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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 the already dwindling 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 study 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 inequality. 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, namely 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 study 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 inequality 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 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 and demographic data will be analysed at the LSOA level. Analytical techniques will include spatial mapping to

identify policing hotspots, as well as regression 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 Hypotheses

This study tests three core hypotheses concerning the relationship between inequality, ethnicity, and the frequency of stop and search (S&S) activity. These expectations are grounded in both theoretical literature and existing empirical findings.

Hypothesis 1: Higher levels of economic inequality within an LSOA are associated with increased rates of stop and search.

Hypothesis 2: The relationship between social make-up, inequality and stop and search will differ significantly between Greater London and Merseyside.

Hypothesis 3: Areas characterised by both higher economic inequality and greater ethnic diversity will experience disproportionately higher levels of stop and search activity due to the interaction of these factors.

1.7 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 policing in different areas. 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 et al.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 . 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 significant 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. This serves as a foundation for [Hypothesis 2](#), emphasising the potential for distinct differences in policing prejudice across regions in the UK. 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 [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. The continued use of suspicionless stop and search powers has disproportionately impacted traditionally diverse areas, reinforcing their portrayal as inherently dangerous. This framing not only sustains racialised narratives within policing but also sets the conceptual groundwork for [Hypothesis 3](#).

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 Flanagan et al.2022, May] 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 de-funding of police institutions have gained significant traction in recent years. The British 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 [UK Parliament¹⁹⁹⁴][UK Parliament²⁰¹⁹]. 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] displays how 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, with even the Metropolitan Police admitting there is “no definitive evidence to prove or disprove the suggested link”.

2.4.2 Drug Crime

[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 measures. 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], 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]. 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.

This study shares thematic similarities with [J. H. Suss and Oliveira²⁰²²]’s research, but aims to broaden the scope by examining differing social make-ups that effect of stop and search patterns. The combination of socio-economic and ethnic factors will allow for a deeper understanding of how these variables interact and influence policing practices across these diverging counties.

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], economic inequality plays a significant role in shaping the distribution of policing activities; with their findings demonstrating a strong link between deprivation and stop and search intensity in London. While this prior work offers compelling support for Hypothesis [Hypothesis 1](#), it also highlights the need to test whether these patterns hold in other contexts. This study addresses that by focusing on Greater London and Merseyside, two counties with distinct social compositions and policing cultures, to examine whether similar dynamics are at play.

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 [Kantrowitz¹⁹⁷⁴] 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 explored 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 counties.

3 Methodology

This study integrates stop and search records from 2022 with demographic and economic data at the LSOA level. By geocoding each stop and linking it to census and deprivation measures, the analysis examines how local area characteristics relate to the frequency of stop and search using regression techniques.

3.1 Data Sources and Preparation

3.1.1 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 % search incidents and the outcomes of criminal cases.

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.

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.

3.1.2 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.

To overcome the lack of LSOA assignment in the stops and searches, LSOA boundary shapefiles were sourced from the [UK Data Service](#). These shapefiles provide the geographic boundaries of each LSOA in England and Wales for 2021, allowing stop and search records to be accurately assigned to their respective areas.

3.1.3 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 score 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 per house data; also obtained from GOV.UK 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.

3.2 Justification for Case Selection

As previously stated 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 next largest population. 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.

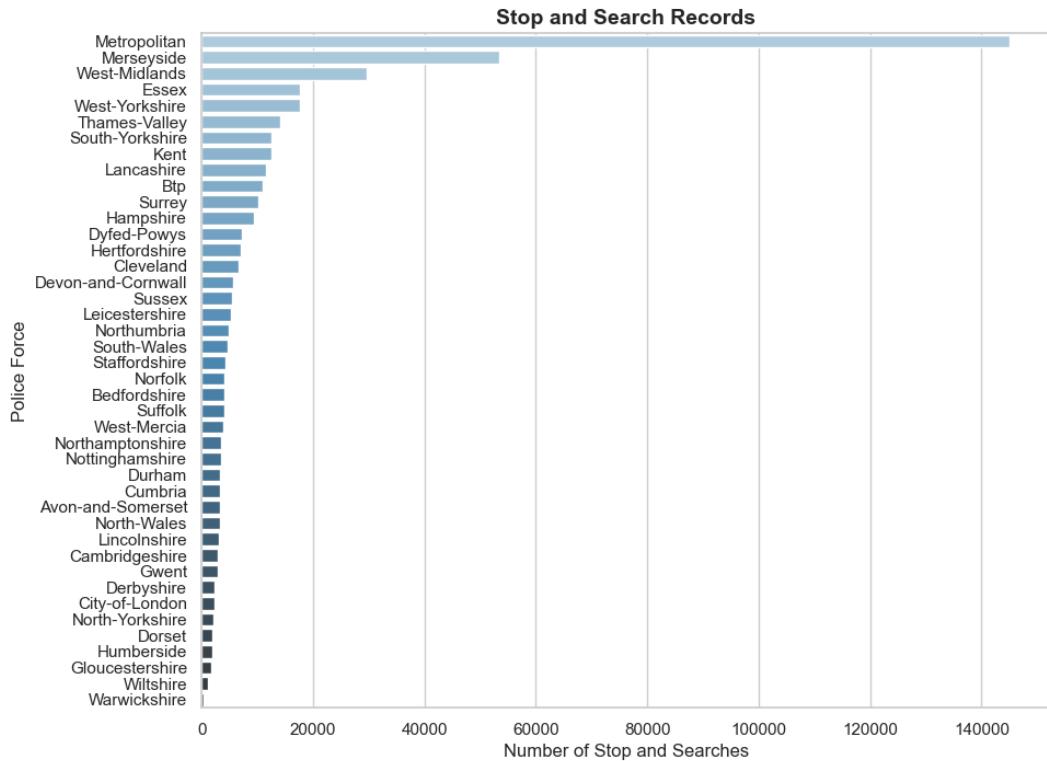


Figure 1: Stop and Search Distribution
(Data source: [Data.Police.UK](#))

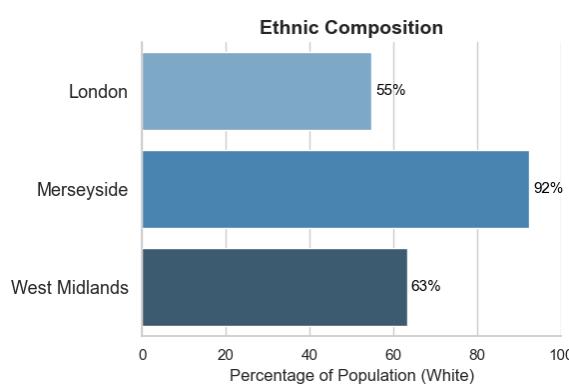


Figure 2: Ethnic Distribution
(Data source: [2021 Census](#))

West Midlands was another potential candidate. However, existing literature suggests that its policing culture is 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, the ethnic minority composition does not differ drastically from London, as shown in [Figure 2](#). Additionally, 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.

3.3 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.

3.3.1 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.

The maps below illustrate the geographical distribution of stop and search events recorded in each region. To allow a fair visual comparison between the two counties, the stop and search counts have been normalised using z-scores, with high z-scores representing concentrations more than 2σ above the mean, and the other extreme representing values more than 1σ below the mean.

Figure 3: Stop and Search locations in London

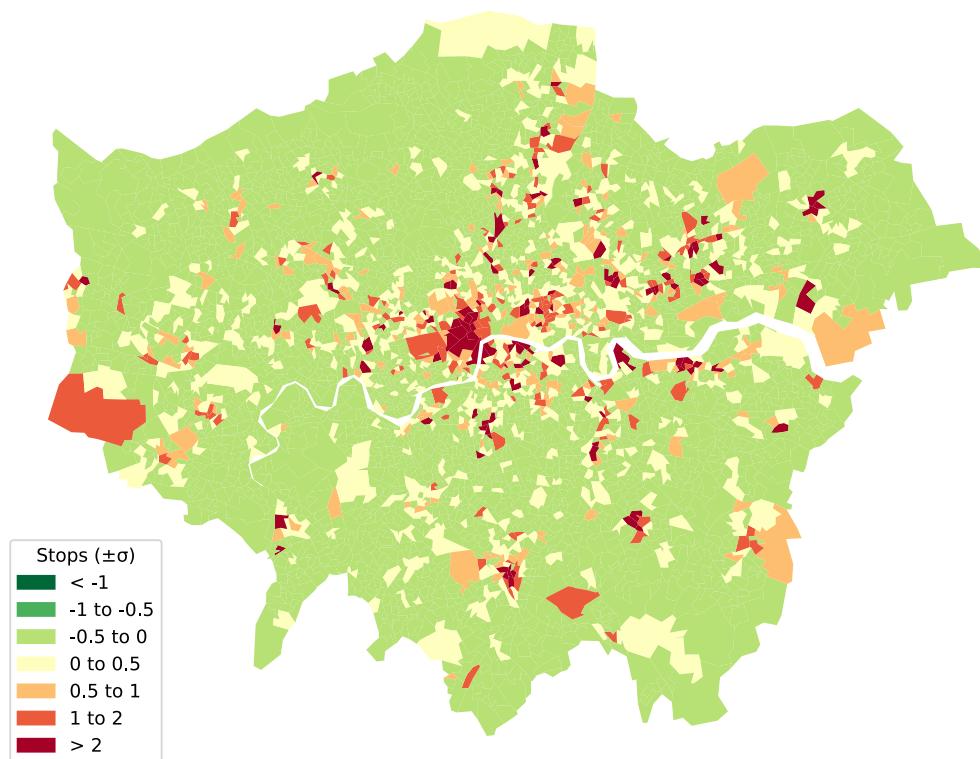
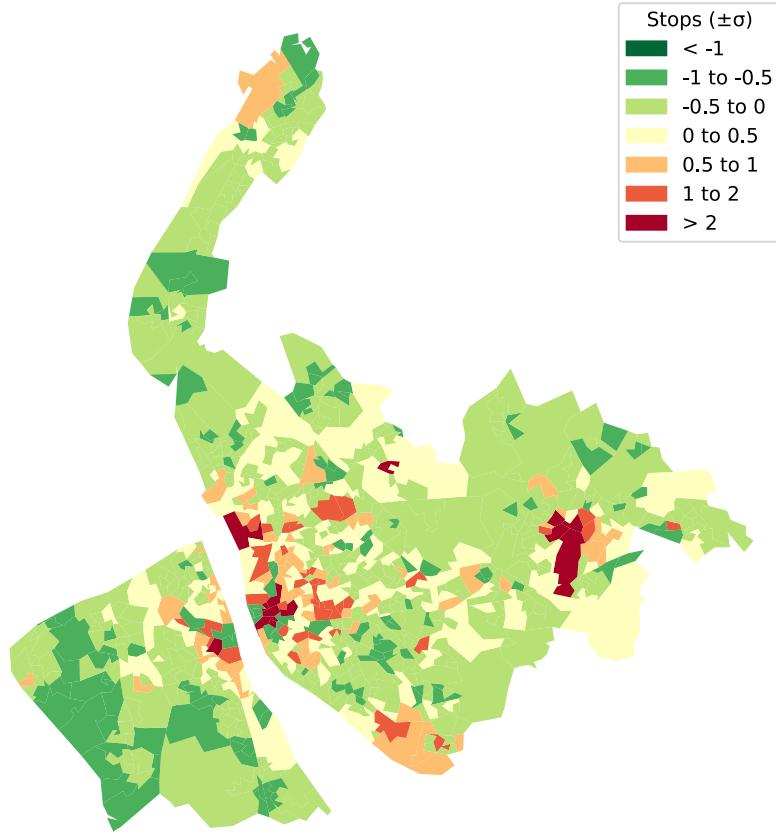


Figure 4: Stop and Search Locations in Merseyside



[Figure 3](#) and [Figure 4](#) 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 will hopefully reveal the underlying drivers of these clustering patterns and help assess whether they align with broader trends in crime and policing practices.

3.3.2 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.

[Figure 5](#) and [Figure 6](#) 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 both high and low Gini coefficients scattered across the region, including notable hotspots of inequality on the outskirts of the county.

Figure 5: Inequality Gini map of London

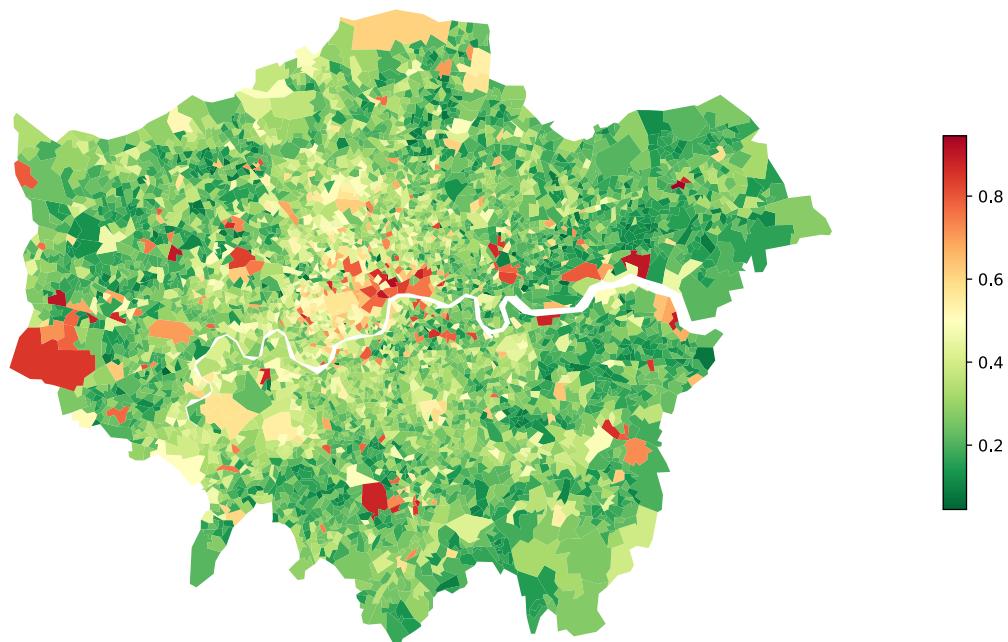
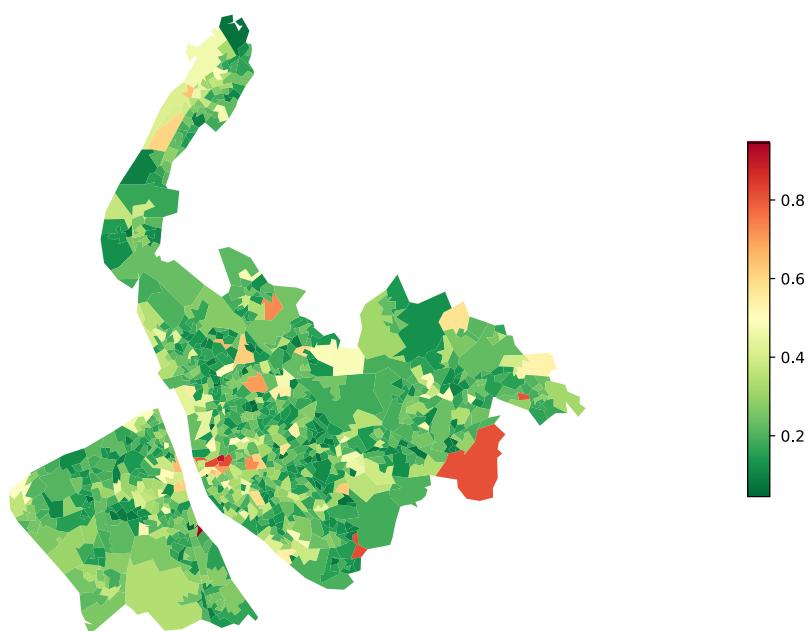


Figure 6: Inequality Gini map of Merseyside



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 2022. The data is 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 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 Office 2021]), 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.

3.3.3 Descriptive Statistics

[Table 1](#) and [Table 2](#) provide an overview of the social and spatial landscape across which stop and search practices occur in London and Merseyside. The figures highlight some key contrasts between the two regions.

In London, stop and search activity is highly uneven. While many areas record relatively modest levels of police intervention, others stand out as clear outliers, with substantially elevated counts. These disparities are mirrored in the underlying social geography: levels of income deprivation vary sharply across the city, as do housing costs, which range from modest to extraordinary. Ethnic composition also differs markedly by area, with a significant number of LSOAs comprising majority ethnic minority populations. The Gini coefficients reinforce the picture of stark internal inequality, particularly concentrated in parts of Inner and West London.

Merseyside exhibits a different pattern. Although stop and search is also unevenly distributed, the overall intensity of activity appears more concentrated in a smaller number of high-activity areas. Social indicators suggest a less polarised landscape than London, but still one marked by visible inequality and deprivation. Ethnic minority populations are smaller overall, but some LSOAs display notable diversity. House prices and crime rates again vary significantly, though within a more compressed range than in the capital.

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	0.135	0.073	0.006	0.437
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

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	0.202	0.129	0.014	0.581
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

Together, these descriptive statistics offer context for the analysis that follows, signalling that both regions feature substantial variation, yet differ meaningfully in their social composition and spatial dynamics.

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.

3.4 Modelling Approach and Rationale

Given that the outcome variable is count data, specifically the number of stop and search incidents recorded per LSOA, two appropriate modelling frameworks are considered: Poisson regression and 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 Oliveira 2022] opted for a Spatial Durbin Model (SDM), this study 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 Fixed Effects

Fixed effects were incorporated to control for unobserved heterogeneity across the boroughs. This approach has been applied in similar spatial regression contexts, such as in [Hilber et al.[2011](#)] and [J. H. Suss and Oliveira[2022](#)], particularly in studies focused on London.

Theoretically, fixed effects help mitigate multicollinearity and account for geographical 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.

As shown in [Table 5](#) and [Table 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. 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.

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

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

Furthermore, Merseyside follows a similar, though less pronounced, trend, with improvements in AIC and log-likelihood when fixed effects are included, as well as a minor increase in pseudo R^2 . 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.

3.5.1 Interaction Terms

To conceptualise [Hypothesis 3](#), which investigates the complex interplay between structural inequalities and ethnicity in shaping stop and search practices, the model incorporates two interaction terms. These terms allow for a nuanced analysis of how socioeconomic factors and ethnic composition jointly influence policing patterns, capturing potential variations in stop and search rates that arise from their intersection.

Ethnic Minority × Income Deprivation

Ethnic Minority × Housing Gini.

Both terms are constructed using z-score standardised variables. The percentage of ethnic minority residents in each LSOA is interacted with measures of local inequality, capturing whether deprivation or income disparity affects stop and search activity differently in racially diverse areas.

The decision to include these interaction terms is informed by prior research emphasising how race and economic marginalisation intersect to shape criminal justice outcomes. For example, [Bright2016] demonstrated that racial disparities in the US criminal justice system are compounded by poverty, significantly increasing the likelihood of receiving a death sentence. This evidence supports modelling the combined effect of ethnicity and structural disadvantage through interaction terms, allowing for a more nuanced understanding of how these factors jointly influence stop and search practices.

Similarly, the background paper by [Perera2019] explores how low-income housing and race intersect in London, particularly in the context of police interactions. They argue that state narratives such as when former Prime Minister David Cameron introduced terms like “gangs” and “ghettos” into policy; have long-lasting effects, shaping both public discourse and enforcement patterns. These examples illustrate how institutional racism is embedded in both government and policing structures.

This rationale directly informs the inclusion of interaction terms focusing on ethnicity and inequality. These variables capture two distinct forms of socioeconomic disadvantage: one through income, the other through housing inequality. Mean house price is excluded from the interaction analysis, as it did not yield significant results in similar studies, such as [J. H. Suss and Oliveira2022].

3.6 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 region. 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.

Not all stop and search records included usable geographic coordinates. In particular, 10.37% of London incidents and 3.90% of those in Merseyside lacked location data and 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 Merseyside 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. 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.

4 Results

4.1 London

The analysis below focuses on the regression models estimated for the Metropolitan Police, 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)
<i>Variables</i>				
Constant	2.70*** (0.032)			
Gini Coefficient	1.83*** (0.111)	1.74*** (0.243)	1.75*** (0.267)	1.67*** (0.243)
Income Deprivation (z)	0.209*** (0.021)	0.125** (0.041)	0.125** (0.041)	0.146*** (0.041)
Mean House Price (z)	-0.023 (0.017)	-0.051 (0.028)	-0.052 (0.030)	-0.029 (0.032)
Crime Rate (z)	0.188*** (0.035)	0.224** (0.069)	0.223** (0.070)	0.214** (0.071)
Ethnic Minority (z)	0.224*** (0.019)	0.281*** (0.047)	0.296*** (0.056)	0.269*** (0.047)
Drug Crime Rate (z)	0.567*** (0.045)	0.506*** (0.065)	0.506*** (0.065)	0.534*** (0.068)
Gini Coefficient × Ethnic Minority (z)			-0.062 (0.180)	
Income Deprivation (z) × Ethnic Minority (z)				-0.111*** (0.031)
<i>Fixed-effects</i>				
Borough	No	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	4,994	4,994	4,994	4,994
Squared Correlation	0.18552	0.18553	0.18553	0.18553
Pseudo R ²	0.05113	0.05843	0.05843	0.05925
BIC	41,782.6	41,734.5	41,742.8	41,706.8
Over-dispersion	0.89242	0.94652	0.94658	0.95297

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 Model Fit

The model fit statistics show modest improvements across the specifications. Pseudo R² 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 R² 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:	Stop Count			
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
Constant	2.90*** (0.067)			
Gini Coefficient	2.38*** (0.256)	2.46*** (0.334)	2.50*** (0.422)	2.23*** (0.323)
Income Deprivation (z)	0.390*** (0.047)	0.361*** (0.068)	0.360*** (0.065)	0.352** (0.134)
Mean House Price (z)	-0.159*** (0.042)	-0.160*** (0.018)	-0.162*** (0.020)	-0.146*** (0.028)
Crime Rate (z)	-0.286*** (0.083)	-0.129 (0.147)	-0.133 (0.153)	-0.133 (0.120)
Ethnic Minority (z)	0.179*** (0.037)	0.237*** (0.048)	0.279*** (0.065)	0.391*** (0.068)
Drug Crime Rate (z)	0.983*** (0.108)	0.806*** (0.147)	0.805*** (0.149)	0.834*** (0.184)
Gini Coefficient × Ethnic Minority (z)			-0.144 (0.345)	
Income Deprivation (z) × Ethnic Minority (z)				-0.213*** (0.044)
<i>Fixed-effects</i>				
Borough	No	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	923	923	923	923
Squared Correlation	0.32066	0.33953	0.33941	0.32649
Pseudo R ²	0.09007	0.09623	0.09627	0.10047
BIC	8,273.8	8,245.5	8,252.0	8,214.0
Over-dispersion	1.2488	1.3217	1.3223	1.3774

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 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

For clarity and consistency, this section focuses on the second models in both [Table 7](#) and [Table 8](#) (Model (2)), as they include the key variables of interest and provide the most comprehensive results for interpretation:

4.3.1 Housing Inequality (Gini)

Both London and Merseyside show strong positive coefficients with respect to the Gini coefficient. These Incidence Rate Ratios (IRRs) correspond to a 1 unit increase. In the case of Gini, this represents an end-to-end change across the entire spectrum (i.e., from least to most unequal). A more interpretable measure is a 0.1 unit increase rather than a full unit: The coefficient (log IRR) for Merseyside is $\ln(2.46) \approx 0.9$, and for London it is $\ln(1.74) \approx 0.55$.

To get the effect of a 0.1 unit increase:

$$\text{Merseyside: } \exp(0.9 \times 0.1) = \exp(0.09) \approx 1.094 \rightarrow \sim 9.4\% \text{ increase}$$

$$\text{London: } \exp(0.55 \times 0.1) = \exp(0.055) \approx 1.056 \rightarrow \sim 5.6\% \text{ increase}$$

Here we see that the effect of inequality at the housing level has a much stronger effect in Merseyside compared to London—nearly double.

This result is a key indicator for [Hypothesis 1](#). We have clear, significant evidence that higher levels of LSOA inequality lead to significant increases in occurrences of stop and search. Many factors may account for this. Notably, as seen in [Table 1](#) and [Table 2](#), London exhibits much larger deviation in house prices. This is due to some of the most expensive housing in the country being located in London, as opposed to Merseyside. Furthermore, and pivotal to this study, this provides evidence for [Hypothesis 2](#): London and Merseyside, having differing social compositions, do experience differing occurrences of stop and search. Although it is important to remember that correlation does not imply causation, this remains a significant finding.

4.3.2 Income Deprivation

Next, looking at Income Deprivation, we observe a broadly similar pattern across both regions. An increase in the Income Domain Score—which reflects lower incomes and a greater proportion of the population on benefits—correlates with a significant rise in stop and search occurrences, though the magnitude of this effect differs between Merseyside and London.

The Incidence Rate Ratios (IRRs) are 1.43*** for Merseyside and 1.25** for London, corresponding to log IRRs of approximately $\ln(1.43) \approx 0.36$ and $\ln(1.25) \approx 0.22$ respectively. To interpret the effect of a 0.1 unit increase in the Income Domain Score, we calculate:

$$\text{Merseyside: } \exp(0.36 \times 0.1) = \exp(0.036) \approx 1.037 \rightarrow \sim 3.7\% \text{ increase}$$

$$\text{London: } \exp(0.22 \times 0.1) = \exp(0.022) \approx 1.022 \rightarrow \sim 2.2\% \text{ increase}$$

These results indicate that income deprivation contributes to increases in stop and search activity in both areas, but its influence is noticeably stronger in Merseyside by approximately

1.5%. This suggests that wealth disparities play a slightly more prominent role in driving stop and search in Merseyside communities.

It is also worth noting that while the effect is statistically significant in both regions, the level of significance differs (Merseyside at *** vs. London at **), reflecting potentially different underlying social dynamics. For London, the somewhat lower significance may indicate that factors beyond income deprivation; such as housing inequality or local policing practices having a comparatively greater influence on stop and search patterns.

Overall, these findings support the hypothesis that socioeconomic factors impact policing outcomes differently across regions, emphasizing the need to consider local context when interpreting these patterns.

4.3.3 House Price

Examining the effect of house prices reveals contrasting patterns between Merseyside and London. For Merseyside, the coefficient is -1.6^{***} , indicating a strong and significant negative association with stop and search occurrences. This suggests that areas with higher house prices tend to experience substantially fewer stop and search incidents. Translating the coefficient to an incidence rate ratio (IRR), a one-unit increase in the standardized house price score corresponds to approximately an 80% decrease in stop and search rates (since $\exp(-1.6) \approx 0.20$).

In contrast, the London coefficient is 0.051 and not statistically significant, indicating little to no measurable relationship between house prices and stop and search activity in that region. This difference may reflect London's broader housing market diversity and more complex socioeconomic landscape, where high house prices alone do not strongly predict stop and search intensity.

The stark contrast between the two regions further emphasizes the role of local context in shaping stop and search dynamics. In Merseyside, house price appears to act as a clear protective factor against such interventions, while in London, other factors may dominate or obscure this relationship. This supports the idea that regional social and economic structures differentially influence policing patterns, aligning with [Hypothesis 2](#) regarding varied social compositions and their effects.

4.3.4 Crime

The results for crime-related variables reveal distinct patterns in Merseyside and London, which may reflect differences in policing focus and urban context.

In Merseyside, the coefficient for general crime is -1.29 but not statistically significant, indicating that higher overall crime rates do not correspond to increased stop and search activity. Conversely, drug crime shows a strong positive and highly significant coefficient of 0.806^{***} . This suggests that stop and search practices in Merseyside are more strongly associated with drug-related offences rather than general crime, implying targeted police interventions in these areas.

In London, both general crime and drug crime coefficients are positive and significant: 0.224^{**} for general crime and 0.506^{***} for drug crime. This indicates that stop and search rates rise with both crime measures, but more sharply for drug crime.

Since both variables are standardized, we can interpret the effect sizes per one standard deviation increase:

London general crime: $\exp(0.224) \approx 1.25 \rightarrow \sim 25\%$ increase in stop and search

London drug crime: $\exp(0.506) \approx 1.66 \rightarrow \sim 66\%$ increase in stop and search

Here we see that drug crime accounts for a larger proportion of the increase in stop and search activity than general crime in London.

These findings suggest that in Merseyside, police activity is more narrowly focused on drug offences, whereas in London, higher stop and search rates are associated with a broader spectrum of crime, possibly reflecting its larger and more complex urban environment.

Overall, this could indicate that police are applying their stop and search powers in line with specific crime concerns, especially drug-related issues, rather than simply targeting areas with high overall crime rates.

4.3.5 Ethnic Minority

Interaction effects between socioeconomic factors and ethnic minority percentage were examined to assess whether the relationship between structural inequalities and stop and search activity varies by racial composition.

Both Merseyside and London show a strong, positive main effect for ethnic minority percentage, with coefficients of 0.237^{***} and 0.281^{***} respectively, indicating higher stop and search counts in areas with larger ethnic minority populations.

The Gini Coefficient \times Ethnic Minority interaction is negative and not statistically significant in both regions (Merseyside: -0.144 , London: -0.062), providing no clear evidence that housing inequality modifies the relationship between ethnic composition and stop and search.

In contrast, the Income Deprivation \times Ethnic Minority interaction is negative and statistically significant in both Merseyside (-0.213^{***}) and London (-0.111^{***}), suggesting that higher income deprivation attenuates the effect of ethnic minority concentration on stop and search rates.

To better understand the magnitude of these interactions, we consider the effect of a 1 standard deviation increase in Income Deprivation \times Ethnic Minority:

$$\text{Merseyside: } \exp(-0.213 \times 1) = \exp(-0.213) \approx 0.808 \rightarrow \sim 19.2\% \text{ decrease}$$

$$\text{London: } \exp(-0.111 \times 1) = \exp(-0.111) \approx 0.895 \rightarrow \sim 10.5\% \text{ decrease}$$

This indicates that in areas with higher income deprivation, the positive association between ethnic minority population and stop and search occurrences is reduced by approximately 19.2% in Merseyside and 10.5% in London. While areas with larger ethnic minority populations generally experience higher stop and search rates, this effect is less pronounced in more deprived areas. This suggests that in the poorest neighbourhoods, stop and search rates may be elevated more uniformly, regardless of ethnic composition. Surprisingly, some of the findings oppose [Hypothesis 3](#), which proposed that areas characterised by both higher economic inequality and greater ethnic diversity would experience disproportionately higher levels of stop and search activity due to the interaction of these factors.

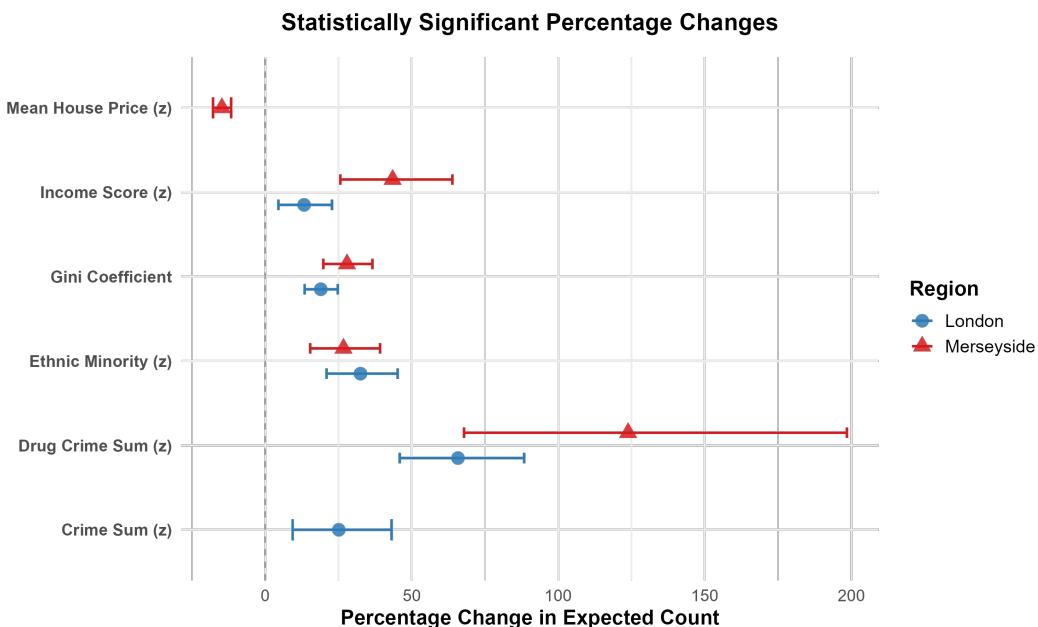


Figure 7: Caption

These findings indicate that stop and search is not a uniform practice but one shaped by the local socio-political landscape, whether economic or racialised.

5 Discussion

5.1 Comparative Summary

5.1.1 Economic Disparities

In both Merseyside and Greater London, poorer areas experience higher rates of stop and search, a clear pattern in both regions. Additionally, areas with greater economic diversity, that is, a wider range of incomes and wealth, face significantly more stop and search activity. This relationship holds strongly in both regions; however, the housing Gini coefficient, which measures local inequality showed a larger effect size at the same significance level. This suggests that local inequality within neighbourhoods has a stronger influence on policing patterns than overall regional inequality.

Interestingly, poorer yet economically diverse areas tend to experience a decrease in stop and search rates. This pattern indicates that ethnicity has a reduced impact in less affluent areas. This effect is more pronounced in London, likely due to its higher racial diversity compared to Merseyside. In Merseyside, which is less racially diverse, policing appears to focus more directly on poorer areas rather than racial factors. Conversely, in London's more ethnically diverse environment, race accounts for about 10% more influence in stop and search practices, reflecting a slight shift in policing focus towards race in these diverse areas.

5.1.2 Policing Biases

London police seem unaffected by house price, potentially showing less bias in their habits, with more of a focus on crime. In contrast, house price is a significant factor in Merseyside, indicating that areas with higher house prices face lower rates of stop and search.

This difference could be due to various factors. One possibility is that London has more high housing Gini LSOAs, meaning there is a wider mix of housing prices and less clearly defined expensive and poorer areas at the LSOA level.

The pattern in Merseyside aligns with the narrative of policing occurring predominantly in lower-income areas. Notably, stop and search rates in Merseyside do not show significant coefficients for crime rates in those areas, raising questions about whether the police are focusing on actual crime or simply the area's reputation.

5.1.3 Policing Goals

The finding that drug crime was a non-significant variable in Merseyside was surprising. This could indicate an increased focus on the drug epidemic in Merseyside, particularly in Liverpool, which would explain the heightened attention towards drug crime since it was a significant factor.

In contrast, London did not show the same pattern. Drug-related crime remained significant, but so did overall crime rates. This likely reflects the broader prevalence of crime in London, with knife crime being a major ongoing issue. Consequently, the police in London may have a wider set of crime-related motives influencing their stop and search practices.

5.2 Implications for Policy

The data suggest that policing practices are influenced by socioeconomic factors and racial dynamics, which vary by region. This indicates a need for policy measures that address differential policing, ensuring that interventions consider local economic inequalities and community diversity to promote fairer law enforcement.

5.3 Limitations and Considerations

This analysis faces several limitations. Possible endogeneity may affect the relationships observed, and ecological inference risks arise from using aggregate area-level data rather than individual-level information. Measurement limitations include the precision of stop and search counts and the methods used to normalise variables. Finally, the findings may not generalise beyond the specific regions studied, highlighting the need for caution when applying these results to other contexts.

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