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Heterogeneous Associations Between Policing Perceptions and Residents' Sense of Safety: A Causal Forest with Double Machine Learning Approach

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Abstract

This study examines whether the association between residents' perceptions of policing and their sense of safety varies across individual characteristics and neighbourhood contexts. Using survey data from 1738 residents of the Humberside region of England, linked to small-area deprivation and police-recorded crime data, we apply a causal forest with double machine learning to estimate this conditional association flexibly while adjusting for demographics, experience of crime and neighbourhood conditions. Because the data are cross-sectional, the estimates are interpreted as adjusted associations rather than causal effects. We find a positive average association between policing perceptions and sense of safety that is present across all groups examined. A calibration test indicates some variation in the strength of this association, but differences between pre-defined demographic and neighbourhood groups are modest, their confidence intervals largely overlap, and much of the variation lies within rather than between groups. The clearest between-group pattern concerns neighbourhood deprivation: the association tends to be somewhat weaker among residents of more deprived neighbourhoods. Differences by ethnicity are suggestive but based on small subgroups. These patterns generate hypotheses for more targeted policing and neighbourhood strategies that should be tested with longitudinal or experimental designs.

Keywords: perception of safety; perception of policing; confidence in policing; deprivation; applied machine learning

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1. Introduction

Sense of safety represents a fundamental aspect of resident wellbeing in neighbourhoods, denoting individuals' general feelings of being protected from crime and disorder in everyday interactions with the social and physical environment (Jackson 2009; Jackson and Gray 2010; Kuo et al. 1998). In residential neighbourhoods, these perceptions of safety are not solely shaped by residents' personal experience related to crime but also tied to a broader environmental context associated with social cohesion and trust in local institutions, notably the police (Ferraro 1995; Holmberg 2005; Warr 2000). Within this context, perception of policing is a key dimension connecting how individuals perceive the police

in relation to their feelings of safety, including attitudes about police behaviour, visibility and judgements of trust or legitimacy (Bradford et al. 2009; Sunshine and Tyler 2003; Tyler and Huo 2002). Herein, understanding how residents perceive local policing and how such perceptions relate to their safety feelings is essential for developing evidence-based policing strategies (Skogan 2006, 2009).

Research suggests that the relationships between perception of policing and sense of safety are unlikely to be uniform but intertwined and complex (Bradford et al. 2024, 2009). In general, positive perceptions of policing are associated with greater willingness to cooperate with law enforcement (Bolger and Walters 2019; Sunshine and Tyler 2003), which may strengthen informal social control and, in turn, may contribute to residents' feelings of safety. For example, studies that measure both constructs show that public confidence in the police is closely related to residents' worry about crime and perceptions of safety (Jackson et al. 2009; Skogan 2009). Theoretically, it has been argued that trust in the police may increase people's belief that authorities are capable, fair, and responsive in preventing crime and protecting neighbourhoods, and may thereby provide reassurance (Skogan 2009). However, empirical evidence also indicates that residents' perceptions of policing do not always contribute to their feelings of safety in their neighbourhoods. Paradoxically, some studies have found that residents' perceived policing patrols do not necessarily increase and may even sometimes decrease the residents' feelings of safety in certain neighbourhoods (Hinkle and Weisburd 2008; Ratcliffe et al. 2015; Rinehart Kochel 2011; Veer et al. 2012).

There is a growing number of studies that indicate residents' perceptions of policing and their feelings of safety vary across demographics and neighbourhood contexts. Factors such as age, ethnicity, gender, socio-economic status, prior victimisation experiences, and the specific condition of one's neighbourhood all shape how local residents view the police and how safe they feel (Skogan 2006; Weitzer and Tuch 2005). While studies have identified factors associated with sense of safety and perceptions of policing, fewer have examined how the strength of this association varies systematically across resident subgroups using flexible, data-driven methods rather than pre-specified interaction terms. For example, traditional regression models require the analyst to specify in advance which interactions to test, which may miss heterogeneity that was not anticipated (Athey et al. 2019; Wager and Athey 2018). Another gap here is that measuring how this relationship varies across different groups of residents with different neighbourhood conditions has not been extensively and rigorously investigated using flexible heterogeneity-detection methods. Since the relationship between policing perceptions and feelings of safety is embedded in the intertwined individual and neighbourhood factors that are related to both of them, machine learning-based methods such as causal forests offer a way to estimate this association at the individual level, capturing how it varies across residents in different conditions. The gaps discussed above raise two research questions in this study: (1) Is there an association between policing perceptions and residents' sense of safety after adjusting for observed factors (e.g., demographics, prior victimisation experience and neighbourhood conditions)? (2) Does the strength of this association differ across demographic groups and neighbourhood conditions (such as deprivation levels or crime rates)? Answering these questions is important for understanding not only whether policing perceptions are associated with safety feelings, but also for whom the association is strongest or weakest, which can generate hypotheses for tailored policing strategies for different resident groups.

Our study aims to address the gap by estimating how the adjusted association between policing perceptions and residents' sense of safety varies across residents with different characteristics. In particular, we seek to identify for whom and under what conditions this association is stronger or weaker. Specifically, perception of policing in this study

is captured across three empirically measured dimensions from the community survey, namely police visibility, police helpfulness, and reporting likelihood in the future. To accomplish this, we employed a machine learning-based estimation approach that is particularly well-suited to uncovering complex, heterogeneous patterns based on survey data collected from residents in the Humberside region of England.

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature on sense of safety, perceptions of police and their relationships, providing theoretical grounding for our empirical analysis. Section 3 describes data sources, measurement strategies, and methods employed in this study, including detailed explanations of principal component analysis and causal forest with double machine learning frameworks. Section 4 presents the results, including both the average association and its variation across different resident populations and neighbourhood contexts. Section 5 discusses the implications of these findings for policing practice and acknowledges limitations. Finally, Section 6 summarises the key findings and suggests future research.

2. Related Works

2.1. Theoretical Foundations

Sense of safety and perception of policing are closely related but are distinct concepts that require unpacking before examining how they interact. 'Sense of safety' is an individual's subjective feelings regarding their safety rather than just the exposure to actual crime in neighbourhoods (Ferraro 1995; Hale 1996). Beyond just worrying about a specific crime, a sense of safety also reflects a more pervasive questioning of whether one's neighbourhood is disordered, and this can lead to a passive feeling in daily life and negatively affect wellbeing (Farrall et al. 2009; Warr 2000). Neighbourhood studies also suggest that residents' safety feelings are associated with neighbourhood social and structural conditions (Brunton-Smith and Sturgis 2011; Brunton-Smith et al. 2014), while local social ties and collective efficacy are key features of how neighbourhoods maintain social control (Sampson et al. 1997).

As the local institution primarily responsible for managing public safety and against crime, police constitute an important factor related to how feelings of safety form. There are two parallel aspects for explaining what drives the perception of policing. One aspect ties to the performance outcome of the police, which is that public confidence tracks assessments of the effectiveness of police in controlling crime and responding to incidents (Jackson and Bradford 2009). Another aspect emphasising the policing operation process, such as procedural justice framework (Tyler and Huo 2002), argues that fairness, respectful treatment, and consistency in the practice of local authority are the primary elements of legitimacy, which is independent from the performance of police's crime-control function (Bolger and Walters 2019; Sunshine and Tyler 2003). Also, individuals' institutional trust (confidence in policing) is closely related to their legitimacy judgements (Tankebe 2013).

Thus, distinct perceptions of policing may be associated with different feelings of safety among residents in local neighbourhoods. Fair and visible policing may signal that the neighbourhood is well-managed by local law enforcement, which may reinforce residents' sense of safety beyond actual crime levels (Innes 2004; Skogan 2009). If policing is instead experienced as coercive, biased, or remote, this signal may reverse and the police may become a source of anxiety (Holmberg 2005; Nofziger and Williams 2005). Understanding under which individual and neighbourhood conditions the association between perception of policing and sense of safety is stronger or weaker is the central question this study pursues.

2.2. Heterogeneity in Safety Feelings and Policing Perception

Sense of safety and perception of policing are not uniform in population, but vary by age, gender, ethnicity, prior victimisation, and neighbourhood conditions. The empirical studies on each of these dimensions are reviewed as follows.

Age. Older residents usually report a lower sense of safety and worry about crime though they experience lower victimisation risk. This has been attributed to perceived vulnerability as older adults feel less able to protect themselves and have higher sensitivity to disorder (Ferraro 1995; Hale 1996). Meanwhile, older people tend to perceive the policing more positively because they have less frequent and less adversarial contact with local police officers (Skogan 2006). However, younger people report lower trust in the police shaped by feelings of unfair treatment and disrespectful engagements, often born from their direct experience of policing (e.g., stop and search) (Gau and Brunson 2010; Mazerolle et al. 2013).

Gender. Though women have lower victimisation rates for most offences than men, women report higher fear of crime than men across several crime types (Ferraro 1995). This gender gap is widely acknowledged in the fear of sexual violence and domestic abuse, which influence how women perceive personal safety alongside broader vulnerability (Chataway and Hart 2019; Franklin and Franklin 2009; Warr 2000). The relationship between gender and police perceptions shows greater variability. While some studies indicate higher satisfaction with police among women, this does not straightforwardly translate into greater safety feelings, particularly for women from ethnic minorities (Cochran and Warren 2012; Pickering et al. 2024).

Ethnicity. In the literature, residents from ethnic minority backgrounds hold more negative perceptions of policing across a wide range of contexts. Survey research in the United States has shown that Black and Hispanic residents rate police legitimacy substantially lower than white residents, which reflects the community's awareness of racial bias in law enforcement (Weitzer 2000). In the UK, similar patterns have been found among Black and Asian communities, where stop-and-search practices and perceived institutional racism shape their deeply sceptical evaluations (Bradford et al. 2009). These effects are also amplified by incidents of police violence. For example, research analysing a high-profile incident of police violence in the US found substantial declines in crime reporting (911 calls) in Black neighbourhoods (Desmond et al. 2016). In the UK context, related studies also reveal inequalities in policing confidence across different ethnic groups (Tura et al. 2026) and this pattern is closely linked to their previous experiences of police contact (Kyprianides et al. 2025).

Prior victimisation. Having been a victim of crime is associated with higher fear of crime and lower feelings of safety (Hale 1996), and can also lower confidence in policing (Bradford et al. 2009; Myhill and Bradford 2012). The direction of the effect on police perception depends on how the police deal with the case. Residents receiving attentive, informative follow-up from police showed no decline in confidence, while those who felt dismissed or ignored showed significant drops in trust of police (Bradford et al. 2009; Myhill and Bradford 2012). More generally, procedural justice has been found to be a consistent predictor of police legitimacy across different groups of residents (Wolfe et al. 2016), suggesting that the quality of the police response at the point of victimisation may matter for how victims view the police.

Neighbourhood conditions. Residents' perceptions of both policing and safety are not formed in isolation but are shaped by the structural conditions of their living neighbourhood. Research also points out that neighbourhood disadvantage, crime, and disorder are associated with greater worry about crime and lower feelings of safety beyond individual conditions (Brunton-Smith and Sturgis 2011; Brunton-Smith et al. 2014), while neighbour-

hood disadvantage is also associated with less favourable views of the police (Reisig and Parks 2000; Sampson and Bartusch 1998). In deprived and high-crime neighbourhoods, residents face a compound disadvantage. They are at greater risk of victimisation and policing tends to be more intensive and enforcement-oriented, which may be associated with lower baseline trust (Rinehart Kochel 2011; Weitzer and Tuch 2005).

2.3. Empirical Evidence on the Relationships Between Policing Perceptions and Sense of Safety

The empirical evidence for linking policing perceptions and sense of safety is well established in the literature, though the direction and underlying mechanisms of this relationship are more varied and complex than commonly assumed. Jackson and Bradford (2009) showed that confidence in policing is closely tied to, and partly an expression of, residents' concerns about neighbourhood disorder and cohesion, while Bradford et al. (2009), using British Crime Survey data, found that the quality of police encounters shapes public confidence. These studies treat perceived safety and neighbourhood concerns as predictors of police perceptions, and studies measuring both constructs similarly show that worry about crime and confidence in policing are closely intertwined (Jackson et al. 2009; Skogan 2009). This indicates that the relationship is likely bidirectional; the present study therefore estimates an association without assuming a causal direction. Also, some studies found that police visibility and trust in police fairness were positively associated with neighbourhood collective efficacy (Sargeant 2017; Yesberg et al. 2023). Studies also found that procedural justice evaluations and perceived collective efficacy are both associated with residents' trust in the police (Nix et al. 2015). A systematic review of community-oriented policing found only modest and inconsistent average improvements in safety feelings (Gill et al. 2014).

However, studies of focused police crackdowns and police patrolling found that police presence sometimes increased rather than decreased fear among residents, who may read heavy enforcement activity as a signal of danger rather than reassurance (Hinkle and Weisburd 2008; Veer et al. 2012), while an evaluation of hot spots policing tactics found no measurable change in residents' perceived safety (Ratcliffe et al. 2015). These paradoxical findings appear concentrated in disadvantaged communities, where enforcement-oriented policing combined with low trust in police may coincide with lower feelings of safety (Rinehart Kochel 2011).

3. Data and Methods

3.1. Data Sources

In this study, the primary dataset is community survey data, which was dedicated to exploring residents' experiences with prior victimisation, perceptions of policing, and sense of safety in their own neighbourhoods of Humberside region, England. It also collected demographic information including age, gender, length of time living in the neighbourhood, education, ethnicity, and residential postcodes. The survey data was collected from July 2024 to March 2025 to provide a long enough time period to engage residents from the Humberside region. The survey was administered online: postcards with a QR code linking to the questionnaire were sent to residents across the Humberside region, who scanned the code to take part, and residents aged 16 and above were eligible to participate. Because participation was voluntary and recruitment was not based on a probability sampling frame or quotas (e.g., by age), a response rate cannot be calculated and the sample should be regarded as a non-probability sample. After removing response samples without a postcode or outside the Humberside area, the final sample was refined to 1738 valid entries from the initial 1792 responses. All the questions, answer options

with encoding values, and the corresponding variables used in this study can be found in Section 3.3.

Additionally, this study uses the neighbourhood-level data for analysis. The first part of the neighbourhood data is the Indices of Deprivation released by the Ministry of Housing, Communities & Local Government in 2025 [1]. In this analysis, we select Index of Multiple Deprivation (IMD), which captures seven dimensions of deprivation (including income, employment, education, health, crime, barriers to housing and services, and living environment) across neighbourhoods in England. The IMD is reported at the Lower Super Output Area (LSOA), which represents a small and standardised neighbourhood level across England. LSOAs are designed by the Office for National Statistics to contain between 1000 and 3000 residents (400 to 1200 households), with an average population of approximately 1700 in England. Their geographic size varies with population density: an LSOA in England covers about 4 km^2 on average, with urban LSOAs (e.g., in Hull) considerably smaller than rural LSOAs (e.g., in the East Riding of Yorkshire and North Lincolnshire). In our analysis, each respondent's residential postcode is linked to the corresponding LSOA to identify the deprivation level of their neighbourhoods. The 1738 respondents are located in 81 LSOAs, with about 21 respondents per LSOA on average.

The second part is police-recorded crime records sourced from Humberside Police via the UK Police Data open platform [2]. We select crime records from July 2023 to June 2024 (the 12 months immediately before fieldwork began) to ensure consistency with our survey time frame and the survey questions referring to 'the last 12 months'. All crime records within this period were aggregated into LSOA-level crime numbers to represent each neighbourhood's recent crime level, which were then also linked to residents' individual postcodes. As responses were collected between July 2024 and March 2025, this window serves as a common reference period for all respondents rather than matching each respondent's exact preceding 12 months.

3.2. Estimation Approach: Causal Forest with Double Machine Learning

The causal forest with double machine learning (CausalForestDML) framework is a machine learning-based method consisting of two components: double machine learning for flexibly adjusting for observed covariates and causal forest for estimating heterogeneous treatment effects (Athey et al. 2019; Chernozhukov et al. 2018; Wager and Athey 2018; Yao et al. 2021). Because our data is from a single cross-sectional survey without an instrument available to isolate the variation in policing perceptions, we do not claim causal identification but a conditional association between policing perception and sense of safety in this study. CausalForestDML remains quite useful in our setting for two reasons. First, it adjusts flexibly for the observed variables (e.g., demographics, prior victimisation, and neighbourhood conditions in section 3.3) without requiring a pre-specified functional form, so the estimated association between policing perceptions and sense of safety is adjusted for these observed influences more flexibly than a linear regression would allow. Second, and central to our research questions, it searches the data directly for the individual resident and neighbourhood conditions where the association between policing perceptions and sense of safety is stronger or weaker. For a study whose central aim is to examine how the association between policing perceptions and residents' sense of safety varies across diverse individual backgrounds and neighbourhood contexts, CausalForestDML is a well-suited analytical method. All analyses were conducted in Python, mainly using scikit-learn (version 1.6.1) for the random forest models and EconML (version 0.16.0) for CausalForestDML.

3.2.1. Formal Setup

We use the partially linear model that underlies CausalForestDML:

$$Y_i = \theta(\mathbf{X}_i)\, T_i + g(\mathbf{X}_i, \mathbf{W}_i) + \varepsilon_i, \qquad E[\varepsilon_i \mid \mathbf{X}_i, \mathbf{W}_i] = 0, \tag{1}$$

$$T_i = \ell(\mathbf{X}_i, \mathbf{W}_i) + \nu_i, \qquad E[\nu_i \mid \mathbf{X}_i, \mathbf{W}_i] = 0, \tag{2}$$

where Y_i is the outcome and T_i the treatment for individual i (resident), and g and ℓ are unknown functions estimated by machine learning. $\theta(\mathbf{x})$ is the slope of sense of safety on policing perceptions among residents with characteristics $\mathbf{x}$ after flexible adjustment for $\mathbf{X}_i$ and $\mathbf{W}_i$. $\theta(\mathbf{x})$ would equal a causal effect only under the additional, untestable assumptions of no unmeasured confounding and no reverse causation; as these are not plausible for cross-sectional survey data, we interpret $\theta(\mathbf{x})$ as a conditional association. In addition, both features $\mathbf{X}_i$ and controls $\mathbf{W}_i$ are covariates (adjustment variables) that may be related to both the treatment T_i and the outcome Y_i. Specifically, the $\mathbf{X}_i$ is a set of covariates that are the key variables of which heterogeneity in the estimated relationship is examined, and controls $\mathbf{W}_i$ are important to adjust for but are not the primary focus of the heterogeneity analysis. Thus, the difference between $\mathbf{X}$ and $\mathbf{W}$ lies in how they are used across the two stages of CausalForestDML as described in subsections below.

In this study, the *treatment* (T) is residents' perception of policing, the *outcome* (Y) is residents' sense of safety, and the *covariates* consist of resident and neighbourhood-level factors ($\mathbf{X}$), and the remaining set of covariates $\mathbf{W}$: residents' prior experience of crime. The detailed measurement of each variable is described in Section 3.3.

3.2.2. Double Machine Learning

In CausalForestDML, the first stage uses double machine learning to remove the shared influence (variation) of all covariates ($\mathbf{X}$ and $\mathbf{W}$) from both treatment T and outcome Y, which ensures the subsequent estimation of the relationship is based only on the independent variation between treatment T and outcome Y (Bach et al. 2022; Chernozhukov et al. 2018; Jung et al. 2021). In practice, two separate predictive models are initially set: a *treatment model* ($\hat{\ell}$) for predicting treatment T from covariates $\mathbf{X}$ and $\mathbf{W}$ alone, and an *outcome model* ($\hat{m}$) for predicting outcome Y from covariates $\mathbf{X}$ and $\mathbf{W}$ alone, where $m(\mathbf{X}, \mathbf{W}) = E[Y \mid \mathbf{X}, \mathbf{W}]$. Then residuals from each model are calculated as:

$$\tilde{Y}_i = Y_i - \hat{m}(\mathbf{X}_i, \mathbf{W}_i), \tag{3}$$

$$\tilde{T}_i = T_i - \hat{\ell}(\mathbf{X}_i, \mathbf{W}_i). \tag{4}$$

where outcome residuals ($\tilde{Y}_i$) are directly generated from the fitted outcome model ($\hat{m}(\mathbf{X}_i, \mathbf{W}_i)$) and observed outcome ($Y_i$), and treatment residuals ($\tilde{T}_i$) are directly generated from the fitted treatment model ($\hat{\ell}(\mathbf{X}_i, \mathbf{W}_i)$) and observed treatment (T_i). In this sense, the residuals remove the shared variation of covariates from both the outcome and the treatment. Specifying our analysis, for each resident i, the outcome residual ($\tilde{Y}_i$) captures the part of safety feelings that cannot be explained by covariates alone, and treatment residual ($\tilde{T}_i$) captures the part of policing perception that cannot be explained by covariates.

In this study, the treatment and outcome models are both fitted using random forest regressor (Athey et al. 2019; Breiman 2001), which is good at capturing non-linear and interaction effects in moderately high-dimensional covariate data without imposing parametric assumptions (Wager and Athey 2018). Specifically, both random forest regressors [3] were implemented using defined settings in our analysis: 500 trees with unlimited depth,

requiring at least two samples to split a node and at least five samples per leaf, with a fixed random state (42) for reproducibility. The treatment and outcome models were cross-fitted with two folds (the EconML default, cv = 2), so that each resident's residuals are obtained from models fitted without that resident's data.

3.2.3. Causal Forest

Causal forest estimates the conditional average treatment effect (CATE), which we interpret in this study as a conditional association, by regressing the residuals $\tilde{T}$ and $\tilde{Y}$ obtained from the DML stage. And only the features $\mathbf{X}$ (the socio-demographic and neighbourhood characteristics of residents in this study) are examined while the controls $\mathbf{W}$ (i.e., the experience of crime) will not be included in this stage.

Causal forest extends random forest in two ways. First, whereas a standard random forest splits nodes in decision trees to optimise prediction performance (by reducing prediction error), the causal forest selects splits to maximise heterogeneity in the estimated treatment effect (i.e., association) across subgroups. Then, the samples used to determine where to split each tree are kept separate from the samples used to estimate the treatment effect within each leaf of a tree, which can prevent overfitting and ensure valid confidence intervals (Athey and Imbens 2016).

The causal forest provides the estimate of $\theta(\mathbf{x})$ in Equation (1), which we denote $\hat{\tau}(\mathbf{x})$ hereafter. For each leaf (a group of individuals with similar characteristics/features), the CATE is estimated by running a local regression from the outcome and treatment residuals ($\tilde{Y}$ and $\tilde{T}$), which can be denoted as:

$$\hat{\tau}(\mathbf{x}) = \arg\min_{\tau} \sum_{i=1}^{N} w_i(\mathbf{x}) \left(\tilde{Y}_i - \tau\, \tilde{T}_i\right)^2 \tag{5}$$

where the $\hat{\tau}(\mathbf{x})$ is the estimated treatment effect for any covariate point $\mathbf{x}$, the value of τ is chosen to minimise the weighted sum of squared residuals across all N units via $\arg\min_{\tau}$ (Nie and Wager 2021; Robinson 1988). And $w_i(\mathbf{x})$ is the weight assigned to resident i, reflecting how often they share a leaf with the target point $\mathbf{x}$ across all B trees (the numbers of trees causal forest generates). In this study, $\hat{\tau}(\mathbf{x})$ is the estimated conditional association for any covariate values $\mathbf{x}$ of residents (e.g., age, gender, or their neighbourhood conditions), and τ is the value that best fits the data by minimising the sum of squared errors across all N samples (residents).

Thus, the estimated function $\hat{\tau}(\mathbf{X}_i)$ captures how the strength of the association between policing perception ($\tilde{T}_i$) and safety feelings ($\tilde{Y}_i$) varies across residents in different conditions by providing the continuous CATE values. In our analysis, the causal forest was set to fit with 2000 trees (i.e., B is 2000) and a minimum leaf size of 10 samples to ensure stable estimates and prevent overfitting.

3.2.4. Calibration Test

To check whether the variation in effects estimated by the causal forest reflects differences between residents rather than estimation noise, we apply the calibration test based on the best linear predictor of the residualised outcome (Athey and Wager 2019; Chernozhukov et al. 2018). The test reuses variables already produced by the CausalForestDML procedure. From the double machine learning stage we take the residualised outcome $\tilde{Y}_i$ and residualised treatment $\tilde{T}_i$. In these residuals, the sense of safety score Y_i and the policing perception score T_i have each been netted out of all the covariates. From the causal forest stage, we take each resident's predicted effect $\hat{\tau}(\mathbf{X}_i)$, which depends only

on the heterogeneity variables $\mathbf{X}_i$, together with the average predicted effect $\bar{\tau}$. These are combined in the regression, which is expressed as:

$$\tilde{Y}_i = \alpha\,(\bar{\tau}\,\tilde{T}_i) + \beta\,((\hat{\tau}(\mathbf{X}_i) - \bar{\tau})\,\tilde{T}_i) + u_i \quad (6)$$

which is fitted without a constant term, since the residualised outcome has mean zero by construction. The first term rescales the residualised treatment by the average predicted effect, and the second rescales it by how far each resident's predicted effect lies from that average. The two coefficients α and β are estimated by ordinary least squares, with standard errors that remain valid even if the error variability differs across residents. The coefficient α shows whether the forest's average effect is on the right scale. A value near one means the average association between policing perceptions and sense of safety is neither over- nor under-stated. The coefficient β shows whether the differences the forest reports across residents are real. A value above zero means that residents whom the forest predicts to have a stronger association, on the basis of their characteristics $\mathbf{X}_i$, do in fact show a stronger association in the data. A one-sided test of $\beta > 0$ is therefore the overall test for whether any heterogeneity is present. In this study, the test is carried out in sample, and its inputs are obtained as follows. The residuals $\tilde{Y}_i$ and $\tilde{T}_i$ are the cross-fitted residuals from the double machine learning stage (two folds, as described above). The predictions $\hat{\tau}(\mathbf{X}_i)$ are obtained by fitting the causal forest to the full sample of 1738 respondents and then predicting the association for each respondent from their own characteristics $\mathbf{X}_i$; $\bar{\tau}$ is the mean of these predictions. These three quantities are then combined as in Equation (6). Because our aim is to interpret associations rather than to make predictions for new respondents, the data were not split into separate training and test sets, and the calibration test reported here is therefore an in-sample test. As each respondent also contributes to the forest that produces their own prediction, an in-sample test can be more favourable to detecting heterogeneity, and its results are interpreted cautiously.

3.3. Measures in This Study

This section describes the measurement of all variables used in the analysis. The outcome variable (residents' sense of safety) is introduced alongside the treatment variable of perceptions of policing, and a set of demographic and neighbourhood condition covariates drawn from the survey questions. For each variable, Table A1 in Appendix A presents the corresponding survey question, variable names, and answer options with encoding scheme (i.e., the variable values).

3.3.1. Outcome: Sense of Safety

Residents' sense of safety (Y) was measured using two survey items (see Q16 and Q17 of the Table A1 in Appendix A) asking residents to rate their feelings of personal safety in their neighbourhood during the daytime and at nighttime, respectively. Rather than treating daytime and nighttime safety as separate outcomes, we constructed a composite sense of safety score by applying Principal Component Analysis (PCA) to the two standardised variables to get a sense of safety score. PCA reduces a set of correlated variables into a smaller number of uncorrelated components that successively maximise variance, which could minimise information loss without imposing arbitrary weights on individual items (Jolliffe and Cadima 2016).

PCA is widely used in social science research to derive composite indicators or scores from multiple related items, like calculating rich survey data into a single measure (Dabbous et al. 2025; Geron et al. 2023). In this analysis, the two variables will be standardised (z-scores) first then go to the PCA. Next, the first principal component from PCA was used as the outcome variable as the sense of safety score (i.e., the outcome Y), with

higher values indicating a greater overall sense of safety level. In addition, the explained variance ratio (EVR) was used for quantifying the proportion of total variance captured by the first component. A higher EVR indicates that the component summarises a greater share of the information contained in the original variables, while a lower EVR suggests that the component captures only a small portion of shared variance.

3.3.2. Treatment: Perception of Policing

Perception of policing (T) was measured using three survey questions reflecting police visibility, helpfulness, and reporting likelihood from residents' perspectives. *Police visibility*. The first item (Q13 of the Table A1 in Appendix A) asked whether respondents had seen the police in their area in the last 12 months, capturing the visibility dimension of policing. *Police helpfulness*. The second item (Q14 of the Table A1 in Appendix A) asked whether respondents found the police to have been more helpful over the same period, reflecting a performance-based judgement of policing quality (Jackson and Bradford 2009). *Reporting likelihood*. The third item (Q15 of the Table A1 in Appendix A) asked how likely respondents were to report any crime to the police in the future, capturing residents' forward-looking confidence in the police as a responsive institution (Sunshine and Tyler 2003; Tyler and Huo 2002). Following the same procedure applied to the sense of safety score, these three items were standardised and reduced to a single composite score as the perception of policing score using PCA. Thus, the first principal component was generated as the treatment variable T, with higher scores indicating more positive overall perceptions of policing. The 'don't know' response to the helpfulness item was placed between 'no' and 'yes' (Table A1). Because the item asks whether the police have become more helpful over the last 12 months, 'yes' indicates a perceived improvement and 'no' indicates that no improvement was perceived, whereas 'don't know' indicates that respondents could neither confirm nor deny an improvement. It was therefore treated as an intermediate (neutral) position on the ordinal scale rather than as missing, which would have required these respondents to be excluded or imputed. Reporting likelihood is often treated as an outcome of evaluations of the police (Sunshine and Tyler 2003); we include it as an indicator of forward-looking confidence in police responsiveness. The composite score is therefore treated as a summary index of three related but distinct aspects of policing rather than as a measure of a single latent construct.

3.3.3. Covariates

A rich set of individual- and neighbourhood-level features ($\mathbf{X}$) and controls including experience of crime ($\mathbf{W}$) were included as covariates in this analysis.

Demographic characteristics. Individual-level demographic variables included age, gender, living time (length of residence in the neighbourhood), ethnicity, and education (see the corresponding survey questions from Q1 to Q5 of Table A1 in Appendix A). Nominal variables (gender, ethnicity, education, and crime types) entered the models with the integer codes shown in Table A1. Because tree-based learners can isolate any single category through successive splits, this coding does not restrict the groupings that the forests can form, although it determines the order in which threshold splits are considered.

Neighbourhood conditions. Two neighbourhood-level variables were linked to each respondent via residents' provided residential postcodes (see Q6 of Table A1). The LSOA-level Index of Multiple Deprivation (IMD) 2025 was attached from corresponding postcodes using ONS official lookup [4] . The number of police-recorded crimes (July 2023 to June 2024) in the respondent's LSOA was also linked to resident's postcode to reflect the recent crime level in neighbourhoods (the 12 months before fieldwork began).

Experience of crime. Three binary variables recorded whether the resident had personally been a victim of crime, had witnessed a crime, or had experienced crime through someone else close to them in the last 12 months with corresponding types of crime involved in each question (see Q7 to Q12 of Table A1). Prior victimisation and crime exposure are well-established factors influencing both safety feelings and police evaluations, so adjusting for them prevents these experiences from being conflated with the association between policing perceptions and sense of safety.

Operationalisation of missing data. In the survey data processing, non-response item was recoded as missing prior to analysis. Then, ordinal variables (age, living time, police visibility, police helpfulness, reporting likelihood, and the two safety items) were imputed using their sample medians. Categorical variables (e.g., gender, ethnicity, education, and crime types) were assigned a distinct -1 category, retaining non-disclosure as an informative category rather than imputing a substantive value.

4. Results

4.1. Variation in Sense of Safety and Perception of Policing Across Demographics and Neighbourhood Conditions

After implementing data preprocessing and PCA, we get the two primary metrics: the perception of policing score and the sense of safety score. The first principal component explained 51% of the standardised variance of the three policing items (police visibility, helpfulness, and reporting likelihood) and 88% of that of the two safety items (daytime and nighttime safety). As an explained variance ratio is not a test of reliability or unidimensionality, the inter-item correlations and component loadings are reported in Tables A4 and A5 in Appendix A. The three policing items are positively but moderately correlated (Spearman ρ = 0.17–0.41), and all three load substantially on the first component (loadings 0.56–0.79), whereas the two safety items are strongly correlated (ρ = 0.74; loadings 0.94). Accordingly, the policing score is interpreted as a summary index of three related but distinct aspects of policing. Table 1 shows the descriptive statistics of the perception of policing and sense of safety variables. Specifically, the higher values of the two scores represent more positive perceptions of policing and greater sense of safety on their neighbourhoods. In addition, Table A2 in Appendix A shows the descriptive statistics for demographics, neighbourhood condition, and experience of crime. It should be noted that among our survey respondents, 20.6% reported being a victim of crime, 40.4% witnessed a crime, and 46.3% knew someone who had been a victim in the last 12 months. In particular, antisocial behaviour was the most frequently reported crime type, followed by burglary and theft.

Table 1. Descriptive statistics: perception of policing and sense of safety.

	Variable	*N*	Missing	Mean	SD	Min	Max
Perception of Policing	Police Visibility	1729	9 (0.5%)	0.67	0.47	0	1
	Police Helpfulness	1731	7 (0.4%)	0.85	0.69	0	2
	Reporting Likelihood	1727	11 (0.6%)	2.92	1.24	0	4
	Perception of Policing Score	1738	—	0.00	1.24	−2.91	1.92
Sense of Safety	Daytime Safety	1729	9 (0.5%)	2.60	1.04	0	4
	Nighttime Safety	1733	5 (0.3%)	2.08	1.12	0	4
	Sense of Safety Score	1738	—	0.00	1.32	−3.08	2.17

We also examined the Pearson correlation across all variables, as shown in Figure 1. Only correlations with a *p*-value below 0.05 are displayed, indicating statistical significance. It can be observed that the perception of policing score is positively correlated with the

sense of safety score, suggesting a promising relationship between the two variables in this study. Additionally, several demographics, such as living time and ethnicity, alongside neighbourhood condition (IMD and crime numbers), and experience of crime are found to be negatively correlated with both perception of policing and sense of safety. As these variables are related to both scores, they are included as covariates in the models to adjust for their relationship with the perception of policing and sense of safety.

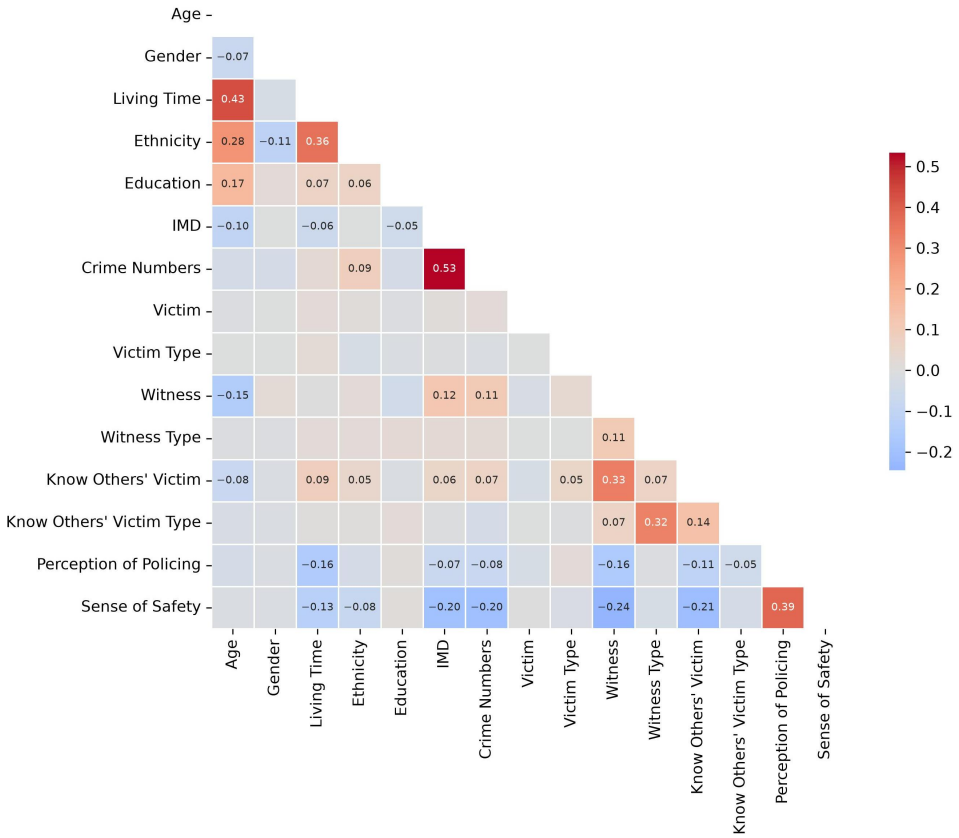


Figure 1. Pearson correlation heatmap of all variables. Categorical variables enter with the codes given in Table A1; correlations involving nominal variables (gender, ethnicity, and education) therefore depend on the coding and should be read as indicative only.

For an examination of how the difference in perception of policing and sense of safety is distributed in the groups with various demographic and neighbourhood conditions, Figure 2 shows the mean scores across four significantly correlated variables: ethnicity, length of residence, IMD, and crime numbers. Regarding ethnicity, Black respondents reported the highest mean scores for both perception of policing and sense of safety, while Mixed respondents scored lowest on both measures. White respondents clustered close to zero, and Asian respondents reported similar perceptions of policing to white respondents but a higher sense of safety; estimates for the Asian, Mixed, and Other groups are based on small samples. In terms of length of residence, both scores were highest among those who had lived in the neighbourhood for less than one year and declined progressively with longer residency, with those living there for more than five years reporting near-zero or slightly negative scores; this descriptive pattern may partly reflect differences in the composition of these groups. For IMD quintile (five levels), sense of safety declined steadily from the least to the most deprived quintile, reaching approximately −0.5 in the most deprived quintile. Perceptions of policing showed a weaker and less consistent gradient: the most deprived quintile had the lowest mean score, but differences among the other quintiles were small and did not follow a monotonic pattern. For crime numbers

(the previous year) quintile (five levels), sense of safety was highest in the lowest-crime neighbourhoods and lowest in the highest-crime neighbourhoods, with a similar but less pronounced pattern for perceptions of policing. For other demographics, Figure A1 in Appendix A shows the distribution of the two scores in different age, gender and education groups. For age and education, which were not linearly correlated with either score (Figure 1), mean scores varied between groups but without a consistent gradient; gender differences were minimal.

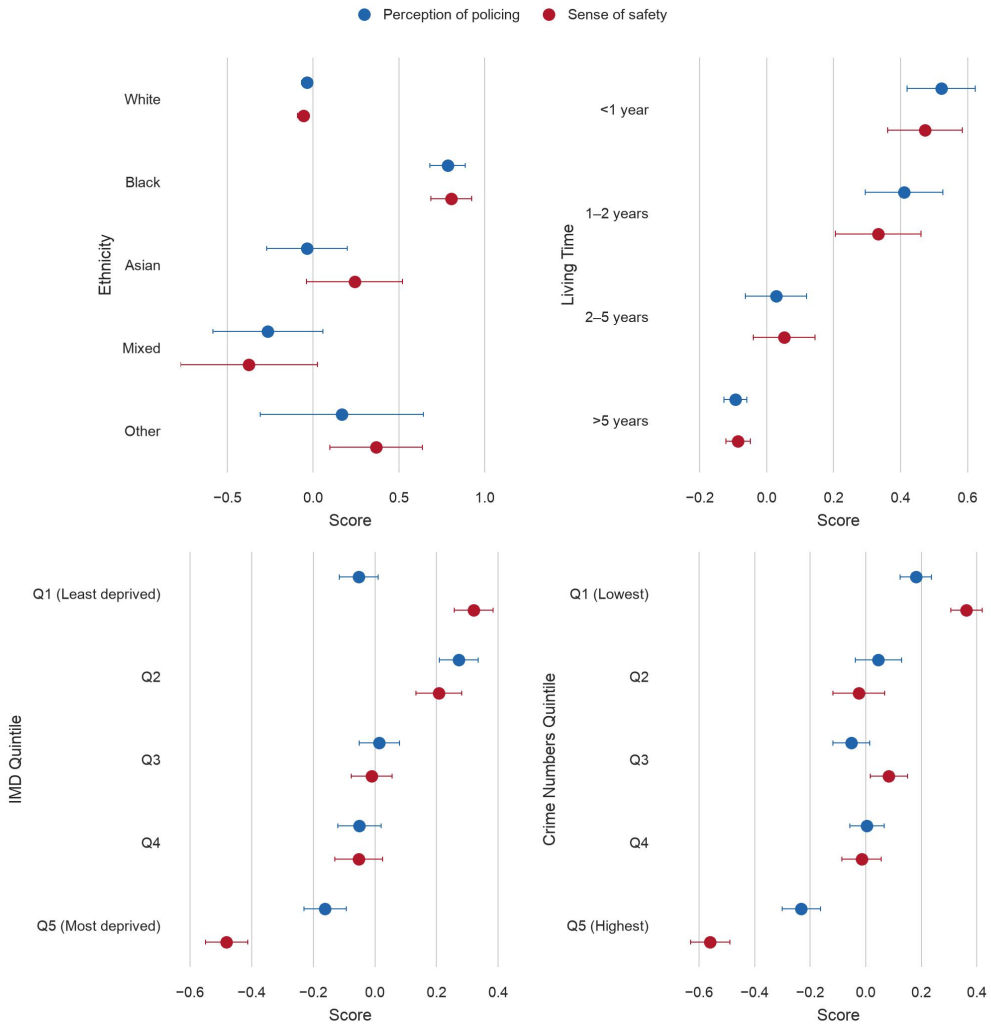


Figure 2. The distributions of perception of policing and sense of safety scores in groups with different ethnicities, living times, IMD, and crime numbers. Points show group means; error bars show ± one standard error.

4.2. Heterogeneity in the Association Between Perception of Policing and Sense of Safety

To estimate this conditional association, the covariates (including demographics, neighbourhood conditions, and experience of crime), treatment (perceptions of policing score), and outcome (sense of safety score) were entered into the causal forest with a double machine learning framework to generate the CATE at the individual level. Figure 3 shows the distribution of the CATE values, i.e., the estimated individual-level conditional association between perceptions of policing and sense of safety. This association was positive and statistically significant on average, with an estimated average CATE of 0.303 (95% CI: [0.181, 0.425]), indicating that residents with more positive perceptions of policing report a greater sense of safety in their neighbourhood. The fitted CATE was positive for every respondent (range 0.17–0.44; Table A3 in Appendix A). Because the policing

and safety scores are PCA scores with standard deviations of 1.24 and 1.32, respectively (Table 1), the average association corresponds to approximately 0.28 of a standard deviation in sense of safety per standard deviation of policing perceptions, reflecting a moderate relationship strength.

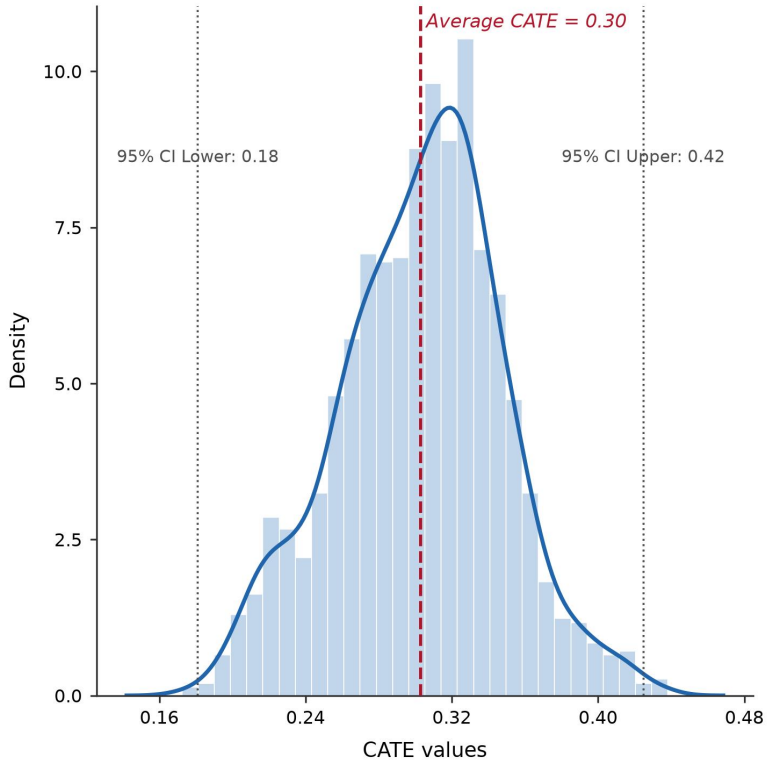


Figure 3. Distribution of estimated conditional associations (CATEs) between perceptions of policing and sense of safety across all respondents. The blue line shows the kernel density estimate of the distribution.

The calibration test (introduced in Section 3.2.4) is reported in Table 2. The average effect coefficient $\alpha = 1.025$ (SE $= 0.069$) is close to, and statistically indistinguishable from, one, indicating that the forest's average estimate of the association (approximately 0.303) is on the right scale. The heterogeneity coefficient $\beta = 6.479$ (SE $= 0.429$, $p < 0.001$) is above zero, so the test rejects the null of no heterogeneity. A value well above one, however, indicates that the forest's individual predictions are strongly compressed towards the mean: they may rank respondents informatively but should not be read as precise estimates of the size of individual differences. Moreover, as described in Section 3.2.4, the test is based on in-sample predictions, which can be more favourable to detecting heterogeneity, so it provides only limited evidence that the forest identifies systematic individual-level heterogeneity beyond estimation noise. Accordingly, we focus on group-level estimates with confidence intervals (Table A3) and interpret the heterogeneity results cautiously.

Table 2. Calibration test result for the association heterogeneity (in-sample forest predictions).

Parameter	Estimate	Std. Error	t	p
α (average effect coefficient)	1.025	0.069	14.93	<0.001
β (heterogeneity coefficient)	6.479	0.429	15.11	<0.001

To assess robustness to tuning choices, the model was re-estimated over a full factorial grid of 81 specifications that varied the maximum depth and minimum leaf size of the

random forests used for the treatment and outcome models and the minimum leaf size and number of trees of the causal forest (Table A6 in Appendix A). The average association was highly stable, ranging from 0.287 to 0.318 across all specifications with 95% confidence intervals well above zero, and α remained close to one (1.00–1.03), indicating that the average association does not depend on the particular tuning choices.

To characterise how the association varies across groups, Figure 4 presents the distributions of fitted CATE values across age, gender, ethnicity, and IMD, and Table A3 in Appendix A reports, for each subgroup, a group-specific estimate of the average association with its 95% confidence interval, together with summary statistics of the fitted CATEs. These subgroup intervals are based on the doubly robust scores (see the note to Table A3) and are therefore narrower than, and not directly comparable with, the interval for the overall average reported above, which is obtained from the causal forest's own inference; they are intended for comparisons between subgroups. Overall, differences between pre-defined groups are modest relative to the variation within them: the median fitted CATEs of most groups differ by only about 0.01–0.04, within-group standard deviations (0.03–0.06) are of similar or larger size, and the confidence intervals of the group-specific estimates overlap for most contrasts. Because the heterogeneity variables are correlated with one another (Figure 1), these one-variable-at-a-time summaries describe how the fitted associations are distributed across groups but cannot show that any single characteristic independently accounts for the variation; the fitted CATEs themselves are a joint function of all heterogeneity variables, so their overall distribution (Figure 3) summarises the joint variation. Regarding age (upper left panel), CATE values were similar across age groups, with no consistent age gradient; the group-specific estimates fluctuate between adjacent age groups and have wide, overlapping confidence intervals. For gender (upper right panel), the association was very similar for women and men (median fitted CATE 0.314 vs. 0.297; group estimates 0.332 [0.266, 0.398] and 0.272 [0.204, 0.341], respectively). In terms of ethnicity (lower left panel), white respondents show a somewhat higher median CATE (0.309) than Black (0.290) and Asian (0.261) respondents; these differences are suggestive only, as the confidence intervals for the Black and Asian groups are wide and overlap with that for white respondents, and the estimates for the Mixed and Other groups ($n < 20$) are too imprecise to interpret. The IMD quintile panel (lower right) shows the clearest pattern among the pre-defined groups: median fitted CATEs are highest in the least deprived quintile (0.327) and lower in the third to fifth quintiles (0.286–0.292), and the group estimates follow the same direction (0.355 in Q1 vs. 0.274 in Q4 and Q5), although their confidence intervals overlap.

In addition, Figure A2 in Appendix A presents the CATE distributions for the remaining three variables: living time, education, and crime numbers. The CATE distributions across living time groups are closely overlapping, with all four groups (less than one year, 1–2 years, 2–5 years, and over five years) showing median CATE values near 0.30 and similar ranges. For education level (upper right panel), a non-linear pattern is observed: residents with A-levels/BTEC qualifications show the lowest median CATE and group estimate (0.192 [0.100, 0.283]), while undergraduates show a higher group estimate (0.366 [0.261, 0.470]). The crime numbers quintile panel (lower) shows a non-monotonic pattern: the association is lowest in the second crime quintile (0.154 [0.005, 0.304]) and highest in the third and fourth quintiles (0.349 and 0.380), before declining again in the highest-crime quintile. These education and crime-level patterns were not anticipated and should be regarded as exploratory. Estimates for small subgroups (Asian respondents, $n = 23$; respondents aged 16–19, $n = 36$; Mixed and Other ethnic groups and the Other gender category, $n < 20$) are imprecise and should be regarded as indicative only. Full statistics of the conditional associations (CATE) between perception of policing and sense of safety for each subgroup is included in Table A3 in Appendix A.

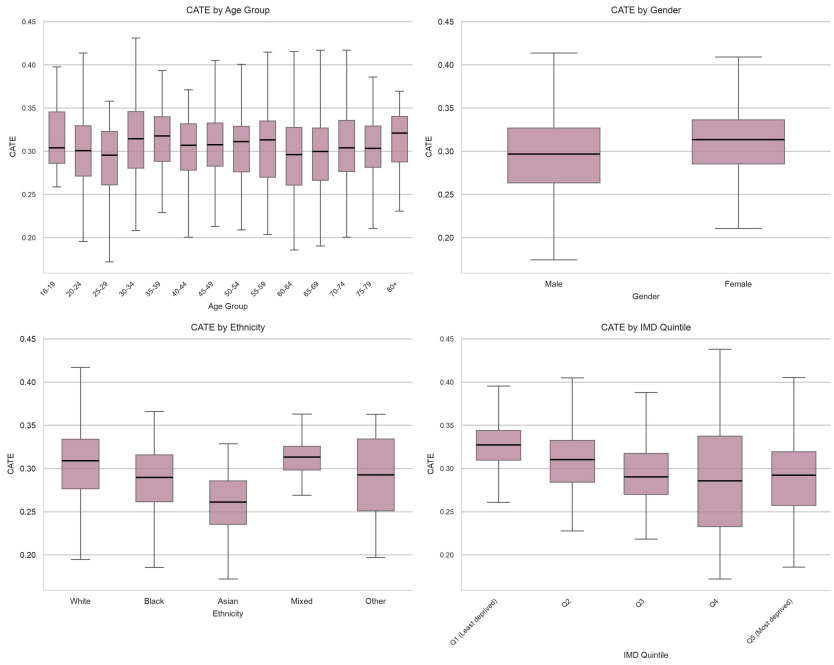


Figure 4. Estimated conditional associations (CATEs) between perceptions of policing and sense of safety across demographic and neighbourhood condition groups (age, gender, ethnicity, and IMD).

5. Discussion

This study provides new empirical insights into the association between policing perceptions and residents' sense of safety, and into how this association varies across individual backgrounds and neighbourhood contexts. The estimated average CATE of 0.303 (95% CI: [0.181, 0.425]) indicates that more positive perceptions of policing are associated with a greater sense of safety (approximately 0.28 of a standard deviation in the safety score per standard deviation of policing perceptions), and this average was stable across alternative model specifications. Beyond this average, the contribution of this study lies in examining how this association varies across residents. Unlike conventional regression, which requires interactions and nonlinearities to be specified in advance, the causal forest searches for such variation in a data-driven way, which is the key advantage of the method in this setting. The dominant pattern, however, is a broadly consistent positive association: differences between pre-defined demographic and neighbourhood groups were modest, their confidence intervals largely overlapped, and the clearest between-group difference concerned neighbourhood deprivation. Furthermore, the variation in the fitted associations within groups was as large as, or larger than, the differences between them. This suggests substantial residual heterogeneity within groups, implying that characteristics not measured here, such as prior police contact, collective efficacy, perceived disorder, and general institutional trust, may account for much of the variation in the association, which points to a need for future research.

Overall, the positive conditional association is consistent with evidence that public confidence in the police and residents' concerns about crime and safety are closely intertwined (Jackson and Bradford 2009; Jackson et al. 2009; Skogan 2009). Contrary to the vulnerability perspective, which proposes that older adults perceive themselves as less capable of self-protection (Golovchanova et al. 2023) and might therefore place greater weight on institutional sources of security (including police), the association did not vary systematically with age. The association was also very similar for women and men. Thus, despite women's generally higher fear of crime (Ferraro 1995), our data do not indicate

that women's sense of safety is more closely tied to their perceptions of policing than that of men.

Our findings suggest a somewhat weaker association among Black and Asian residents than among white residents, which would be consistent with evidence that residents from ethnic minority backgrounds in both the United States and the United Kingdom hold more sceptical evaluations of police legitimacy (Millings 2013; Tuch and Weitzer 1997; Weitzer 2000). However, these differences are imprecise and based on small subgroups (particularly Asian respondents, $n = 23$), and should be regarded as indicative only; larger samples are needed to establish whether they are reliable.

Consistent with theoretical expectations, the association (alongside the sense of safety score) tends to be weaker in more deprived neighbourhoods, although the confidence intervals for the deprivation quintiles overlap. This finding is in line with structural accounts of neighbourhood safety, which argue that concentrated disadvantage suppresses residents' sense of safety through multiple factors (like elevated victimisation risk, reduced collective efficacy, and greater exposure to physical and social disorder) that may also reduce the potential of positive policing perceptions (Brunton-Smith and Sturgis 2011). The finding also resonates with research showing that residents of disadvantaged neighbourhoods tend to be less satisfied with the police and more cynical about the law (Reisig and Parks 2000; Sampson and Bartusch 1998), which may weaken the extent to which positive views of policing accompany feeling safe. The association also varied non-monotonically across crime quintiles (lowest in Q2, highest in Q3–Q4). This pattern was not anticipated and should be regarded as exploratory. One possible interpretation, to be tested in future work, is that policing perceptions are most closely tied to feelings of safety where crime is salient but not overwhelming, whereas in the highest-crime areas intensive enforcement activity may signal danger rather than reassurance (Hinkle and Weisburd 2008; Veer et al. 2012).

Several alternative explanations for these patterns should be considered. First, the association may run partly from safety to policing perceptions: residents who feel unsafe may evaluate the police more negatively, and prior research treats confidence in policing partly as an expression of concerns about neighbourhood order and cohesion (Jackson and Bradford 2009; Jackson and Sunshine 2007). Second, unmeasured factors such as general institutional trust, neighbourhood attachment, collective efficacy, prior police contact and perceived disorder may shape both perceptions. If these processes differ by deprivation or ethnicity, they could produce heterogeneity in the conditional association without any corresponding heterogeneity in the effect of changing policing perceptions. Double machine learning improves the flexibility of adjustment for observed covariates but does not address reverse causation or unmeasured common causes. The subgroup differences reported here should therefore be read as descriptive of the adjusted association, not as differences in responsiveness to policing.

These findings generate hypotheses for policing practice that require testing rather than immediate implementation. First, if the stronger association observed in less deprived neighbourhoods reflects a causal pathway, visibility- and responsiveness-oriented activities might yield larger improvements in felt safety there than in more deprived areas. Second, the weaker association in the most deprived neighbourhoods (and, more tentatively, among Black and Asian respondents) is consistent with, though cannot demonstrate, the argument that procedural fairness and community legitimacy condition whether positive views of policing accompany feeling safe. Because this study measured neither procedural fairness, legitimacy, intervention effects, nor costs, these hypotheses require experimental or longitudinal evaluation of specific policing initiatives. Finally, the weaker association in deprived neighbourhoods is compatible with the view that policing alone is unlikely to be sufficient to improve feelings of safety where structural disadvantage is concentrated,

and that complementary investments in social infrastructure (like housing, employment, education, and community services) may also be needed.

Methodologically, this study illustrates how CausalForestDML can complement standard regression approaches by adjusting flexibly for observed covariates and searching for heterogeneity without imposing parametric assumptions or pre-specifying interaction terms. Regression with pre-specified interactions remains a transparent alternative and can recover the same group contrasts when the relevant moderators are specified in advance; the causal forest is most useful when, as here, it is not known beforehand which characteristics, or combinations of characteristics, may moderate the association. This allows the identification of sub-populations in which the adjusted association between policing perceptions and sense of safety is stronger or weaker. Whether these groups would also respond more strongly to policing interventions cannot be established with cross-sectional data and should be tested with experimental or longitudinal designs.

Several limitations of this study should be acknowledged. First, while a rich set of covariates was included (demographics, neighbourhood conditions, and experience of crime), they can only be measured with current observational data; unmeasured confounding and reverse causation may bias the estimated associations, as discussed above, and the estimates should not be read as causal effects. Second, because policing perceptions and sense of safety were reported by the same respondents at the same time, the association may be inflated by common-method variance, including mood-congruent responding, whereby respondents in a more positive mood rate both the police and their neighbourhood more favourably. Third, there is potential bias in the survey data. The sample is a non-probability sample in which older, long-resident, and white respondents are over-represented: 89.7% of respondents identified as white, 74.6% had lived in the area for over five years, and around 38% of respondents with valid age data were aged 65 or over. The survey also has limited sample sizes for certain subgroups; estimates for small subgroups (Asian respondents, $n = 23$; respondents aged 16–19, $n = 36$; mixed and other ethnic groups; and the Other gender category, $n < 20$) are imprecise and should be regarded as indicative only. In addition, the data were collected from a single region (Humberside, England), so the findings may not transfer directly to other policing contexts across England and Wales or internationally. Fourth, the policing perception score is a summary index of three moderately correlated items (EVR = 0.51) rather than a measure of a single latent construct, so the measurement model could be strengthened in future surveys. Fifth, missing values in the treatment and outcome items were median-imputed and missing categorical responses were coded as a separate category. Median imputation reduces variance, alters the covariance structure among items and treats imputed values as observed, so uncertainty may be understated; multiple imputation or machine-learning-based imputation (Enders 2025) is a direction for future research. Sixth, tree-based estimators can be conservative in detecting heterogeneity, and the degree of heterogeneity detected can depend on the learner used (Carvalho et al. 2019). In addition, because the data were not split into separate training and test sets, the calibration test was carried out in sample only, and no out-of-sample test of heterogeneity is reported; as in-sample tests can be more favourable to detecting heterogeneity, the evidence for individual-level heterogeneity in this study is limited. Comparing alternative heterogeneity learners was also beyond the scope of this study. Finally, respondents are nested within 81 LSOAs (about 21 respondents per LSOA on average) and the neighbourhood variables (IMD and crime numbers) vary only at the LSOA level; as the models do not account for this dependence, the precision of estimates relating to neighbourhood characteristics may be overstated.

6. Conclusions

This study investigated how the association between policing perceptions and residents' sense of safety varies across residents, using a CausalForestDML framework applied to community survey data from the Humberside region of England. The findings suggest that the link between public confidence and feelings of safety may not be identical across all resident subgroups, although differences between pre-defined groups are modest.

Firstly, we find a positive average association between policing perceptions and safety feelings (average CATE = 0.303, 95% CI: [0.181, 0.425]), consistent with established evidence linking public confidence in the police to perceived personal safety. Then, the analysis indicates some variation in this association across residents, although differences between pre-defined groups were modest, their confidence intervals largely overlapped, and much of the variation lay within rather than between groups. The association was somewhat stronger among residents of less deprived areas and weaker among residents of the most deprived neighbourhoods and, more tentatively, among Black and Asian respondents, although the latter estimates are imprecise. The association did not vary systematically with age and was very similar for women and men.

Future research should extend this approach to other geographic regions and policing contexts to assess the generalisability of these heterogeneous associations. Longitudinal data would allow examination of how the association between policing perceptions and sense of safety changes over time as communities evolve and policing styles shift. Furthermore, there is a vital need for larger datasets to ensure the accurate representation of ethnic minorities and more broadly marginalised groups, which is essential for obtaining precise subgroup estimates. Additional dimensions of policing, such as the quality of police-initiated contacts, procedural justice in specific interactions, and exposure to community policing initiatives, may further condition the associations identified here and warrant investigation, as may other unmeasured characteristics (such as prior police contact, collective efficacy, perceived disorder, and general institutional trust) that could account for the variation within groups. Experimental and quasi-experimental designs that can directly test whether the associations reported here reflect causal effects would also provide valuable validation of the observational estimates reported in this study.

Author Contributions: Conceptualization, T.C., N.O. and S.G.; methodology, T.C.; software, T.C.; validation, T.C., N.O., S.G. and B.D.; formal analysis, T.C.; investigation, T.C., N.O. and S.G.; resources, N.O. and S.G.; data curation, T.C.; writing—original draft preparation, T.C.; writing—review and editing, T.C., N.O., S.G. and B.D.; visualization, T.C.; supervision, N.O. and S.G.; project administration, N.O. and S.G.; funding acquisition, N.O. and S.G. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Full ethical approval was obtained from the Faculty of Arts, Cultures, and Education Ethics Committee at the University of Hull (Reference number: 2324STAFF32).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The Index of Multiple Deprivation and police-recorded crime data used in this study are publicly available from the sources described in Section 3. The survey data are not publicly available because of the sensitivity of individual-level data. Further inquiries can be directed to the corresponding author.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BTEC	Business and Technology Education Council
CATE	Conditional Average Treatment Effect
CausalForestDML	Causal Forest with Double Machine Learning
CI	Confidence Interval
DML	Double Machine Learning
EVR	Explained Variance Ratio
GCSE	General Certificate of Secondary Education
IMD	Index of Multiple Deprivation
LSOA	Lower Super Output Area
ONS	Office for National Statistics
PCA	Principal Component Analysis
SD	Standard Deviation
SE	Standard Error
UK	United Kingdom
US	United States

Appendix A

Table A1. Survey variable codebook.

Category	Variable	Question	Answer Options & Encoding
Demographics	Age	Q1. Age	16–19 (0); 20–24 (1); 25–29 (2); 30–34 (3); 35–39 (4); 40–44 (5); 45–49 (6); 50–54 (7); 55–59 (8); 60–64 (9); 65–69 (10); 70–74 (11); 75–79 (12); 80+ (13)
	Gender	Q2. Gender	Man (0); Woman (1); Other (2)
	Living Time	Q3. How long have you lived in the area?	Less than 1 year (0); 1–2 years (1); 2–5 years (2); Over 5 years (3)
	Ethnicity	Q4. Ethnicity	Asian (0); Black (1); Mixed (2); Other (3); White (4)
	Education	Q5. Highest earned level of qualification	GCSE (0); A-levels/BTEC (1); Undergraduate (2); Postgraduate (3); PhD (4); Other (5)
Neighbourhood Conditions	IMD	Q6. Please enter your full postcode here	Postcode is used to link the IMD score (higher = more deprived) at LSOA-level
	Crime Numbers		Postcode is used to link to area crime count at LSOA-level
Experience of Crime	Victim	Q7. In the last 12 months, would you describe yourself as the victim of a crime?	No (0); Yes (1)
	Victim Type	Q8. What type of crime? (as victim)	Anti-Social Behaviour (0); Burglary (1); Theft (2); Violent crime (3)
	Witness	Q9. Have you witnessed a crime in the last 12 months?	No (0); Yes (1)
	Witness Type	Q10. What type of crime? (as witness)	Anti-Social Behaviour (0); Burglary (1); Theft (2); Violent crime (3)
	Know Others' Victim	Q11. Do you know anyone that has experienced crime in the last 12 months?	No (0); Yes (1)
	Know Others' Victim Type	Q12. What type of crime? (experienced by someone else)	Anti-Social Behaviour (0); Burglary (1); Theft (2); Violent crime (3)
Perception of Policing	Police Visibility	Q13. Have you seen the police in your area?	No (0); Yes (1)
	Police Helpfulness	Q14. In the last 12 months, have you found the police to have been more helpful?	No (0); Yes (2); I don't know (1)
	Reporting Likelihood	Q15. In the future, how likely are you to report any crime to the police?	Very unlikely (0); Not likely (1); Neutral (2); Likely (3); Very likely (4)
Sense of Safety	Daytime Safety	Q16. Your neighbourhood is safe—Daytime	Strongly disagree (0); Disagree (1); Neutral (2); Agree (3); Strongly agree (4)
	Nighttime Safety	Q17. Your neighbourhood is safe—Night-time	Strongly disagree (0); Disagree (1); Neutral (2); Agree (3); Strongly agree (4)

Table A2. Descriptive statistics: demographics, neighbourhood condition, and experience of crime.

	Variable	Type/Value	*n*	%
Demographics	**Age** ($N = 1615$; Missing: 123, 7.1%)	16–19	36	2.2
		20–24	56	3.5
		25–29	82	5.1
		30–34	103	6.4
		35–39	80	5.0
		40–44	103	6.4
		45–49	94	5.8
		50–54	122	7.6
		55–59	151	9.3
		60–64	172	10.7
		65–69	228	14.1
		70–74	199	12.3
		75–79	129	8.0
		80+	60	3.7
	Gender ($N = 1659$; Missing: 79, 4.5%)	Man	810	48.8
		Woman	831	50.1
		Other	18	1.1
	Living Time ($N = 1712$; Missing: 26, 1.5%)	Less than 1 year	140	8.2
		1–2 years	106	6.2
		2–5 years	189	11.0
		Over 5 years	1277	74.6
	Ethnicity ($N = 1664$; Missing: 74, 4.3%)	White	1493	89.7
		Black	117	7.0
		Asian	23	1.4
		Mixed	19	1.1
		Other	12	0.7
	Education ($N = 1534$; Missing: 204, 11.7%)	GCSE or equivalent	280	18.3
		A-level/BTEC	427	27.8
		Undergraduate degree	327	21.3
		Postgraduate degree	348	22.7
		PhD	36	2.3
		Other	116	7.6
Neighbourhood Condition	**IMD** ($N = 1738$)	Mean: 24.59 (SD: 18.06) Min: 1.79; Max: 82.88		
	Crime Numbers ($N = 1738$)	Mean: 128.02 (SD: 109.06) Min: 0.00; Max: 556.00		
Experience of Crime	**Victim** ($N = 1702$; Missing: 36, 2.1%)	No	1351	79.4
		Yes	351	20.6
		Anti-Social Behaviour	186	56.2
		Burglary	44	13.3
		Theft	53	16.0
		Violent crime	48	14.5
	Witnessed ($N = 1700$; Missing: 38, 2.2%)	No	1013	59.6
		Yes	687	40.4
		Anti-Social Behaviour	488	73.8
		Burglary	33	5.0
		Theft	81	12.3
		Violent crime	59	8.9
	Known Others' Victim ($N = 1681$; Missing: 57, 3.3%)	No	902	53.7
		Yes	779	46.3
		Anti-Social Behaviour	313	42.7
		Burglary	197	26.9
		Theft	152	20.7
		Violent crime	71	9.7

Table A3. Conditional associations between perception of policing and sense of safety across respondent and neighbourhood subgroups. *Subgroup estimate*: the group-specific average association, computed as the mean of the doubly robust scores $\psi_i = \hat{\tau}(\mathbf{X}_i) + \tilde{T}_i(\tilde{Y}_i - \hat{\tau}(\mathbf{X}_i)\tilde{T}_i)/\mathrm{Var}(\tilde{T})$ of the respondents in the subgroup, where $\tilde{Y}$ and $\tilde{T}$ are the cross-fitted residuals. Because ψ_i adds a residual-based correction to each fitted CATE, the subgroup estimate is not the average of the fitted CATEs and can lie outside their min–max range, particularly in small subgroups. The 95% CI of each subgroup estimate is based on the standard error of the doubly robust scores within the subgroup, so intervals narrow with subgroup size. For the overall row, the estimate and its 95% CI are those of the average association obtained from the causal forest's own inference, as reported in the main text. *Individual CATEs*: median, SD, min, and max of the fitted CATEs within the subgroup. Missing age and living time were median-imputed before the analysis, so the imputed respondents are counted in the 55–59 (123 respondents) and >5 years (26 respondents) categories; respondents with missing gender, ethnicity or education are excluded from the breakdown but retained in the overall row.

Subgroup	*N*	Subgroup Estimate		Individual CATEs			
		Estimate	95% CI	Median	SD	Min	Max
All respondents	1738	0.303	[0.181, 0.425]	0.306	0.045	0.172	0.438
Gender							
Male	810	0.272	[0.204, 0.341]	0.297	0.044	0.175	0.414
Female	831	0.332	[0.266, 0.398]	0.314	0.045	0.172	0.438
Other	18	0.388	[0.055, 0.721]	0.316	0.037	0.264	0.412
Age							
16–19	36	0.591	[0.285, 0.898]	0.304	0.036	0.259	0.398
20–24	56	0.216	[−0.008, 0.439]	0.301	0.049	0.196	0.414
25–29	82	0.212	[−0.021, 0.446]	0.296	0.042	0.172	0.358
30–34	103	0.293	[0.139, 0.447]	0.315	0.048	0.175	0.431
35–39	80	0.503	[0.292, 0.715]	0.318	0.044	0.195	0.421
40–44	103	0.223	[0.020, 0.426]	0.307	0.044	0.186	0.422
45–49	94	0.448	[0.226, 0.670]	0.308	0.046	0.213	0.428
50–54	122	0.161	[−0.010, 0.332]	0.311	0.040	0.185	0.416
55–59	274	0.352	[0.215, 0.489]	0.313	0.047	0.204	0.438
60–64	172	0.282	[0.140, 0.424]	0.296	0.052	0.186	0.430
65–69	228	0.249	[0.122, 0.377]	0.300	0.040	0.191	0.417
70–74	199	0.359	[0.230, 0.488]	0.304	0.045	0.201	0.417
75–79	129	0.189	[0.056, 0.322]	0.303	0.041	0.204	0.386
80+	60	0.379	[0.184, 0.574]	0.321	0.036	0.231	0.370
Ethnicity							
White	1493	0.312	[0.263, 0.360]	0.309	0.044	0.186	0.438
Black	117	0.273	[0.076, 0.471]	0.290	0.040	0.186	0.366
Asian	23	0.001	[−0.342, 0.343]	0.261	0.042	0.172	0.329
Mixed	19	0.866	[0.425, 1.308]	0.313	0.056	0.195	0.421
Other	12	0.045	[−0.395, 0.485]	0.293	0.054	0.197	0.363
Living time							
<1 year	140	0.364	[0.187, 0.541]	0.302	0.043	0.201	0.416
1–2 years	106	0.275	[0.049, 0.500]	0.301	0.047	0.186	0.422
2–5 years	189	0.338	[0.200, 0.475]	0.311	0.039	0.215	0.431
>5 years	1303	0.294	[0.241, 0.346]	0.306	0.046	0.172	0.438
Education							
GCSE	280	0.286	[0.159, 0.414]	0.308	0.042	0.186	0.400
A-levels/BTEC	427	0.192	[0.100, 0.283]	0.286	0.034	0.202	0.393
Undergraduate	327	0.366	[0.261, 0.470]	0.314	0.049	0.172	0.428
Postgraduate	348	0.268	[0.179, 0.358]	0.298	0.042	0.185	0.412
PhD	36	0.411	[0.038, 0.784]	0.311	0.038	0.223	0.370
Other	116	0.378	[0.200, 0.556]	0.328	0.027	0.250	0.415
IMD quintile							
Q1 (Least deprived)	374	0.355	[0.263, 0.447]	0.327	0.027	0.261	0.421
Q2	321	0.302	[0.200, 0.403]	0.310	0.036	0.228	0.431
Q3	359	0.305	[0.217, 0.392]	0.291	0.032	0.218	0.388
Q4	341	0.274	[0.153, 0.396]	0.286	0.063	0.172	0.438
Q5 (Most deprived)	343	0.274	[0.161, 0.388]	0.292	0.044	0.186	0.405
Crime quintile							
Q1 (Lowest)	480	0.318	[0.232, 0.404]	0.305	0.038	0.228	0.438
Q2	219	0.154	[0.005, 0.304]	0.252	0.050	0.172	0.409
Q3	353	0.349	[0.252, 0.446]	0.322	0.030	0.249	0.421
Q4	341	0.380	[0.288, 0.472]	0.327	0.036	0.241	0.434
Q5 (Highest)	345	0.253	[0.140, 0.365]	0.285	0.039	0.186	0.372

Table A4. Spearman correlations among perception of policing and sense of safety items.

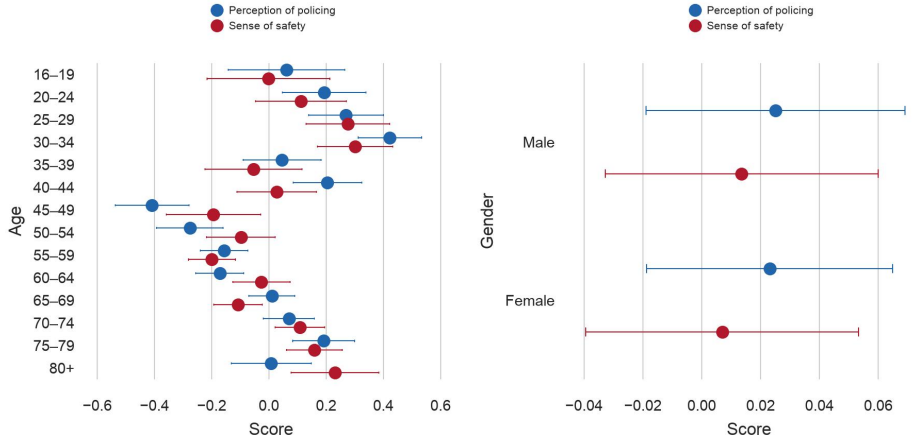
Variable	(1)	(2)	(3)	(4)	(5)
(1) Police Visibility	1.00				
(2) Police Helpfulness	0.22 ***	1.00			
(3) Reporting Likelihood	0.17 ***	0.41 ***	1.00		
(4) Daytime Safety	0.15 ***	0.29 ***	0.34 ***	1.00	
(5) Nighttime Safety	0.14 ***	0.29 ***	0.30 ***	0.74 ***	1.00

Note. Spearman rank correlations on pairwise complete cases. *** $p < 0.001$.

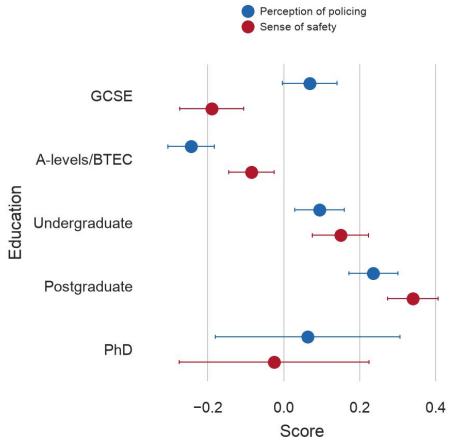
Table A5. PCA loadings of the composite scores (first principal component)

Composite/Item	Weight	Loading	Eigenvalue	Var. Expl.
Perception of Policing Score			1.53	51.1%
Police Visibility	0.46	0.56		
Police Helpfulness	0.64	0.79		
Reporting Likelihood	0.62	0.77		
Sense of Safety Score			1.76	87.7%
Daytime Safety	0.71	0.94		
Nighttime Safety	0.71	0.94		

Note. PCA on the standardised items, fitted separately for each composite. Weight = eigenvector coefficient; loading = correlation between the item and the component.

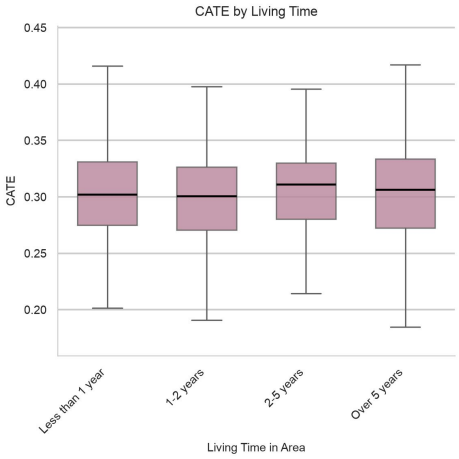


(**a**) Age groups (**b**) Gender groups

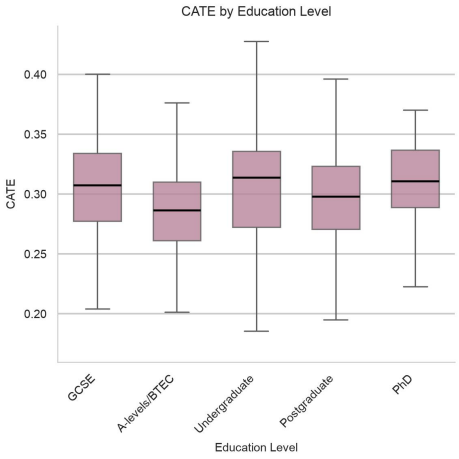


(**c**) Education groups

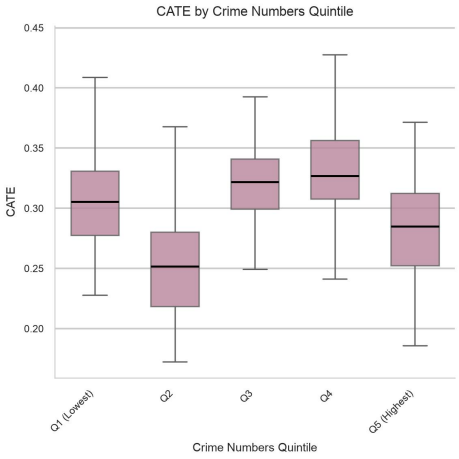
Figure A1. The distributions of perception of policing and sense of safety scores in groups with different ages, genders, and education. Points show group means; error bars show ± one standard error.



(**a**) Living time groups



(**b**) Education groups



(**c**) Crime level groups

Figure A2. Estimated conditional associations (CATEs) between perceptions of policing and sense of safety across demographic and neighbourhood condition groups (living time, education, and crime levels).

Table A6. Robustness of the causal forest estimates to tuning choices. The model described in Section 3.2 was re-estimated over a full factorial grid of four tuning parameters with three values each ($3^4 = 81$ fits): for the random forests of the treatment and outcome models (varied jointly), `max_depth` $\in$ {None, 10, 5} and `min_samples_leaf` $\in$ {1, 5, 20}; for the causal forest, `min_samples_leaf` $\in$ {5, 10, 20} and `n_estimators` $\in$ {1000, 2000, 4000}. All fits use 500 trees for each random forest, two cross-fitting folds and random seed 42. *Main specification*: the model used in the main analysis (random forests: `max_depth` = None, `min_samples_leaf` = 5; causal forest: `min_samples_leaf` = 10, `n_estimators` = 2000). *Level*: the value at which the parameter is fixed; each row averages over all $3 \times 3 \times 3 = 27$ combinations of the other three parameters. *All alternative specifications*: the 80 fits other than the main specification. *ATE (95% CI)*: the average association between perception of policing and sense of safety and its 95% confidence interval, averaged over the N fits. *ATE range*: the minimum and maximum ATE across the N fits. α, β: coefficients of the in-sample calibration test (Section 3.2.4), averaged over the N fits; $\alpha \approx 1$ indicates a well-calibrated average association.

Parameter	Level	N	ATE (95% CI)	ATE Range	α	β
Main specification	(Section 3.2)	1	0.303 (0.181, 0.425)	[0.303, 0.303]	1.025	6.479

Table A6. *Cont.*

Parameter	Level	N	ATE (95% CI)	ATE Range	α	β
Random forest `max_depth`	None	27	0.303 (0.177, 0.429)	[0.287, 0.318]	1.02	6.35
	10	27	0.304 (0.178, 0.430)	[0.291, 0.318]	1.01	6.23
	5	27	0.312 (0.184, 0.439)	[0.307, 0.318]	1.01	6.04
Random forest `min_samples_leaf`	1	27	0.295 (0.167, 0.424)	[0.287, 0.308]	1.02	6.42
	5	27	0.305 (0.179, 0.431)	[0.302, 0.310]	1.02	6.32
	20	27	0.318 (0.193, 0.443)	[0.318, 0.318]	1.00	5.89
Causal forest `min_samples_leaf`	5	27	0.306 (0.145, 0.468)	[0.287, 0.318]	1.01	5.11
	10	27	0.306 (0.184, 0.429)	[0.287, 0.318]	1.02	6.19
	20	27	0.306 (0.211, 0.402)	[0.287, 0.318]	1.02	7.32
Causal forest `n_estimators`	1000	27	0.306 (0.178, 0.434)	[0.287, 0.318]	1.02	6.10
	2000	27	0.306 (0.181, 0.432)	[0.287, 0.318]	1.01	6.31
	4000	27	0.306 (0.180, 0.433)	[0.287, 0.318]	1.01	6.21
All alternative specifications		80	0.306 (0.180, 0.433)	[0.287, 0.318]	1.02	6.20

Notes

[1] English indices of deprivation 2025: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2025/english-indices-of-deprivation-2025-statistical-release (accessed on 10 August 2026).

[2] DATA.POLICE.UK: https://data.police.uk/data/ (accessed on 10 August 2026).

[3] RandomForestRegressor in scikit-learn: https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html (accessed on 10 August 2026).

[4] ONS Geography https://geoportal.statistics.gov.uk/datasets/c01336febabe4c76ac14fbe71dbb99e1/about (accessed on 10 August 2026).

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