical dimension in understanding stop and search practices is public trust in the police. Murray (2021) investigates this through a city based cross-sectional survey of school children across Scotland and England, focusing on their experiences of crime and victimisation [Murray et al.2021]. Respondents were asked about their exposure to stop and search, including the frequency and nature of their most recent encounters. This study reveals significant variation in the prevalence of stop and search across cities, with Sheffield showing higher rates among non-white respondents, while Glasgow showed the opposite trend. Interestingly, in cities like Birmingham and Edinburgh, there was no notable ethnic disparity in stop and search prevalence.

These findings show how local social compositions and policing cultures may shape the implementation and perceived fairness of stop and search powers. Such contextual patterns echo the central concern of this dissertation, which examines spatial disparities in stop and search practices between Merseyside and Greater London.

However, Murray's study also highlights methodological limitations. Key among them is its reliance on self-reported data, which may introduce recall bias or inaccuracies in reporting sensitive interactions with law enforcement.

Although, the use of self reported data may truly be the only way to evaluate UK policing interactions. This is due to the lack of interaction documentation from stop and searches, there is often little to no documented evidence of how the 'suspect' was actually treated or how they perceived their treatment. This has lead to the introduction of Body Worn Cameras (BWC) to document the interactions.

The introduction of this video evidence has lead to studies such as [Henstock and Ariel2017], which conducted a six month randomised controlled trial to assess the impact of BWCs on police use of force. While the findings indicated a 50% reduction in the odds of force being used when BWCs were present, the study faced significant limitations. Notably, the sample size was relatively small, with only 46 officers participating, what more with the officers having to volunteer for the study this introduces potential selection bias.

Or [Owens et al.2014] which investigated the effect the body worn cameras had on the officers perceptions of themselves. Using surveys they assessed how the officer felt they behaved with or without the BWCs. This style of self reporting perhaps obviously lead to professional PR style statements such as "I am just as professional, whether it is switched on or off"[Owens et al.2014]. Such self-reported statements, however, often lack substantive value for any form of analysis.

These studies often "lack consistency and sample sizes are often small" [Criminal Justice Alliance2021], limiting their suitability as rigorous empirical evidence within academic research. Given these limitations, the focus of this dissertation will not be on BWCs.

2.2 Stop and Search in the UK: Policy and Historical Context

The development of stop and search powers in the UK cannot be separated from their historical application to ethnic minority communities. [Yesufu2013] traces the origins of this policing tool to the Vagrancy Act 1824, which introduced the so-called 'sus' laws. These gave officers the authority to stop and search individuals based purely on suspicion – a loosely defined term at the time[Roberts2023]. These powers, widely criticised for their arbitrary use, were disproportionately applied to young Black men and played a central role in fuelling distrust between ethnic minority communities and the police; as stated by the [The Police Foundation2012].

Yesufu's work highlights how early legal frameworks have shaped modern perceptions of policing legitimacy and fairness. This is especially relevant in the context of the ongoing conversation surrounding institutional racism. While the most notorious examples are often associated with US police forces, the UK is by no means exempt from such concerns [Delsol2006].

Although the 'sus' laws were eventually repealed, their legacy persists in current stop and search practices. Today, Black individuals remain significantly more likely to be stopped by police, pointing to a continuity of racialised surveillance under a different legislative guise

[Alam et al.2024]. This is particularly evident in the modern use of stop and search powers under Section 60 of the Criminal Justice and Public Order Act 1994, which allows police to stop and search individuals without suspicion in specific areas where there is a perceived threat of violence [Government1994]. Critics argue that these powers disproportionately target Black communities, reflecting an ongoing pattern of institutionalised racism within policing practices. As highlighted by [Gillborn2008], institutional racism is "not limited to individual acts of discrimination but is embedded in the policies and practices that perpetuate unequal outcomes for ethnic minorities". This has been echoed in more recent studies, such as by [Shiner et al.2018], who conducted a comprehensive analysis of the National Stop and Search Data in England and Wales. Their work reveals that Black individuals are still significantly more likely to be stopped than their white counterparts, even after controlling for factors like location and crime rates.

2.3 Racial and Socioeconomic Disparities in Stop and Search

Dominating much of the discourse on stop and search is the question of racial and socioeconomic disparities, with race, in particular, occupying a central focus. While this is not the primary concern of this research, the topic cannot be ignored. The racialised implementation of stop and search powers has been a longstanding and heavily scrutinised aspect of policing in the UK.

[Farrell2024] uses NYPD Stop, Question, and Frisk data to examine how the intersections of gender, race and place simultaneously shape the nature and frequency of stop and frisk encounters. Though based in the US, the study's insights are instructive, particularly in showing how location and identity are jointly implicated in patterns of policing. In the UK context, similar dynamics are evident, with stop and search powers disproportionately exercised in areas with high ethnic minority populations and elevated socioeconomic deprivation [Buil-Gil et al.2022].

Although gender is not directly addressed in this study, it remains important to acknowledge its interplay with race. [Duff and Kemp2025] highlights how stop and search disproportionately targets "young people and people of colour, especially Black young men and boys". These patterns reflect deeper institutional biases and are symptomatic of broader structural inequalities in British society.

The use of police powers to humiliate, intimidate or exert dominance over individuals, particularly racialised individuals is not new. [Yates et al.2024] situates such practices within a historical continuation of institutionalised racism, where law enforcement has functioned not just as a tool of public safety but as an instrument of racialised social control.

Despite these challenges, public resistance has been substantial. Campaigns aimed at legislative reform, increased accountability and, in some cases, the complete defunding of police institutions have gained significant traction in recent years. The UK arm of the Black Lives Matter movement, for example, has been vocal in highlighting the racial injustices embedded within stop and search practices and in pushing for fundamental changes to the policing system [Elliott-Cooper2023].

While this research focuses primarily on spatial and socioeconomic dynamics, it is essential to recognise that these are inextricably linked to race. A complete analysis of stop and search practices must account for how these dimensions converge to shape both the implementation and the lived experience of police encounters. Policing is rarely experienced in isolation from identity. As such, race remains a central axis along which stop and search powers are disproportionately exercised, especially in urban areas with high ethnic diversity.

2.4 Legislative Foundations of Stop and Search in the UK

Stop and search powers in the UK have long been justified through the lens of crime prevention, particularly in relation to knife and drug crime. Political rhetoric around these issues has consistently shaped public policy. Successive Prime Ministers, especially during periods of rising youth violence have used stop and search as a visible commitment to public safety. Often invoking it as a deterrent against knife related offences, the strategy gained prominence in the late 2000s and early 2010s, when public concern over knife crime was met with aggressive policing measures rather than social intervention.

2.4.1 Knife Crime

The introduction of the *Offensive Weapons Act 2019*, alongside earlier legislation such as the *Criminal Justice and Public Order Act 1994*, granted police broader authority to conduct suspicionless searches in designated areas. These powers were presented as necessary tools to address a surge in knife-related violence, especially in cities like London. However, evidence from the College of Policing indicates that stop and search has only a limited and inconsistent impact on reducing violent crime [College of Policing2022]. [Shiner et al.2018] argue that these powers are disproportionately applied to Black individuals, reinforcing perceptions of bias and contributing to a breakdown in trust between communities and the police. Similarly, the Runnymede Trust has criticised such policies for neglecting the underlying causes of youth violence and has instead called for investment in preventative, community-led approaches [Runnymede Trust2021].
Keeling highlights how stop and search practices shape the lived experiences of young Black and minority ethnic men, often fostering feelings of humiliation and exclusion [Keeling2017]. Drawing on government data, Keeling argues that stop and search is less about preventing crime and more about exerting social control. Crucially, the belief that such practices reduce knife crime is increasingly disputed—even the Metropolitan Police admit there is "no definitive evidence to prove or disprove the suggested link".

2.4.2 Drug Crime

Talk about laws and legistlation for drug related stop and searches
[Koch et al.2024] outlines how shifting government strategies around drug crime, particularly the 'county lines' phenomenon have marked a partial move away from punitive approaches. While this shift has been welcomed, the policing of drug-related offences continues to reflect racialised patterns of suspicion and enforcement. In the context of urban hubs like London and Merseyside, drug-related stop and search is often justified through vague associations with gang activity or low-level dealing.
A report by the European Harm Reduction Network highlights how drug suspicion is frequently used as a pretext for stop and search, with Black individuals disproportionately targeted [Pomfret2024]. Despite the volume of searches conducted, the majority do not result in the discovery of drugs or related paraphernalia. This raises questions about both the efficacy and the true motives behind these practices, particularly when considered alongside the broader social costs of over-policing already marginalised communities.

2.5 Gaps in the Literature and Positioning of this Study

A common limitation in existing research on stop and search is the narrow geographical focus of many studies. For instance, [Dippie and Hasan2024] examine stop and search practices within only four London boroughs, restricting the scope of their findings to a highly specific urban context. While their work provides valuable insights into the dynamics of stop and search in these areas, the findings may not be easily generalisable to other regions with different social and ethnic compositions. By examining diverse contexts such as Merseyside and the whole of Greater London, this study aims to contribute a more comprehensive understanding of how social and ethnic factors shape stop and search practices at both the local and national levels.
A key source of inspiration for this study is the work of [J. H. Suss and Oliveira2022, August], who introduced an innovative approach to exploring the spatial and economic distribution of stop and search practices. Their study utilised Linear Regressions (OLS) and Species Distribution Models (SDM) to assess the distribution of stops and searches in London, aiming to identify potential patterns and underlying factors. Their findings revealed a strong, statistically significant relationship between stop and search frequencies and "highly unequal neighbourhoods where the rich and the poor co-exist" [J. H. Suss and Oliveira2022, August]. This analysis highlighted the role of economic inequality in shaping policing practices, contributing to a relatively under explored area within the literature on economic disparities in law enforcement.
OLS for count data?

While this study shares thematic similarities with [J. H. Suss and Oliveira2022, August]'s research, but broadens the scope by examining the effects of social and ethnic composition on stop and search, providing a more nuanced comparison across different regions. The combination of socio-economic and ethnic factors will allow for a deeper understanding of how these variables interact and influence policing practices across urban contexts.

2.6 Building on the Literature

Building on the insights provided by previous studies, this research expands on the exploration of spatial and socioeconomic factors influencing stop and search practices. As highlighted by [J. H. Suss and Oliveira2022, August], economic inequality has a significant role in shaping the distribution of policing practices, but it is crucial to extend this investigation to other intersecting factors, such as ethnicity and social composition. [J. H. Suss and Oliveira2022, August]'s use of both Linear Regressions (OLS) and Spatial Durbin Model (SDM) offers an interesting methodological approach, which this dissertation aims to adapt and refine to fit a broader set of urban contexts.
In contrast to studies that focus on the relationship between stop and search and demographic variables in isolated urban areas such as [Dippie and Hasan2024], this research addresses the gap by comparing regions with markedly different social and ethnic compositions, such as Merseyside and Greater London. London the more obvious choice, has been the centre of the majority of the research in this area, specifically in England and Wales. Merseyside by contrast, has featured more frequently in studies concerned with community dynamics and regional identity. From [and1974] investigating the Social geography of the county since the 19th centenary to the more recent [Back et al.1999] looking at what makes a community. This study explores the "*changing cultures of racism in English football*", highlighting Merseyside's markedly different racial composition compared to cities like London and Manchester. It notes how Merseyside fans are often implicitly characterised as white, a framing that becomes particularly relevant in the context of racially charged chants exchanged between supporters [Back et al.1999]. These insights stress the importance of regional specificity when examining social dynamics and public perceptions of fairness in policing.
These cities differ not only in size but in their socioeconomic and ethnic make-up, providing a useful basis for comparative analysis. By situating stop and search within these distinct contexts, this research seeks to uncover how structural inequalities play out across location. While quantitative methods will be used to examine the spatial distribution of stop and search activity, these patterns must also be understood alongside qualitative accounts that foreground the lived experience of over-policed communities. In doing so, this study aims to move beyond simple metrics of crime and enforcement, instead offering a more grounded understanding of how race, class and place intersect to shape the realities of contemporary policing in England and Wales.

3 Methodology

3.1 Research Design

This research begins by collecting Stop and Search (S&S) data for the year 2022 from Police.uk. Each recorded stop is geocoded using its latitude and longitude and assigned to a Lower Super Output Area (LSOA) based on the 2021 boundary shapefiles provided by the Office for National Statistics (ONS). Once all stops have been spatially attributed to their respective LSOAs, the data is aggregated to produce total counts of stop and search events per LSOA.
Following this, the aggregated stop and search data is merged with additional contextual variables at the LSOA level, such as demographic indicators from the 2021 Census and economic deprivation measures from the Indices of Deprivation 2019.
The final dataset is then used to perform regression analysis, enabling the investigation of associations between the frequency of stop and search and various area-level characteristics.

3.2 Data Sources and Preparation

This study relies on three primary data sources:

3.2.1 UK Police Data

This study draws on CSV files provided by the official UK Policing website. The dataset includes every recorded crime within each policing jurisdiction, all stop and search incidents, and the outcomes of criminal cases — such as whether a prosecution was successful.
While the crime data is already matched with the LSOA where each incident occurred, the stop and search data only includes geographic coordinates (longitude and latitude), making it more difficult to directly associate with specific areas. This reflects a broader issue of inconsistency in reporting practices across police forces in the UK.
To overcome this limitation, LSOA boundary shapefiles were sourced from the UK Data Service. These shapefiles provide the geographic boundaries of each LSOA in England and Wales, allowing stop and search records to be accurately assigned to their respective areas. The Python package `GeoPandas` was used to carry out the spatial join, mapping each set of coordinates to the correct LSOA for aggregation and analysis.
Importantly, this study focuses only on stop and search data from the Metropolitan Police Service (London) and Merseyside Police. Although other forces such as the City of London Police are available, they were excluded due to limited jurisdiction and a disproportionate number of stop and search incidents. Limiting the scope to these two major forces enables a clearer and more meaningful comparison between two densely populated urban regions with differing social and demographic structures.

3.2.2 Office for National Statistics

The Office for National Statistics (ONS) provided the primary socio-economic data for this study. The ONS offers a comprehensive list of Lower Layer Super Output Areas (LSOAs), which was essential for ensuring that areas with zero stop and search incidents were still represented. Additionally, the ONS provides detailed information on the social composition of each LSOA, accessed through the 2021 Census data. While the Census covers a wide array of variables, from sexual orientation to the number of UK armed forces veterans, only the ethnicity data was utilised for this analysis. Furthermore, the ONS publishes mean house prices by LSOA; and for consistency with the stop and search data, the 2022 edition of this dataset was used.

3.2.3 UK Government's Official Website (GOV.UK)

Data was also sourced from the UK Government's official website (GOV.UK), specifically the Indices of Deprivation 2019 for England and Wales. This dataset combines income and employment domain scores to evaluate levels of deprivation across LSOAs. For this analysis, the rank measure has been used, as it provides a consistent basis for comparison between regions, such as London and Merseyside.

Finally, and perhaps most significant, the Price Paid Data; also obtained from GOV.U was used. This dataset contains information on the sale price of individual properties across England and Wales. This data is crucial in assessing spatial disparities in housing markets and understanding how these disparities relate to patterns of policing, including the calculation of housing inequality using the Gini coefficient.

3.3 Justification for Case Selection

This study focuses on London and Merseyside as case study areas. Originally, Greater Manchester was considered, but data availability issues prevented its inclusion. Specifically, as noted on the official police data changelog, Greater Manchester Police stopped releasing crime, outcome, and stop and search data from July 2019 onwards due to a change in IT systems, making it unsuitable for this analysis.
As illustrated in Figure 1, the Metropolitan Police Service dominates stop and search incidents nationally. Merseyside is selected as the second focus area because it represents the next largest police force in terms of stop and search activity, despite not having the largest population (which lies with West Midlands). Thus, Merseyside provides a useful contrast to London, allowing exploration of how policing patterns differ across two distinct urban contexts without data constraints affecting the analysis.

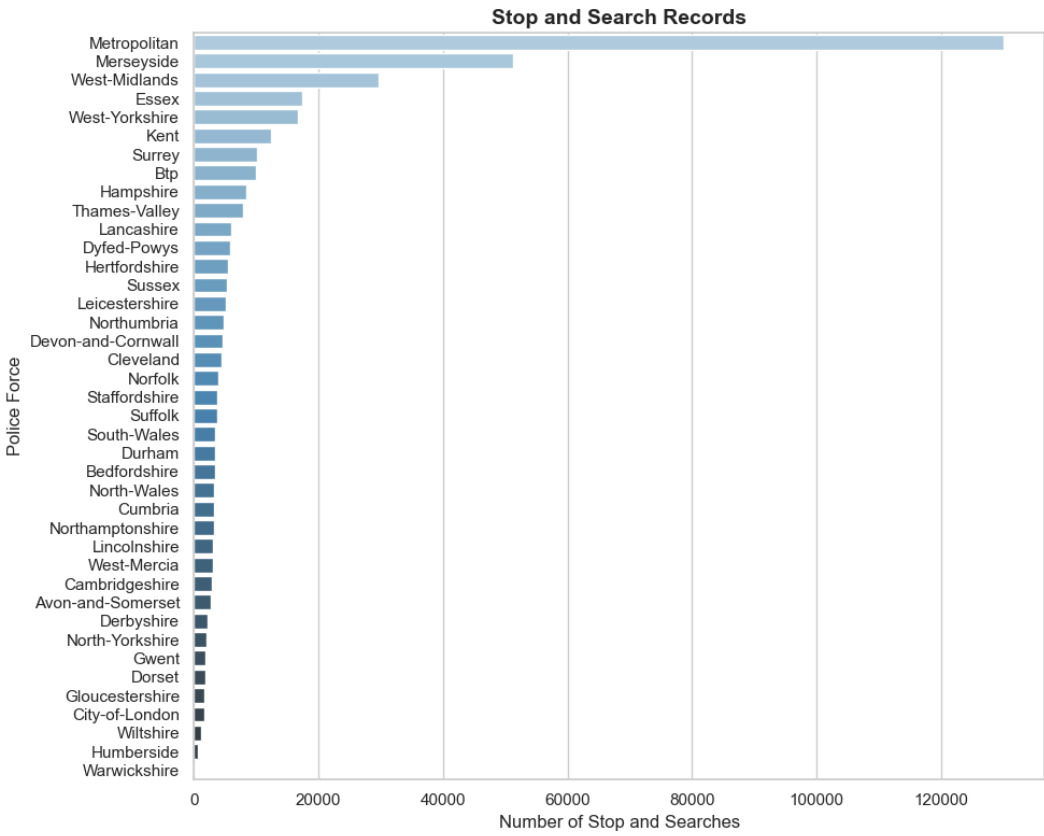

Figure 1: Stop and Search Distribution

West Midlands was another potential candidate. However, existing literature suggests that its policing culture and social dynamics are not substantially different from London, which reduces the benefit of including it as a separate case. Particularly [Wessendorf2019], who outlines the similarities in experience that migrants face across the two regions. Furthermore, after accounting for the missing Longitude and Latitude data of the stops and searches the sample size was too small for accurate analysis.
This case study design is driven by data availability and the desire to compare two major, yet distinct, urban policing environments, rather than simply focusing on population size or geographical proximity.

3.4 Variable Selection

The selection of variables for this analysis was guided by the data sources available and the specific objectives of the study. These variables were operationalised to ensure a comprehensive understanding of the relationships between socio-economic factors and stop and search practices across different regions.

3.4.1 Dependant Variable

The primary dependent variable in this analysis is the count of Stop and Search incidents per LSOA. As previously mentioned, this data was spatially aggregated using the geographic coordinates provided in the raw dataset. Any entries where the LSOA was missing or could not be assigned were reclassified as zero counts, under the assumption that these represent areas with no recorded stops.
This analysis focuses on two policing forces: the Metropolitan Police Service and the Merseyside Police. The maps below illustrate the geographical distribution of stop and search events recorded in each region:

Figure 2: Stop and Search locations in London

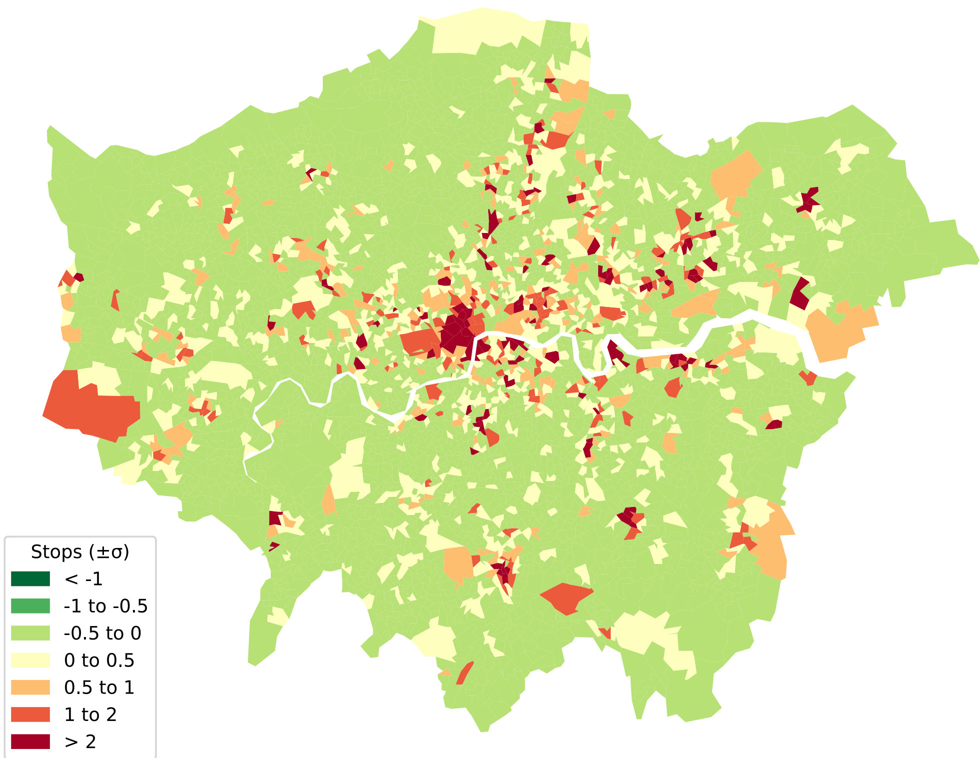

Figure 3: Stop and Search Locations in Merseyside

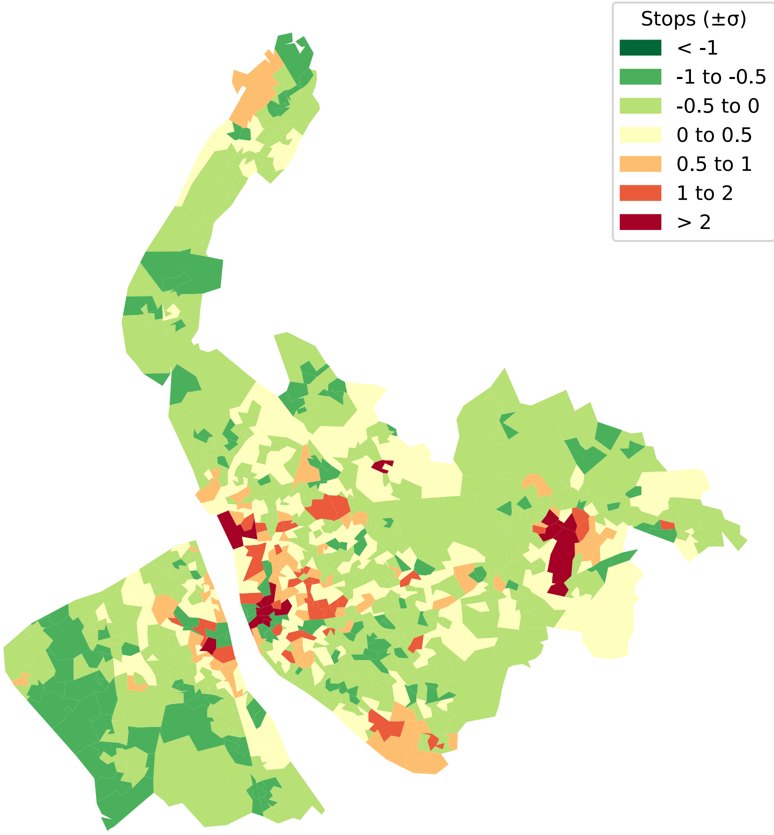

Figure 2 and Figure 3 illustrate the distribution of stop and search incidents in both London and Merseyside. In both regions, there is a noticeable concentration of stops around the city centres, which may be indicative of higher population density and greater policing activity in these areas. Additionally, pockets of increased stop and search activity appear on the outskirts of both regions, suggesting that areas with varying demographic and socioeconomic characteristics may experience different policing priorities. These patterns could reflect a combination of factors, including targeted policing strategies, areas with known crime hotspots, or the availability of resources in more densely populated urban areas. Further analysis could reveal the underlying drivers of these clustering patterns and help assess whether they align with broader trends in crime and policing practices.

3.4.2 Independent Variables

The primary independent variable of interest in this analysis is housing inequality, which is conceptually distinct from absolute house prices. This measure follows the approach developed by [J. Suss2023], who introduced the use of a Gini coefficient at the MSOA level as a means of capturing inequality in the housing market. While the present study draws on a slightly different data source, the same methodological framework is applied.
Specifically, housing inequality is calculated using the Gini coefficient derived from house prices within each LSOA. The formula used is:

$$G = \frac{\frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}|y_i - y_j|}{2\bar{y}}$$

as outlined by [J. Suss2023]. This metric captures the degree of variation in house prices within an area; lower Gini values reflect more uniform house prices, indicating lower levels of inequality. Conversely, higher values signal greater disparity in property values.

Figures 4 and 5 display the spatial distribution of housing inequality in London and Merseyside, respectively. In London, higher Gini coefficients, indicating greater housing inequality, appear concentrated in certain inner and western areas, while lower inequality is more prevalent in the outer boroughs. Similarly, Merseyside exhibits a varied distribution of housing inequality, with pockets of higher and lower Gini coefficients scattered across the region.

Figure 4: Inequality Gini map of London

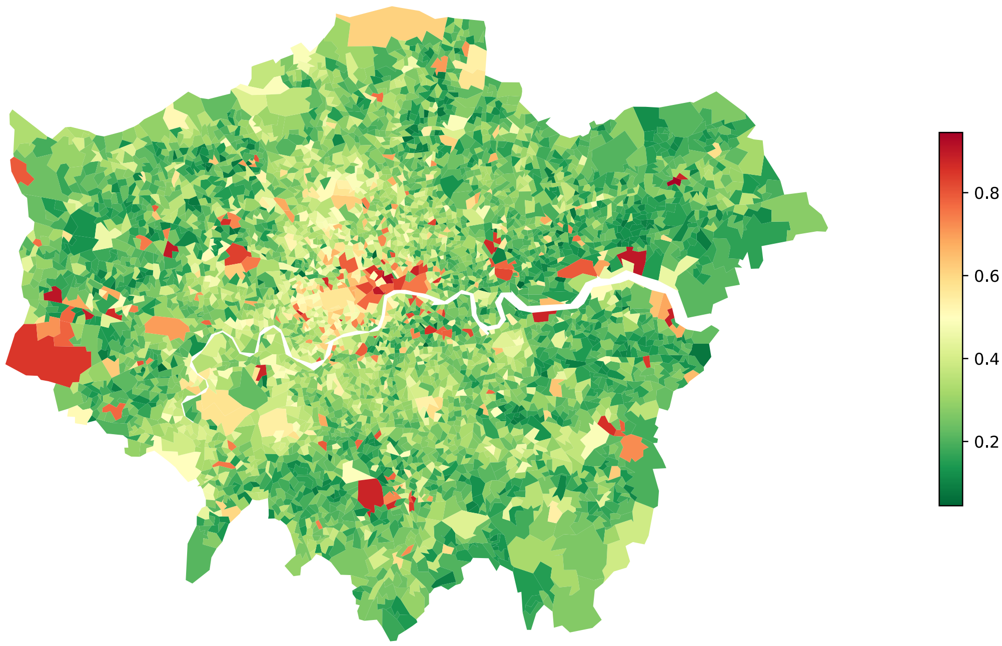

Figure 5: Inequality Gini map of Merseyside

In addition to housing inequality, several other independent variables are included in the model to control for key socioeconomic and demographic factors:

- **Income Domain Score**

  This variable is derived from the Index of Multiple Deprivation (IMD) 2019 and reflects the proportion of the population in an area experiencing income deprivation. It is based on data from means-tested benefits, including Income Support, income-based Jobseeker's Allowance, Pension Credit, and Universal Credit. A higher score indicates a greater prevalence of income deprivation in the LSOA.

- **Mean House Price**

  The average house price in each LSOA, based on sales data, serves as a proxy for the overall affluence and market value of properties in the area. Unlike the Gini coefficient, which captures inequality, this variable provides a sense of absolute economic value in the housing market.

- **Crime Sum**

  This variable captures the total number of police-recorded crimes occurring within each LSOA during the time period under analysis. The data are sourced from the UK Police API, consistent with the stop and search dataset, ensuring comparability. This figure functions as a proxy for the general security conditions and perceived disorder within an area. Higher crime totals may reflect both genuine incidence and potential differences in policing intensity or reporting practices. It is included to account for local criminal activity, which may influence the frequency of stop and search practices.

- **Drug Crime Sum**

  This is a disaggregated subset of the overall crime total, comprising only those incidents classified as drug-related offences. It represents both the prevalence of drug-related activity and the policing priorities in a given LSOA. The inclusion of this variable allows the model to assess whether there is a targeted focus on drug-related issues that might disproportionately affect certain areas, particularly in relation to stop and search operations. It also provides insight into how drug enforcement varies across different neighbourhoods.

- **Percentage of Ethnic Minorities**

  This variable denotes the percentage of the LSOA population identifying as an ethnic minority (ethnic groups except the White British group, [Cabinet Office2021]), based on the most recent census estimates. It acts as a key demographic indicator and is used to investigate potential disparities in policing outcomes across ethnically diverse areas. Including this variable helps to control for racial composition, enabling a more robust assessment of whether stop and search activity is disproportionately concentrated in areas with higher minority populations. Moreover, it provides context for exploring structural inequalities that may underpin spatial patterns of police attention.

3.4.3 Descriptive Statistics

Table 1 presents summary statistics for 4,994 LSOAs in London. On average, each area recorded 32 stop and searches, with a high degree of dispersion (SD = 78) and a maximum of 2,393. Drug-related stops form the bulk of activity, averaging 20 per LSOA. Socioeconomic conditions vary widely, as shown by the broad range in Gini coefficients (0 to 0.93) and income deprivation scores. The average ethnic minority population stands at 45%, with some areas as high as 98%. Mean house prices exhibit substantial inequality, ranging from £156,810 to over £8.3 million, reflecting London's stark socioeconomic disparities. These descriptive patterns underscore the highly uneven social landscape across which stop and search practices occur.

Table 1: Descriptive Statistics for Stop and Search Data in London

Statistic	N	Mean	St. Dev.	Min	Max
Total Stop Count	4,994	32	78	0	2,393
Drug Related Stop Count	4,994	20	50	0	1,654
Gini	4,994	0.25	0.15	0	0.93
LSOA Population	4,994	1,762	320	1,002	4,282
Ethnic Minority Percentage	4,994	45	19	3	98
Income Domain Score	4,994	15,626	8,715	203	34,742
Total Crime Count	4,994	195	290	0	9,956
Drug-Related Crime Count	4,994	7	16	0	731
Mean House Price	4,994	680,011	494,341	156,810	8,325,277

3.4.4 Descriptive Statistics

Table 2 presents summary statistics for 923 LSOAs within Merseyside. The average total stop and search count per LSOA is 54, with considerable dispersion indicated by a standard deviation of 127 and a maximum value of 2,198. Drug-related stops comprise the majority of incidents, averaging 43 per LSOA. Socioeconomic conditions exhibit moderate variability, as reflected by Gini coefficients ranging from 0.05 to 0.95 and income domain scores spanning from 3 to 34,549. The average LSOA population is approximately 1,542 residents, with ethnic minority representation averaging 8% and reaching up to 78% in some areas. Total crime counts average 188 incidents per LSOA, with drug-related crimes averaging 12. House prices show less disparity compared to London, ranging from £67,866 to just over £1 million, though still indicative of significant local economic variation.

Table 2: Descriptive Statistics for Stop and Search Data in Merseyside

Statistic	N	Mean	St. Dev.	Min	Max
Total Stop Count	923	54	127	0	2,198
Drug Related Stop Count	923	43	104	0	1,733
Gini	923	0.23	0.13	0.05	0.95
LSOA Population	923	1,542	294	1,009	3,789
Ethnic Minority Percentage	923	8	9	1	78
Income Domain Score	923	11,782	9,984	3	34,549
Total Crime Count	923	188	266	0	5,067
Drug-Related Crime Count	923	12	28	0	565
Mean House Price	923	199,443	98,194	67,866	1,020,604

Although the raw variables will not be used directly in the analysis, they provide useful insight into the overall structure of the data. To ensure consistent comparison between London and Merseyside, all independent variables were standardised using z-score normalisation. This process transforms each variable to indicate how many standard deviations it is from the mean, putting all variables on the same scale. This standardisation makes it easier to compare data across regions and improves the robustness of the analysis.

3.5 Modelling Approach and Rationale

Given the outcome variable is count data, the number of stop and search incidents recorded per LSOA two appropriate modelling frameworks are considered: the Poisson regression and the Negative Binomial regression. Although Ordinary Least Squares (OLS) regression was run, it was ultimately disregarded as neither accurate nor appropriate for this type of data. While [J. H. Suss and Oliveira2022, August] employs an OLS specification as a baseline, this study opts not to include a Spatial Durbin Model (SDM), and instead focuses on comparing count-based models.

To evaluate model performance and address potential overdispersion, both Poisson and Negative Binomial (NB) regressions were estimated for the London and Merseyside datasets. Model comparison statistics, namely the Akaike Information Criterion (AIC) and log-likelihood values overwhelmingly favoured the Negative Binomial specification.

Table 3: Model Fit Comparison: London

Metric	Poisson Model	Negative Binomial Model
AIC	228,422	42,115
Log Likelihood	-114,205	-21,052

Table 4: Model Fit Comparison: Merseyside

Metric	Poisson Model	Negative Binomial Model
AIC	44,980.430	8,289.780
Log Likelihood	-22,484.210	-4,138.890

As shown in Table 3 and Table 4, the Negative Binomial model yields a significantly lower AIC for both regions: a reduction of approximately 200,000 for London and nearly 30,000 for Merseyside. Similarly, log-likelihood values improved substantially, moving closer to zero by around 80,000 and 15,000 for London and Merseyside respectively.
These diagnostics clearly indicate the presence of overdispersion in the count data, making the Poisson model unsuitable. Consequently, the Negative Binomial model is selected as the more robust and appropriate framework for modelling variation in stop and search activity across LSOAs.

3.5.1 Interaction Terms

[justification for interaction terms]

3.6 Fixed Effects

Fixed effects were incorporated to control for unobserved, time-invariant heterogeneity across boroughs. This approach has been applied in similar spatial regression contexts, such as in [Hilber et al.2011] and [J. H. Suss and Oliveira2022, August], particularly in studies focused on London.
Theoretically, fixed effects help mitigate multicollinearity and account for place-based biases For example, boroughs that carry reputations for being 'rough' may experience disproportionate levels of policing that are not directly explained by observable variables. Including fixed effects captures these latent, area-specific factors, improving model accuracy.

Table 5: Fixed Effects Model Fit Statistics: London

	No Fixed Effects	With Fixed Effects
AIC	42,115.290	41,751.330
Log Likelihood	-21,051.640	-20,837.670
Pseudo R-squared	0.049	0.057
Dispersion (Theta)	0.960	1.030

As shown in Tables 5 and 6, the inclusion of fixed effects improves model fit for both regions. AIC values decrease and log-likelihoods become less negative; both indicators of stronger model performance. Additionally, the pseudo R^2 increases, suggesting a greater proportion of variance in stop and search counts is explained.

Table 6: Fixed Effects Model Fit Statistics: Merseyside

	No Fixed Effects	With Fixed Effects
AIC	8,289.780	8,250.540
Log Likelihood	-4,138.890	-4,115.270
Pseudo R-squared	0.087	0.092
Dispersion (Theta)	1.290	1.350

Regarding the dispersion parameter (theta), there is only a negligible increase for London (less than 0.01), indicating a very marginal rise in overdispersion. For Merseyside, theta increases slightly more (by 0.08), which may suggest a minor trade-off in model accuracy. Nonetheless, these changes are minimal, and the consistent improvements across AIC, log-likelihood and pseudo R^2 support the inclusion of fixed effects.

While the modest increase in overdispersion warrants mention, the overall evidence justifies the use of fixed effects for both regions. For transparency and robustness, both the fixed and non-fixed effects models are presented in the final analysis.

3.7 Limitations

Firstly, aggregating data to the LSOA level introduces the Modifiable Areal Unit Problem (MAUP). This refers to the fact that statistical patterns can vary depending on the spatial scale or zoning system used. Patterns observed at the LSOA level may look different if data were grouped by MSOAs, wards or police beats. For example, an apparent hotspot may disappear or shift if boundaries are redrawn or data are aggregated differently. This limitation is structural and inherent in spatial analysis, but it remains important to acknowledge as it may obscure within-area variation or exaggerate between-area differences.

Next, not all stop and search incidents included usable geographic coordinates. In some cases, records lacked location data altogether or could not be reliably mapped to an LSOA. These incidents were effectively treated as missing or zero-counts. If the missing data are randomly distributed, the effect may be minimal. However, if certain types of stops (e.g. vehicle searches) or certain locations (e.g. boundary areas or town centres) are more prone to data loss, the result may be biased spatial representations of stop and search intensity.

Then, the LSOA boundaries used in this study are based on the 2021 census geography. However, urban areas are not static. Gentrification, regeneration, population churn and new housing developments can alter the character and population structure of a neighbourhood within a short period. Using fixed 2021 boundaries to analyse data from earlier years may lead to mismatches between the actual social geography at the time of the searches and the boundaries used in the analysis. This is particularly relevant in areas experiencing rapid demographic or infrastructural change.

The case study design limits the scope of generalisation. By focusing only on Liverpool and Greater London, this research captures the dynamics of stop and search within two very specific urban contexts. Both cities have unique demographic profiles, policing histories and political environments. As such, the findings may not be representative of patterns in rural areas, smaller towns, or other regions of England and Wales. That said, the aim here is depth over breadth — to understand how social composition shapes spatial policing in particular contexts.

Finally, several important factors lie beyond the reach of this analysis. While the study incorporates demographic and deprivation indicators, it does not account for organisational culture within police forces, differences in leadership, local crime reporting practices or political pressures. Nor does it capture the role of officer discretion, which is central to how stop and search powers are exercised. These unmeasured variables may significantly influence where and how stops occur, meaning that the observed spatial patterns should not be interpreted as purely or even primarily determined by demographic variables.

This study combines spatial, socioeconomic and policing data at the LSOA level to better understand how structural inequalities influence where stop and search powers are used. By modelling the link between housing inequality and police activity, while also accounting for crime rates, ethnic make-up and levels of deprivation, the analysis aims to highlight some of the broader area-level factors behind stop and search patterns. The next section outlines what the results show and what they might mean.

4 Results

Having evaluated the overall model specifications and concluded that the Negative Binomial model is the most appropriate for this analysis, this section now turns to a detailed examination of the regression results for each region.

4.1 London

The analysis below focuses on the regression models estimated for Greater London, assessing how area-level socioeconomic and demographic characteristics relate to stop and search activity.
Table 7 presents four model specifications. Model (1) provides the baseline results, estimated without borough-level fixed effects. Model (2) extends this by incorporating fixed effects to control for unobserved heterogeneity at the borough level. Models (3) and (4) further investigate whether the associations between key predictors—particularly income deprivation and income inequality—are moderated by the ethnic composition of boroughs, through the inclusion of interaction terms.

Table 7: London Stop and Search Regression Table

Dependent Variable:	StopCount			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	2.70***			
	(0.032)			
Gini Coefficient	1.80***	1.72***	1.73***	1.65***
	(0.110)	(0.236)	(0.260)	(0.243)
Income Deprivation (z)	-0.232***	-0.154***	-0.154***	-0.123**
	(0.021)	(0.040)	(0.040)	(0.045)
Mean House Price (z)	-0.003	-0.035	-0.036	-0.026
	(0.018)	(0.028)	(0.030)	(0.030)
Crime Rate (z)	0.172***	0.214**	0.213**	0.211**
	(0.035)	(0.068)	(0.070)	(0.071)
Ethnic Minority (z)	0.212***	0.269***	0.281***	0.280***
	(0.019)	(0.046)	(0.056)	(0.047)
Drug Crime Rate (z)	0.573***	0.507***	0.508***	0.533***
	(0.045)	(0.065)	(0.065)	(0.068)
Gini Coefficient × Ethnic Minority (z)			-0.050	
			(0.181)	
Income Deprivation (z) × Ethnic Minority (z)				0.088*
				(0.035)
Fixed-effects				
Borough	No	Yes	Yes	Yes
Fit statistics				
Observations	4,994	4,994	4,994	4,994
Squared Correlation	0.18552	0.18553	0.18553	0.18553
Pseudo R^2	0.05146	0.05872	0.05873	0.05922
BIC	41,768.1	41,721.4	41,729.8	41,707.9
Over-dispersion	0.89477	0.94881	0.94885	0.95282

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1, : 1*

The results in Table 7 highlight consistent and significant relationships between key structural variables and stop and search activity across the Greater London boroughs.
In all model specifications, income inequality (as measured by the Gini coefficient) is strongly and positively associated with stop and search rates. This suggests that boroughs with greater levels of economic disparity tend to experience higher levels of police intervention.

Likewise, the proportion of ethnic minorities and the local drug crime rate both display strong positive associations with stop and search counts, aligning with broader patterns of racialised and offence-targeted policing.
Conversely, income deprivation is negatively associated with stop and search across all models, though the magnitude of this effect decreases as more controls and interaction terms are included. One interpretation is that, independent of income inequality, deprivation alone may not drive increased stop and search—possibly reflecting complex spatial dynamics where affluent yet unequal areas are disproportionately targeted.
Crime rate also remains positively associated with stop and search in every specification, albeit with smaller effect sizes. Mean house prices, on the other hand, do not show a significant relationship, suggesting that housing wealth alone is not a key determinant of search activity.
Overall, the patterns observed in the London models point to a persistent targeting of boroughs with higher inequality, higher ethnic diversity and elevated drug-related offences.

4.1.1 Fixed Effects

From Model (2) onwards, borough fixed effects are included to account for unobserved heterogeneity across London's administrative areas. This helps isolate the within-borough variation over time, thereby strengthening causal interpretation of the key predictors.
The fact that the signs, magnitudes and significance levels of most variables remain relatively stable before and after the inclusion of fixed effects suggests that the relationships identified are not solely driven by static, area-level characteristics. Rather, the findings reflect consistent structural patterns in stop and search activity.

4.1.2 Interaction Effects

Interaction terms are introduced in Models (3) and (4) to assess whether the relationship between socioeconomic predictors and stop and search activity is moderated by the ethnic composition of boroughs.
In Model (3), the interaction between the Gini coefficient and ethnic minority share is negative but not statistically significant, indicating that inequality's effect on stop and search does not differ systematically across areas with varying ethnic diversity.
However, in Model (4), the interaction between income deprivation and ethnic minority share is positive and statistically significant at the 0.05 level. This suggests that in boroughs with higher ethnic minority populations, the negative association between income deprivation and stop and search is less pronounced. In other words, the combination of poverty and ethnic diversity appears to attract disproportionately higher police scrutiny—supporting theories of compounded marginalisation.

4.1.3 Model Fit

The model fit statistics show modest improvements across the specifications. Pseudo R^2 increases slightly from 0.051 in Model (1) to 0.059 in Model (4), while the BIC decreases from 41,768.1 to 41,707.9, suggesting improved explanatory power with additional controls and interaction terms.
Despite the relatively low pseudo R^2 values—common in count models with complex social processes—the consistent directional effects, statistical significance and improved BIC indicate that the selected predictors meaningfully contribute to explaining variation in stop and search activity.

4.2 Merseyside

Table 8: Merseyside Stop and Search Regression Table

Dependent Variable:	StopCount			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	2.92***			
	(0.065)			
Gini Coefficient	2.25***	2.33***	2.35***	2.14***
	(0.250)	(0.314)	(0.392)	(0.292)
Income Deprivation (z)	-0.459***	-0.425***	-0.424***	-0.384*
	(0.049)	(0.090)	(0.085)	(0.160)
Mean House Price (z)	-0.085·	-0.090***	-0.091**	-0.080*
	(0.046)	(0.027)	(0.029)	(0.040)
Crime Rate (z)	-0.320***	-0.172	-0.173	-0.180
	(0.083)	(0.142)	(0.147)	(0.132)
Ethnic Minority (z)	0.184***	0.259***	0.278***	0.364***
	(0.037)	(0.044)	(0.064)	(0.055)
Drug Crime Rate (z)	1.04***	0.873***	0.873***	0.919***
	(0.106)	(0.164)	(0.166)	(0.194)
Gini Coefficient × Ethnic Minority (z)			-0.064	
			(0.337)	
Income Deprivation (z) × Ethnic Minority (z)				0.220***
				(0.059)
Fixed-effects				
Borough		Yes	Yes	Yes
Fit statistics				
Observations	923	923	923	923
Squared Correlation	0.31666	0.32785	0.32784	0.31817
Pseudo R^2	0.09144	0.09738	0.09739	0.09996
BIC	8,261.5	8,235.1	8,241.8	8,218.6
Over-dispersion	1.2647	1.3363	1.3364	1.3711

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1, : 1*

The regression results for Merseyside reveal a distinct pattern from Greater London, with income deprivation showing a consistent and significant negative association with stop and search counts across all models. This suggests that, contrary to expectations and the London results, areas with higher income deprivation experience fewer stop and searches, indicating possibly different policing dynamics or reporting in Merseyside.

Income inequality, measured by the Gini coefficient, shows a strong and positive relationship with stop and search rates, remaining significant at the 0.1% level in all specifications. This indicates that economic disparity does have a robust association with police stop and search activity in Merseyside, contrary to the earlier qualitative summary.

The ethnic minority share is positively and significantly associated with stop and search, with coefficients increasing slightly after controlling for borough fixed effects and interaction terms. This supports the idea that areas with higher ethnic minority populations face greater police scrutiny.

Drug crime rate consistently exhibits a strong positive effect on stop and search counts, statistically significant in all models. This aligns with expectations that police activity is responsive to drug-related crime prevalence.

Interestingly, the mean house price has a small but statistically significant negative effect across most models, suggesting that wealthier areas might experience slightly fewer stop and searches. The general crime rate coefficient is negative but not statistically significant once fixed effects are included, implying limited predictive power for general crime in explaining stop and search variation in this context.

4.2.1 Fixed Effects

From Model (2) onwards, borough fixed effects are included to control for unobserved, time-invariant characteristics at the borough level. Their inclusion slightly increases the coefficients for ethnic minority share and drug crime rate while decreasing the magnitude of the negative association for income deprivation. This indicates that some variation previously attributed to deprivation is explained by stable borough-specific factors. Fixed effects improve model fit as indicated by the reduced BIC values.

4.2.2 Interaction Effects

Model (3) introduces an interaction between the Gini coefficient and ethnic minority share, which is negative but statistically insignificant, indicating no meaningful moderation effect. In Model (4), the interaction between income deprivation and ethnic minority share is positive and statistically significant, suggesting that in boroughs with higher ethnic minority populations, the negative association between income deprivation and stop and search is attenuated. This implies that ethnic diversity may amplify the effects of deprivation on police interventions, pointing to compounded socio-demographic influences.

4.2.3 Model Fit

Model fit improves modestly across specifications, with pseudo R^2 increasing from 0.091 in the baseline model to 0.100 in Model (4). The Bayesian Information Criterion (BIC) decreases steadily from 8,261.5 to 8,218.6, supporting the value of including fixed effects and interaction terms. Although pseudo R^2 values remain low, these are typical for count data models of complex social phenomena, and the consistent statistical significance of key variables confirms their explanatory relevance.

4.3 Coefficient Estimates

4.3.1 Economic Inequality

In Greater London, the Gini coefficient is strongly associated with stop and search activity. A one-unit increase in Gini is associated with a 6.05-fold increase in the expected count of stop and search incidents, corresponding to a 505% rise. Since the Gini index ranges from 0 to 1, a one-unit increase represents a complete shift from perfect equality to maximum inequality and is therefore a theoretical extreme. A more plausible change, such as a 0.1 increase in the Gini coefficient, is associated with an estimated 18.0% increase in stop and search activity ($exp(0.18) \approx 1.20$).
In Merseyside, the effect of income inequality appears even more pronounced. A one-unit increase in Gini is associated with a 9.49-fold increase in stop and search rates, equivalent to an 849% increase. For a more realistic 0.1 increase in Gini, the expected rise in stop and search activity is approximately 25.3% ($exp(0.225) \approx 1.253$). This comparison suggests that income inequality is more strongly linked to stop and search practices in Merseyside than in Greater London.

4.3.2 Ethnic Minority

4.3.3 Crime

4.3.4 Interaction Terms

The interaction effects between socioeconomic factors and ethnic minority percentage were evaluated for both Greater London and Merseyside.
In London, the interaction between the Gini coefficient and ethnic minority percentage was negative but not statistically significant (coefficient = -0.050, standard error = 0.181), indicating no clear combined effect on stop and search rates. The interaction between income deprivation and ethnic minority percentage was positive and marginally significant

(coefficient = 0.088), suggesting a modest association whereby areas with higher income deprivation and larger ethnic minority populations experience slightly increased stop and search activity.

For Merseyside, the interaction between the Gini coefficient and ethnic minority percentage was also negative and not significant (coefficient = -0.064, standard error = 0.337). However, the interaction between income deprivation and ethnic minority percentage was both positive and highly significant (coefficient = 0.220, standard error = 0.059), implying a stronger synergistic effect in this region, where stop and search counts tend to increase more substantially in areas with both higher income deprivation and greater ethnic minority presence.

These results highlight regional differences in how socioeconomic and demographic factors jointly relate to stop and search practices.

5 Discussion

6 Discussion

6.1 Comparative Summary

6.2 Interpretation of Key Predictors

6.2.1 Income Deprivation and Housing

6.2.2 Ethnic Composition

6.3 Interaction Effects in Context

6.4 Geographic/Structural Factors

6.5 Implications for Policy

6.6 Limitations and Considerations

References

Alam, S., O'Halloran, S., & Fowke, A. (2024). What are the barriers to mental health support for racially-minoritised people within the uk? a systematic review and thematic synthesis. *The Cognitive Behaviour Therapist*, *17*, e10. https://doi.org/10.1017/S1754470X24000084

and, N. K. (1974). The index of dissimilarity: A measurement of residential segregation for historical analysis. *Historical Methods Newsletter*, *7*(4), 285–289. https://doi.org/10.1080/00182494.1974.10112683

Back, L., Crabbe, T., & Solomos, J. (1999). Beyond the racist/hooligan couplet: Race, social theory and football culture. *The British Journal of Sociology*, *50*(3), 419–442. https://doi.org/https://doi.org/10.1111/j.1468-4446.1999.00419.x

Buil-Gil, D., Moretti, A., & Langton, S. H. (2022). The accuracy of crime statistics: Assessing the impact of police data bias on geographic crime analysis. *Journal of Experimental Criminology*, *18*(3), 515–541. https://doi.org/10.1007/s11292-021-09457-y

Cabinet Office. (2021). Writing about ethnicity [Accessed: 2025-05-19]. https://www.ethnicity-facts-figures.service.gov.uk/style-guide/writing-about-ethnicity

College of Policing. (2022). *Stop and search: Effectiveness and fairness*. College of Policing. https://www.college.police.uk/research/stop-and-search/stop-and-search-effectiveness

Criminal Justice Alliance. (2021). *More harm than good: A super-complaint on section 60 stop and search and independent community scrutiny* (tech. rep.) (Accessed: 2025-05-12). Criminal Justice Alliance. https://assets.publishing.service.gov.uk/media/60a7a10cd3bf7f7377976b01/CJA_super-complaint_section_60.pdf

Delsol, R. (2006). *Institutional racism, the police and stop and search: A comparative study of stop and search in the uk and usa* [Unpublished], University of Warwick. http://webcat.warwick.ac.uk/record=b2217204~S15

Dippie, A., & Hasan, M. (2024). Public influence on the ethnic disparity in stop-and-search statistics in four london boroughs. *Social Sciences*, *13*(2), 19–27. https://doi.org/10.11648/j.ss.20241302.11

Duff, K., & Kemp, T. (2025). Strip-searching as abjectification: Racism and sexual violence in british policing. *Theoretical Criminology*, *29*(1), 65–90. https://doi.org/10.1177/13624806241230485

Elliott-Cooper, A. (2023). Abolishing institutional racism. *Race & Class*, *65*(1), 100–118. https://doi.org/10.1177/03063968231166901

Farrell, C. (2024). Policing gender, race, and place: A multi-level assessment of stop and frisks. *Race and Justice*, *14*(3), 290–312. https://doi.org/10.1177/21533687221078970

Gillborn, D. (2008). *Racism and education: Coincidence or conspiracy?* Routledge.

Government, U. (1994). Criminal justice and public order act 1994, c. 33, section 60 [Accessed: 2025-05-12]. https://www.legislation.gov.uk/ukpga/1994/33/section/60

Henstock, D., & Ariel, B. (2017). Testing the effects of police body-worn cameras on use of force during arrests: A randomised controlled trial in a large british police force. *European Journal of Criminology*, *14*(6), 720–750. https://doi.org/10.1177/1477370816686120

Hilber, C. A., Lyytikäinen, T., & Vermeulen, W. (2011). Capitalization of central government grants into local house prices: Panel data evidence from england [Special Issue: The Effect of the Housing Crisis on State and Local Governments]. *Regional Science and Urban Economics*, *41*(4), 394–406. https://doi.org/https://doi.org/10.1016/j.regsciurbeco.2010.12.006

Keeling, P. (2017). No respect: Young bame men, the police and stop and search. *Criminal Justice Alliance*. https://www.criminaljusticealliance.org/wp-content/uploads/No-Respect-Young-BAME-men.pdf

Koch, I., Williams, P., & Wroe, L. (2024). 'county lines': Racism, safeguarding and statecraft in britain. *Race & Class*, *65*(3), 3–26. https://doi.org/10.1177/03063968231201325

Murray, K., McVie, S., Farren, D., Herlitz, L., Hough, M., & and, P. N. (2021). Procedural justice, compliance with the law and police stop-and-search: A study of young people in england and scotland. *Policing and Society*, *31*(3), 263–282. https://doi.org/10.1080/10439463.2020.1711756

Owens, C., Mann, P., & Mckenna, R. (2014). *The essex body worn video trial: The impact of body worn cameras on criminal justice outcomes of domestic abuse incidents* (tech. rep.). College of Policing. https://whatworks.college.police.uk/Research/Documents/BWV_Report.pdf

Pomfret, A. (2024). City report–london. the disproportionate harms of drug prohibition on oppressed peoples. civil. *City of London*. https://correlation-net.org/wp-content/uploads/2024/04/2023_CEHRN-Monitoring_City-Report-London.pdf

Roberts, C. (2023). Discretion and the rule of law: The significance and endurance of vagrancy and vagrancy-type laws in england, the british empire, and the british colonial world. *Duke Journal of Comparative International Law*, *33*(2), 195–240. https://djcil.law.duke.edu/article/discretion-and-the-rule-of-law-roberts-vol33-iss2/

Runnymede Trust. (2021). *Over-policed and under-protected: The road to safer communities*. The Runnymede Trust. https://www.runnymedetrust.org/publications/over-policed-and-under-protected

Shiner, M., Carre, Z., Delsol, R., & Eastwood, N. (2018a). The colour of injustice: 'race', drugs and law enforcement in england and wales. *StopWatch and Release*. https://www.stop-watch.org/uploads/documents/The_Colour_of_Injustice.pdf

Shiner, M., Carre, Z., Delsol, R., & Eastwood, N. (2018b). The colour of injustice: 'race', drugs and law enforcement in england and wales. *StopWatch and Release (Drugs charity)*. https://www.stop-watch.org/uploads/documents/The_Colour_of_Injustice.pdf

Suss, J. (2023). Measuring local, salient economic inequality in the uk [Available at SSRN: https://ssrn.com/abstract=3958731]. *Environment and Planning A: Economy and Space*. https://doi.org/10.2139/ssrn.3958731

Suss, J. H., & Oliveira, T. R. (2022). Economic inequality and the spatial distribution of stop and search: Evidence from london. *The British Journal of Criminology*, *63*(4), 828–847. https://doi.org/10.1093/bjc/azac069

The Police Foundation. (2012). The briefing: Stop and search [Series 2, Edition 3 – March 2012]. https://www.police-foundation.org.uk/wp-content/uploads/2017/08/stop_and_search_briefing.pdf

Wessendorf, S. (2019). Migrant belonging, social location and the neighbourhood: Recent migrants in east london and birmingham. *Urban Studies*, *56*(1), 131–146. https://doi.org/10.1177/0042098017730300

Yates, A. K., Obus, E., Peele, H., Petrovic, L., Wing, S., & Cunningham, M. (2024). The function of power: A herstorical model of power, trauma, and policing african americans. *Psychological trauma: theory, research, practice, and policy*, *16*(3), 363.

Yesufu, S. (2013). Discriminatory use of police stop-and-search powers in london, uk. *International Journal of Police Science & Management*, *15*(4), 281–293. https://doi.org/10.1350/ijps.2013.15.4.318