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ARTICLE

'Left Behind' neighbourhoods in England: Where they are and why they matter

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Abstract
The term 'left behind' has come to connote political disaffection, alongside social and spatial inequalities in wealth and opportunity. Yet the term is also widely contested, often prioritising a regional and economic perspective at the expense of a more local and nuanced approach. In response, we argue that neighbourhood context is integral to understanding and identifying 'left behind' places. Building a neighbourhood classification of 'left behindness' for England, we evaluate the extent to which the neighbourhood trajectory contributes to our understanding of a range of multidimensional individual-level outcomes. Our findings reveal a geography of neighbourhoods that are systematically disadvantaged over time, concentrated in major urban conurbations, and post-industrial and coastal towns. The magnitude and impact is highlighted through poorer economic, health, social and political outcomes for those living in 'left behind' areas.

KEYWORDS
'left behind', inequality, multilevel modelling, neighbourhoods, sequence analysis

1 | INTRODUCTION

Decades of uneven investment, austerity, state retrenchment, and high levels of socio-economic inequality have left many places and people economically and culturally peripheralised (Tups et al., 2023; Wheatley, 2015). In the UK, especially since the 2008 global financial crisis and 2016 Brexit referendum, the predicament of areas variously termed 'peripheralised', 'left behind' or 'places that don't matter' has emerged as a key topic, in part due to a heightened awareness of the potential for 'left behind' areas to impact *all* regions, especially through the ballot box (Dijkstra et al., 2020; Rodríguez-Pose, 2018). Yet despite the increasing currency of the term 'left behind' in academic, policy and popular imaginations, it remains contested and vaguely defined (Pike et al., 2023).

Direct criticisms have been levelled at terms such as 'left behind', arguing that they are reductionist and mask the predicaments of different kinds of places at a range of spatial scales (Kinossian, 2019). MacKinnon et al. (2022) highlight

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that what it means to be 'left behind' is often highly localised and nuanced, and yet research to date typically adopts a primarily regional perspective (e.g., Rodríguez-Pose, 2018). The operational scales at which the effects of 'left-behindness' are felt has been under-explored, particularly at the neighbourhood and individual level (Fierro et al., 2023). Existing research also tends to obscure the processes that produce peripheralised regions over time (Lang et al., 2015), prioritising economic dimensions at the expense of a more multidimensional and holistic understanding.

In this paper, we foreground the need to understand the role of neighbourhood context as integral to a more complete understanding of whether people are 'left behind'. To do so, we build on a large and growing body of neighbourhood effects research that has established that the local, or neighbourhood, context has an important influence on a range of outcomes for individuals and households (Chetty & Hendren, 2018; Galster, 2012; Galster & Sharkey, 2017). In addition, we recognise the importance of understanding self-reported perceptions and outcomes of people who live in particular neighbourhood types (McKay et al., 2023).

Specifically, we aim to propose a definition of 'left behindness' based on the long-term deprivation trajectory of neighbourhoods, and analyse the extent to which individuals living in these areas report poorer social, economic and health outcomes. We first interrogate patterns of deprivation over time at the local scale to explore what it means to be 'left behind' in a multidimensional, temporal and neighbourhood sense. Our resulting classification of 'left behind' areas analyses established deprivation metrics in new ways to examine the characteristics and geographies associated with 'left behind' neighbourhoods across England. We then test the extent to which this classification holds predictive power for explaining a range of individual outcomes across a range of important dimensions, including economic and social, as well as health, political engagement using multilevel modelling. We find that although populations are demographically comparable across types of places, those living in neighbourhoods classified as 'left behind' typically (although not exclusively) experience poorer individual health, economic outcomes, and ratings of their living environment. Crucially, our analysis illuminates the importance of interrelations between the neighbourhood level and other geographical scales.

The paper is organised as follows. Section 2 reviews the 'left behind' literature, linking to related research in the concentration of poverty and neighbourhood effects. Sections 3 and 4 provide an overview of the data and methods, and Section 5 details the analytical results. The findings and conclusions are set out in Sections 6 and 7.

2 | DEFINING 'LEFT BEHIND'

'Left behind' is an evocative term that has been applied in various geographical settings, notably the UK (Furlong, 2019; McCann, 2020; McKay, 2019; Sanderson et al., 2023), mainland Europe (Dijkstra et al., 2020; Gordon, 2018) and the US (Ulrich-Schad & Duncan, 2018), as well as at differing spatial scales. There is a lack of consensus about what is meant when a place is referred to as 'left behind', with the phrase used as shorthand for a variety of circumstances and places (Pike et al., 2023). However, several common themes emerge from existing research which we focus on in turn, conceptualising left-behindness as (i) multiscalar; (ii) temporally dynamic; and (iii) multidimensional.

Firstly, the term 'left behind' evokes some form of spatial peripherality, whether economic (i.e., lack of opportunity, jobs or income), material (i.e., lack of infrastructures or access to services) or social (i.e., feeling politically disaffected or culturally marginalised) (Rodríguez-Pose, 2018). What is less well understood is the geographical scale at which it is most appropriate to understand, explain and respond to these conditions. Are cities the locus for 'left behind'? Or perhaps regions? And what is the role of the individual? On the one hand, focus is rightly on the units for which policy is made (e.g., UK local authorities, or US counties) (Ulrich-Schad & Duncan, 2018). Much of the current literature employs voting constituencies, or internationally consistent geographical areas, such as NUTS (Nomenclature of Territorial Units for Statistics) regions (Essletzbichler et al., 2018; Furlong, 2019; Watson, 2018). While important for understanding some dimensions of inequality (e.g., politics and regional policy), these regions are likely less useful for illuminating everyday experiences (OCSI, 2019).

On the other hand, where behaviours, preferences and lived experience are concerned, the appropriate spatial unit of analysis is less clear (Essletzbichler et al., 2018). Critically, effects on individuals are related and likely compounded across and between spatial scales: the 'left-behindness' that leads to political disaffection and economic malaise is potentially produced at the neighbourhood, as well as the regional, urban, and even national, scales. Indeed, parallel literatures on the concentration of poverty and neighbourhood effects emphasise that places—and, specifically, neighbourhoods—matter, particularly for shaping individual life outcomes as well as individuals' perceptions of their living environment (Massey, 1996; McKay, 2019; Van Ham et al., 2012). Evidence indicates that living in, or exposure to, economically and socially deprived neighbourhoods is likely to lead to poorer individual outcomes in terms of salary, health, education and employment prospects (e.g., Sampson, 2019), particularly if this exposure occurs early in life (Chetty & Hendren, 2018).

Secondly, the term typically reflects how places evolve over time. Certain areas remain relatively disadvantaged as a result of often long-established processes, intricately tied to social, economic and political decisions (Nelson et al., 2024; Patias et al., 2021; Rodríguez-Pose, 2018). Existing literature tends to adopt a more static view, classifying 'left behind' areas as those ranked at the bottom of the development distribution (Iammarino et al., 2019). For example, in neighbourhood scale metrics of 'left behind' places developed by the Local Trust (an organisation that distributes community funding from the lottery to neighbourhoods across England), additional indicators reflecting spatial peripheralisation supplement the most recent Indices of Multiple Deprivation (IMD) classification (OCSI, 2019). Yet, understanding past trajectories of inequalities in an area is key to identifying present 'left behind' areas (Jessen, 2023; Patias et al., 2021).

Finally, the literature remains unclear about the measurement or identification of a proxy for economic development or wellbeing—the utilitarian challenge of selecting data to represent a real-world phenomenon. When a place is 'left behind' on what dimension is this determination made? Measures employed are typically economic: GDP per capita or household income (Iammarino et al., 2019). However solely regional economic variables are unlikely to reflect people's lived experiences that manifest in a variety of ways. Instead, they require subjective multidimensional measures that reflect health, political engagement and life satisfaction (Dorling & Koljonen, 2021; Kemeny & Storper, 2020; Leibert & Golinski, 2016; Watson, 2018). Research must extend beyond just the economic to adopt a broader, more holistic approach (Gordon, 2018). This arguably more holistic approach is evidenced in long-standing research into geodemographics, that combines a wide range of measures to characterise areas, often using cluster analysis to identify groups of areas that share common characteristics (McLachlan & Norman, 2021; Singleton et al., 2020). In response, the analysis that follows attends to the importance of multiscalar, temporally dynamic and multidimensional aspects in understanding of 'left-behindness' in England.

3 | DATA

We identify 'left behind' neighbourhoods in England using a multidimensional deprivation indicator, deriving trajectories of deprivation over time using sequence analysis and K-mediods clustering (Section 3.1). We then combine individual-level data with our neighbourhood classification to explore the extent to which neighbourhood context matters when considering who is 'left behind' (Section 3.2). Employing a multilevel modelling approach, we assess the effects of neighbourhood type on a host of individual attributes associated with wellbeing, across health (Dorling & Koljonen, 2021), environment (Tomaney et al., 2019), economic (McKay, 2019) and political domains (Watson, 2018).

3.1 | Neighbourhood deprivation data over time

We define 'left behind' neighbourhoods as those that have experienced sustained high levels of deprivation, as documented in the IMD. The IMD is a well understood measure of relative deprivation calculated every five years across *multiple* dimensions of disadvantage: income, employment, health and disability, education, skills and training, barriers to housing and services, living environment, and crime (DCLG, 2019).[1] Indicators are selected to be up-to-date, statistically robust, and capable of being used on a regular basis across the whole of England. The IMD is available at Lower Super Output Area (LSOA) scale, an administrative neighbourhood unit representing approximately 1500 persons (ONS, 2011).

We categorise LSOA according to the deprivation decile within which they were classified over three years in the past decade (2010, 2015, and 2019). Deciles are calculated relative to the particular year (i.e., whether an area was in the 10% most deprived areas compared with other LSOA in England each year) making them comparable across the different time periods. To include data from 2010 (prior to the 2011 Census), data are recalculated from the former 2001 LSOA boundaries into the current 2011 boundaries, reflecting changes in population distribution.[2]

3.2 | Individual multidimensional wellbeing data

Wellbeing and contextual variables are drawn from the ninth wave of the UK Longitudinal Household Panel Study (UKHLS), known as *Understanding Society*. The UKLHS comprises biennial surveys of people aged over 15 in a random sample of households within stratified postcode sectors (Buck & McFall, 2011). The selected wave ran from 2017 to 2019 and provides detailed socio-economic, health and political data, as well as identifying the LSOA in which they live. Our sample is restricted to residents of England in wave nine, for compatibility with the IMD data, and to respondents who had not relocated during the last ten years, to observe the effects of exposure to various neighbourhood types.

We explore the predictive power of our classification in capturing individual wellbeing outcomes. While previous research has focused predominantly on economic wellbeing, our analysis offers a more holistic insight into both objective and subjective experiences, including economic (McKay, 2019), political (Watson, 2018), health (Dorling & Koljonen, 2021) and environmental dimensions (Tomaney et al., 2019). Hereafter referred to as wellbeing outcomes, these comprise: general health, life satisfaction, mental health (health domain); receiving benefits, income, subjective financial situation (economic domain); household space, neighbourhood cohesion (living environment domain); and political interest and political disaffection (political domain). A range of individual covariates were also included, which cover demographic, socio-economic status, and urban/rural but are not reported here.

4 | METHODS

In the following two sections, we describe how we use sequence and cluster analysis to define 'left behind' neighbourhoods (Section 4.1), before using multilevel modelling to integrate individual-level wellbeing outcomes and neighbourhood types (Section 4.2).

4.1 | Defining 'left behind' neighbourhoods using sequence analysis

To define 'left behind' neighbourhoods, we construct a classification based on changes in relative deprivation over time, using IMD data at the LSOA scale. Sequence analysis is a technique widely adopted to study trajectories of neighbourhood change (Delmelle, 2016; Patias et al., 2019). Sequence analysis finds similar representative sequences of transitions between statuses by measuring dissimilarity between individual trajectories (Gabadinho et al., 2011). Optimal matching measures dissimilarity between sequences, using two operations: substitution and indel (insertion and deletion), to estimate the minimal cost of transforming one sequence into another. The result is a dissimilarity matrix between individual sequences. Clustering groups similar individual sequences and identifies a reduced set of representative trajectories. Sequence analysis captures distinctive differences in the extent, timing, duration and order of sequences (Gabadinho et al., 2011; Studer & Ritschard, 2016).

We use an optimal matching technique, Dynamic Hamming Matching (Lesnard, 2010), to account for the timing of transitions between deprivation deciles and to measure dissimilarity. A Partitioning Around Medoids (PAM) clustering algorithm then identifies six distinctive trajectories of deprivation. PAM is considered more robust than other clustering algorithms as it is less sensitive to outliers. Measures of model fit are used to assess the optimal number of clusters. We examine solutions for one to 20 clusters. In Figure 1, gap refers to the gap statistic (Tibshirani et al., 2001). The gap statistic seeks to compare the total within intra-cluster variation for different values of k with their expected values under null reference distribution of the data. The optimal value is that which maximises the gap statistic. Silouette refers to the average silouette value for different values of k. The optimal number of clusters k is the one that maximises the average silouette over a range of possible values of k (Kaufman & Rousseeuw, 1990). The within-cluster sum of square (WSS) identifies the number of clusters that minimises variation within clusters. To select the number of clustes we aimed for a parsimonious solution following Rowe et al. (2021). This required balancing greater detail offered through more specific clusters with a higher number of clusters, as well as ease of interpretation. Based on the results we decided that six clusters provided the optimal solution, minimising within cluster variation but maximising between cluster variation. Sequence analysis is implemented using the *TraMineR* package (Gabadinho et al., 2011) classifying all LSOA into a set of common trajectories, from this point forwards referred to as neighbourhood types (Figure 1).

4.2 | Modelling the effects of living in a 'left behind' neighbourhood on wellbeing

To prepare for multilevel modelling, individual-level data from Understanding Society are spatially joined with LSOA neighbourhood types. We first describe characteristics and distributions within the study sample, test for collinearity in the predictor variables, and cross-tabulate associations between all variables, particularly focusing on the variation of wellbeing outcomes across the six neighbourhood types to explore which individual characteristics are prevalent amongst neighbourhoods classified as 'left behind'.

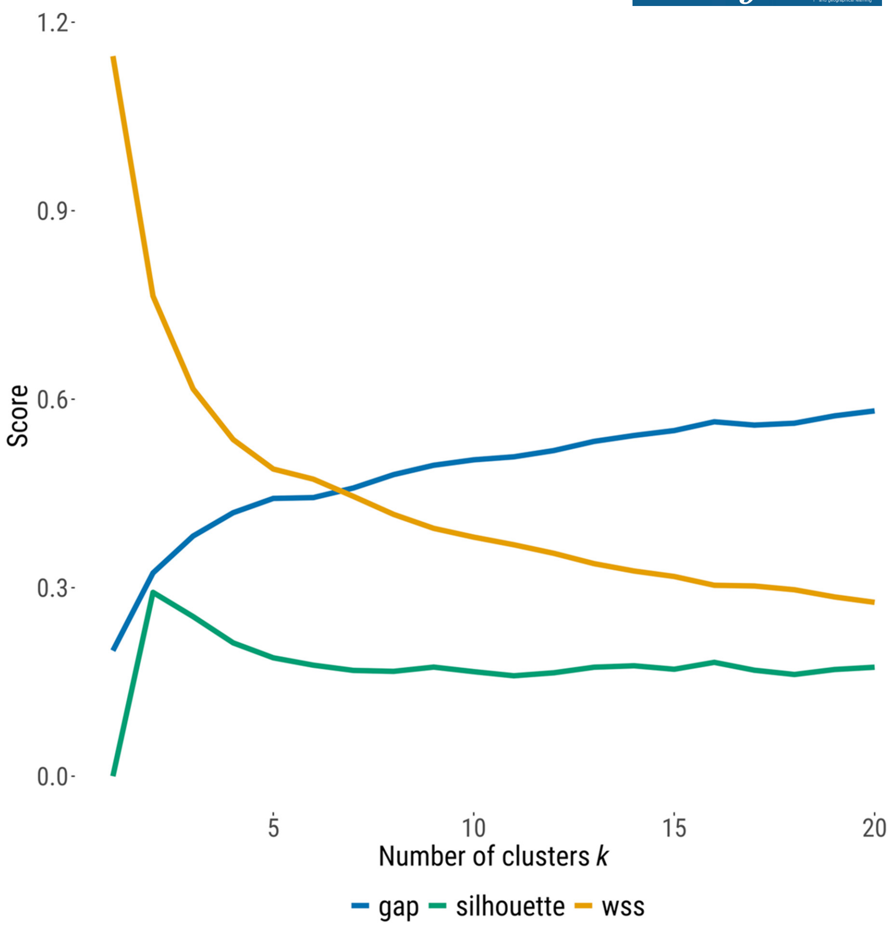

FIGURE 1 Gap, silhouette and WSS statistics to evaluate model fit and optimal number of clusters. WSS score is divided by 100 thousand to make it comparable.

Multilevel regression models measure associations between the individual wellbeing outcomes, region of residence, and the six neighbourhood types, controlling for individual characteristics. Individual predictors are included at level one, with LSOA and neighbourhood type as random intercepts at levels 2 and 3, respectively.

All models are fitted using iteratively reweighted least squares estimators. Variance partition coefficients (VPCs = level variance/total variance) quantify the proportion of variation captured at each level. Likelihood ratios (LRs), Akaike information criteria (AIC), and Bayesian information criteria (BIC) are computed to assess model fit and the impact of adding covariates and level groupings on overall model performance. For predicting continuous measures (mental health, neighbourhood cohesion, household space), linear regression is used. Binary logistic (logit) regression is employed to predict both receipt of benefits and political disaffection, while associations with the ordinal measures (subjective health, life satisfaction, subjective finance, income, political interest) are estimated with ordinal logistic regression. For the regression models (Equation 1), regression coefficients (B) represent an estimate in the increase of the outcome variable, for a one-unit increase in each predictor:

$$\mathrm{LB}_{ijk} = \beta_0 + \beta_1 x_{1ijk} + \ \ldots \ + \beta_n x_{nijk} + u_{jk} + v_k + e_{ijk} \tag{1}$$

where LB_{ijk} is the predicted outcome for the individual measure for individual i in LSOA j in neighbourhood deprivation trajectory k; β_0 is the overall intercept; β_1 to β_n represent the coefficients for each individual-level (level one) predictor, for individual x_i in LSOA j within cluster k; u_{jk} represents a random effect estimate at level two indicating differences around the regression intercept across LSOA j experiencing a given neighbourhood type, k. Similarly, v_k represents a random effect estimate capturing differences around the regression intercept across neighbourhood types, k. The error term at the individual level is indicated by e_{ijk}. For linear models, the LB_{ijk} predicts the individual dependent variable. For logit models, this is the log-odds that $\mathrm{LB}_{ijk} = 1$. Ordinal logistic regression models also include a threshold response for the outcome variable, which stratifies the sum of predictors and coefficients according to the cumulative log-odds of being in each category.

5 | RESULTS

We begin by describing the results of our neighbourhood-level classification, highlighting those areas classified as 'left behind' (Section 5.1). We then situate individuals within 'left behind' neighbourhoods, exploring variation in individual outcomes across neighbourhood types (Section 5.2), before discussing the results of the multilevel models (Section 5.3).

5.1 | Classifying 'left behind' neighbourhoods

Between 2010 and 2019, neighbourhoods in the most (and least) deprived deciles, according to the IMD, experienced the smallest change in relative deprivation. Of LSOA in the most deprived decile in 2010, 75.9% were still there in 2019. Between 2015 and 2019, 87% of LSOA in the most deprived decile and 84% in the least deprived decile remained unchanged, compared with 55% in middle deciles (5 and 6). LSOA that ranked among the most deprived across all three years also concentrated spatially in selected local authorities. Almost half (155) of the 327 local authorities in England contain no LSOA that ranked among the most deprived in the country. In contrast, for some local authorities in the North of the country and the Midlands, the majority fell into this category, with over 40% in the most deprived decile between 2010 and 2019 in Middlesbrough (North West), Knowsley (North West), Liverpool (North West), and Kingston upon Hull (Yorkshire and the Humber). These findings are consistent with existing assessments of multiple deprivation as highly spatially concentrated and temporally persistent (Rae, 2012).

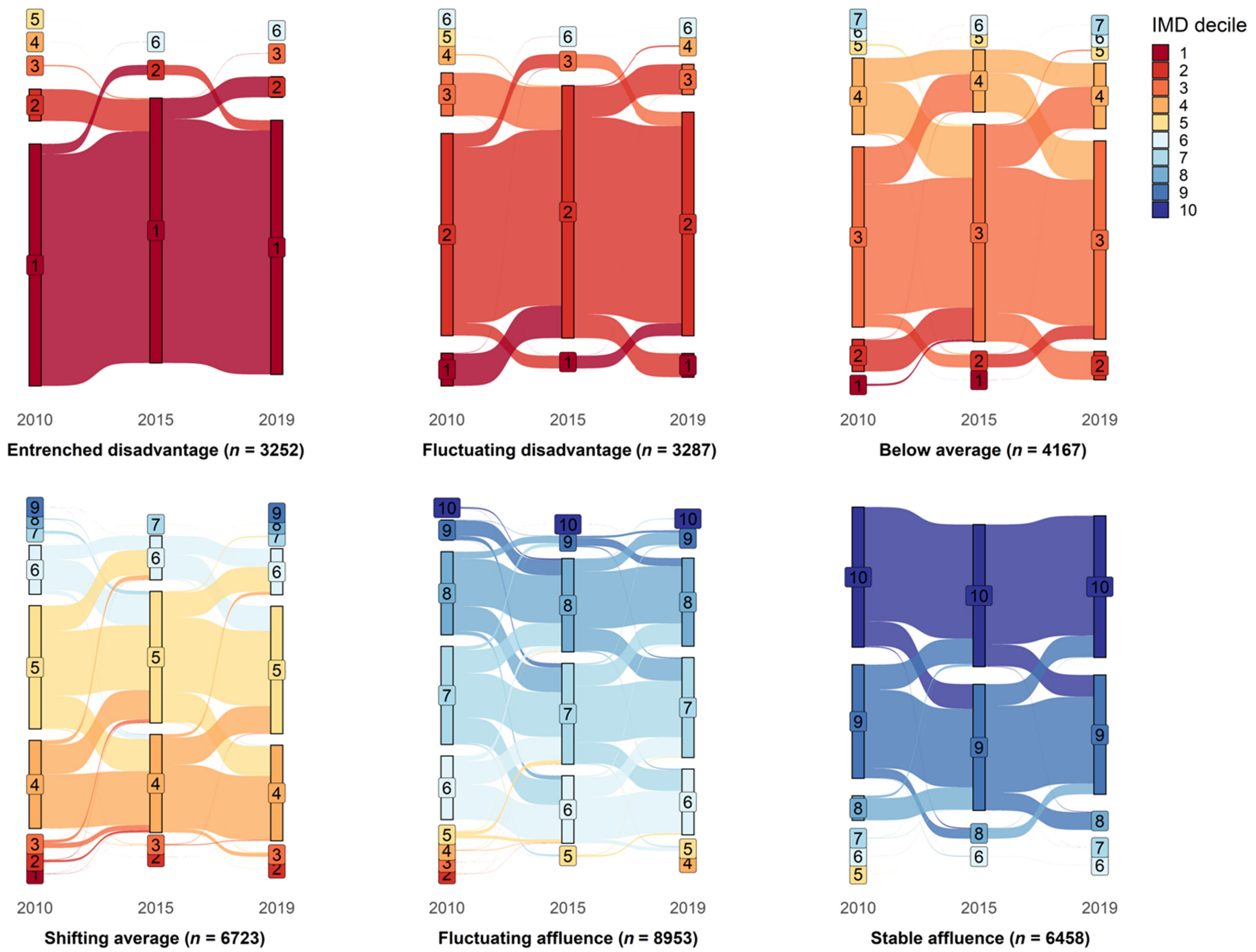

FIGURE 2 Sankey diagram showing trajectories of LSOA across deprivation deciles between 2010, 2015 and 2019 for each neighbourhood type. Created using *ggsankey* R package (Sjoberg, 2021). *Data source*: DCLG (2019).

Each of the six neighbourhood types identified reflects a distinctive trajectory based on changes in deprivation over time. These neighbourhood types are: *Entrenched Disadvantage*; *Fluctuating Disadvantage*; *Below Average*; *Shifting Average*; *Fluctuating Affluence*; and *Stable Affluence*. Figures 2 and 3 report these neighbourhood types in separate panels, which are further disaggregated by IMD domain type (Figure 3). There is a remarkably high level of persistence in deprivation levels across England, with very few transitions occurring across similar levels of deprivation—areas that are 'left behind' tend to stay behind. Here we classify 'left behind' neighbourhoods as areas experiencing prolonged deprivation, namely: *Entrenched Disadvantage* and *Fluctuating Disadvantage*. Our results focus primarily on these two types of neighbourhoods.

The *Entrenched Disadvantage* neighbourhood type is characterised by enduring high levels of deprivation, spatially concentrated in major urban conurbations and post-industrial or coastal towns (Figure 4). Compared with smaller conurbations, Greater London has a lower proportion of *Entrenched Disadvantage* LSOA. Here, high levels of deprivation have declined over the ten-year period. *Entrenched Disadvantage* areas are recognisable by their poorer performance in crime, education, employment, income, and health and disability IMD domains (Figure 3).

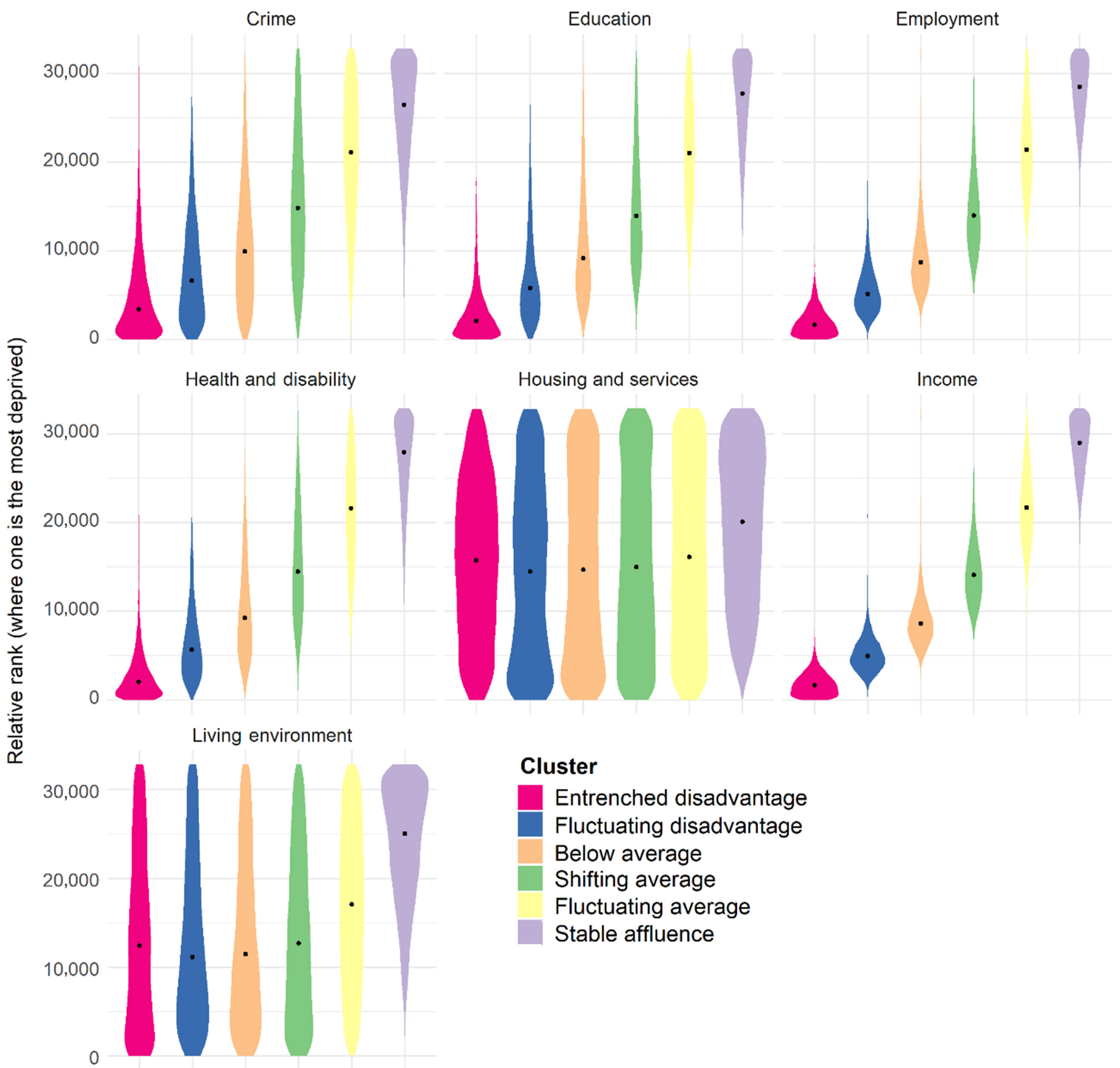

FIGURE 3 Neighbourhood types broken down by IMD domain. The dots in each violin represent the median value. *Data source*: DCLG (2019).

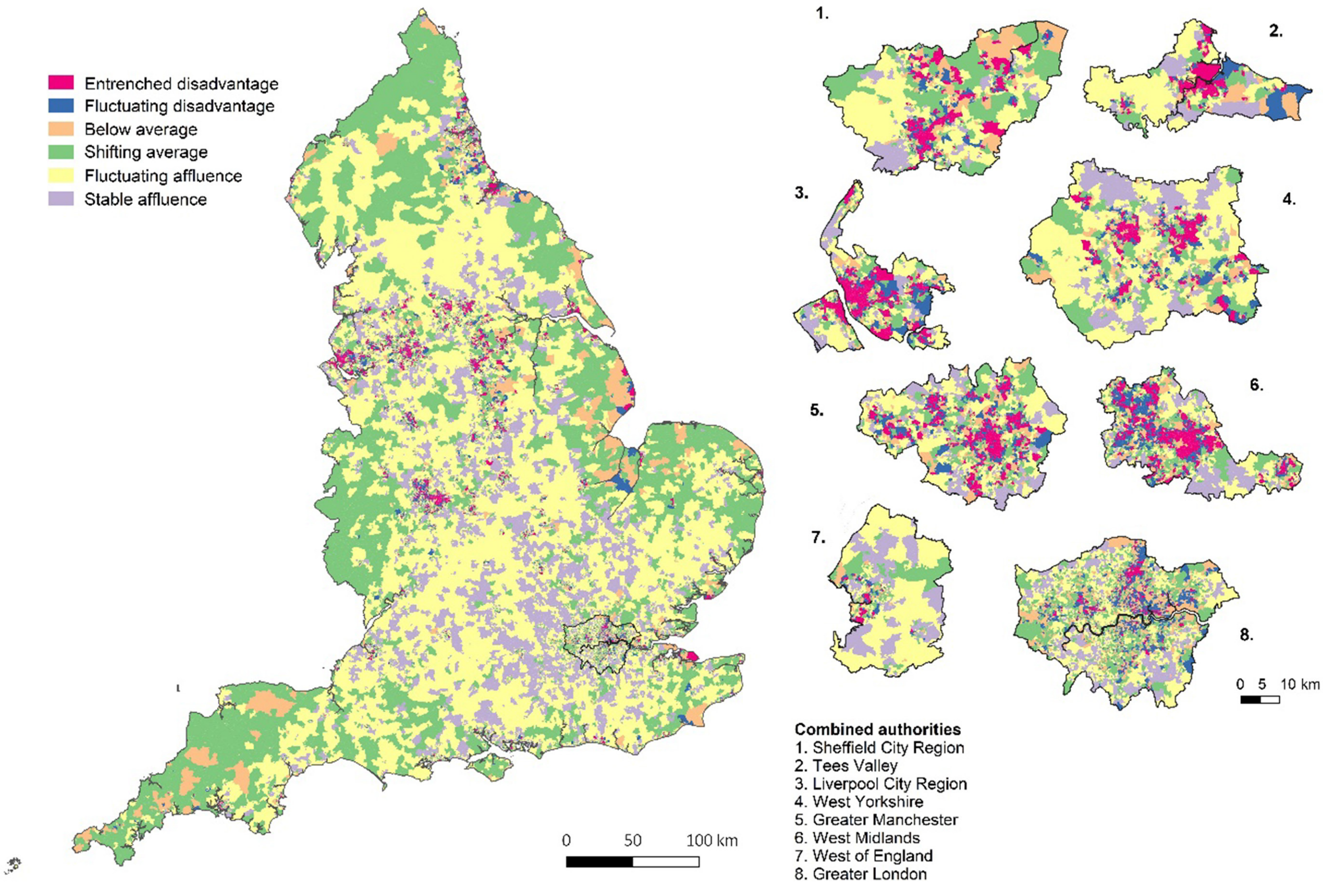

FIGURE 4 Neighbourhood types mapped for LSOA across England; inset showing combined authorities. Combined authorities are made up of two or more local authorities to which selected statutory functions have been devolved. *Data source*: ONS (2011, 2018).

Fluctuating Disadvantage neighbourhoods show less severe or entrenched deprivation (typically the 20% most deprived), with slightly greater potential for transition. These LSOA are typically found on the peripheries of large concentrations of places identified as *Entrenched Disadvantage* (Figure 4). Compared with the most deprived category, there is a higher proportion of *Fluctuating Disadvantage* LSOA in Greater London (approximately 25% of LSOAs), suggesting that neighbourhoods in the capital are better placed than northern cities to transition out of deprivation (Bailey & Minton, 2018). However, these results should be treated with caution, as this is also likely to reflect growing levels of inequality *within* some of the most deprived areas of the city, owing to increasing numbers of relatively wealthy incomers (Trust for London, 2020).

The *Below Average* type has a similar distribution to *Fluctuating Disadvantage*, though less intensely deprived, with LSOA typically in the most deprived 30%–40% of areas. *Shifting Average* and *Fluctuating Affluence* neighbourhoods experience greater transition between deprivation deciles over time. *Shifting Average* areas are typically concentrated in the middle deciles. *Fluctuating Affluence* includes the largest number of LSOA ($n = 8953$), indicative of the high level of transition across deciles for this neighbourhood type—although almost all LSOA rank within the top 50% least deprived throughout the period. Areas in *Shifting Average* and *Fluctuating Affluence* types are relatively rural but encompass some suburbs of major cities (Figure 4). Across the seven deprivation domains, *Shifting Average* and *Fluctuating Affluence* neighbourhoods experience the greatest spread of area rankings, suggesting that characteristics of these areas are likely varied. The *Stable Affluence* neighbourhood type has a similar spatial distribution to *Fluctuating Affluence*, but with markedly different trajectories, characterised by stability and affluence (with many remaining in the two least deprived deciles between 2010 and 2019).

5.2 | Situating individuals in 'left behind' neighbourhoods

Across all six neighbourhood types, populations are demographically similar (Table 1), particularly in terms of age, gender and ethnicity distributions. Area-level differences are more noticeable, with those in 'left behind' neighbourhoods more likely to reside in urban areas, and in the North of England, reflecting the geographical distribution of 'left behind' neighbourhoods across England.

TABLE 1 Descriptive statistics of the study sample by neighbourhood type, *N* (%).

Variable	Value	*N* (10,542)	Entrenched disadvantage	Fluctuating disadvantage	Below average	Shifting average	Fluctuating affluence	Stable affluence
Predictors			952	1043	1189	2158	2934	2266
Age	18–24	150 (1.4)	24 (2.5)	20 (1.9)	22 (1.9)	19 (0.9)	33 (1.1)	32 (1.4)
	25–34	775 (7.4)	94 (9.9)	68 (6.5)	88 (7.4)	143 (6.6)	220 (7.5)	162 (7.1)
	35–44	1714 (16.3)	156 (16.4)	177 (17.0)	203 (17.1)	344 (15.9)	442 (15.1)	393 (17.3)
	45–54	2941 (27.9)	198 (20.8)	266 (25.5)	270 (22.7)	514 (23.8)	685 (23.3)	508 (22.4)
	55–64	2904 (27.5)	199 (20.9)	225 (21.6)	263 (22.1)	516 (23.9)	673 (22.9)	528 (23.3)
	Over 65	2058 (19.5)	281 (29.5)	288 (27.6)	343 (28.8)	622 (28.8)	881 (30.0)	643 (28.4)
Gender	Male	5886 (55.8)	404 (42.4)	443 (42.4)	518 (43.6)	959 (44.4)	1333 (45.4)	1000 (44.1)
	Female	4656 (44.2)	548 (57.6)	601 (57.6)	671 (56.4)	1199 (55.6)	1601 (54.6)	1266 (55.9)
Relationship	Single	1433 (13.6)	146 (15.3)	151 (14.5)	164 (13.8)	297 (13.8)	388 (13.2)	287 (12.7)
	Partnered	7581 (71.9)	673 (70.7)	726 (69.5)	856 (72.0)	154 (72.0)	2124 (72.4)	1649 (72.8)
	Post-partnership	1528 (14.5)	133 (14.0)	167 (16.0)	169 (14.2)	307 (14.2)	422 (14.4)	330 (14.6)
Ethnicity	White	8589 (81.5)	781 (82.0)	847 (81.1)	938 (78.9)	1792 (83.0)	2426 (82.7)	1806 (79.7)
	Black	391 (4.7)	33 (3.5)	42 (4.0)	38 (3.2)	72 (3.3)	111 (3.8)	95 (4.2)
	South Asian	41 (<1.0)	2 (0.2)	2 (0.2)	5 (0.4)	10 (0.5)	11 (0.4)	11 (0.5)
	Other Asian	876 (8.3)	27 (8.0)	93 (8.9)	133 (11.2)	141 (6.5)	228 (7.8)	205 (9.0)
	Mixed	142 (1.3)	13 (1.4)	10 (1.0	14 (1.4)	35 (1.6)	34 (1.2)	36 (1.6)
	Other	503 (4.8)	47 (4.9)	50 (4.8)	61 (5.1)	108 (5.0)	124 (4.2)	113 (5.0)
Economic activity	Employed	5766 (54.7)	490 (51.5)	573 (54.7)	623 (52.4)	1202 (55.7)	1595 (54.4)	1272 (56.1)
	Unemployed	957 (9.1)	103 (10.8)	88 (8.4)	119 (10.0)	166 (7.7)	259 (8.8)	222 (9.8)
	Retired	3362 (31.9)	305 (32.0)	313 (30.0)	271 (31.2)	689 (31.9)	982 (33.5)	702 (31.0)
	Student	69 (1.0)	28 (2.9)	6 (0.6)	12 (1.0)	15 (0.7)	4 (0.1)	4 (0.2)
	Other	399 (3.8)	26 (2.7)	64 (6.1)	371 (31.2)	86 (4.0)	94 (3.2)	66 (2.9)
UK born	No	1540 (14.6)	136 (14.3)	154 (14.8)	192 (16.1)	288 (13.3)	424 (14.5)	347 (15.3)
	Yes	9002 (85.4)	816 (85.7)	890 (85.2)	997 (83.9)	1870 (86.7)	2510 (85.5)	1919 (84.7)
Urban	No	2278 (21.5)	9 (0.9)	31 (3.1)	120 (10.1)	522 (24.2)	1008 (34.4)	577 (25.5)
	Yes	8274 (78.5)	943 (99.1)	1012 (96.9)	1069 (89.9)	1636 (75.8)	1926 (65.6)	1689 (74.5)

(Continues)

TABLE 1 (Continued)

Variable	Value	*N* (10,542)	Entrenched disadvantage	Fluctuating disadvantage	Below average	Shifting average	Fluctuating affluence	Stable affluence
Region	North East	527 (5.0)	58 (6.1)	57 (5.5)	76 (6.4)	138 (6.4)	101 (3.4)	97 (4.3)
	North West	1377 (13.1)	215 (22.6)	154 (14.8)	156 (13.1)	256 (11.9)	371 (12.6)	225 (9.9)
	Yorkshire	1173 (11.1)	203 (21.3)	100 (9.6)	131 (11.0)	197 (9.1)	357 (12.2)	185 (8.2)
	East Midlands	1026 (9.7)	71 (7.5)	98 (9.4)	99 (8.3)	82 (8.4)	326 (11.1)	250 (11.0)
	West Midlands	1116 (10.6)	194 (20.4)	133 (12.7)	109 (9.2)	196 (9.1)	285 (9.7)	199 (8.8)
	East of England	1174 (11.1)	39 (4.1)	77 (7.4)	108 (9.1)	182 (8.4)	390 (13.3)	287 (12.7)
	London	1472 (14.0)	90 (9.5)	309 (29.6)	308 (25.9)	328 (15.2)	290 (9.9)	148 (6.5)
	South East	1599 (15.2)	33 (3.5)	55 (5.3)	109 (9.2)	302 (14.0)	478 (16.3)	622 (27.4)
	South West	1078 (10.2)	49 (5.1)	61 (5.8)	93 (7.8)	286 (13.3)	336 (11.5)	225 (9.9)
Individual 'left behind' measures								
General health	Excellent	852 (8.1)	45 (4.7)	45 (4.3)	88 (7.4)	166 (7.7)	259 (8.8)	249 (11.0)
	Very good	3175 (30.1)	205 (21.5)	238 (22.8)	288 (4.2)	633 (29.3)	1003 (34.2)	808 (35.7)
	Good	3490 (33.1)	277 (29.1)	329 (31.5)	394 (33.1)	732 (33.9)	952 (32.4)	806 (35.6)
	Fair	1818 (17.2)	198 (20.8)	221 (21.2)	238 (20.0)	398 (18.4)	476 (16.2)	287 (12.7)
	Poor	627 (5.9)	120 (12.6)	96 (9.2)	94 (7.9)	123 (5.7)	135 (4.6)	59 (2.6)
Life satisfaction	0 (least)	612 (5.8)	115 (12.1)	119 (11.4)	95 (8.0)	111 (5.1)	115 (3.9)	58 (2.6)
	1	244 (2.3)	39 (4.1)	29 (2.8)	37 (3.1)	57 (2.6)	58 (2.0)	24 (1.1)
	2	560 (5.3)	65 (6.8)	75 (7.2)	69 (5.8)	106 (4.9)	147 (5.0)	98 (4.3)
	3	696 (6.6)	84 (8.8)	87 (8.3)	68 (5.7)	151 (7.0)	163 (5.6)	143 (6.3)
	4	1048 (9.9)	136 (14.3)	127 (12.2)	135 (11.4)	217 (10.1)	227 (9.4)	156 (6.9)
	5	1647 (15.6)	132 (13.9)	161 (15.4)	236 (19.8)	346 (16.0)	464 (15.8)	308 (13.6)
	6	4452 (42.2)	273 (28.7)	344 (33.0)	423 (34.7)	926 (42.9)	1316 (44.9)	1180 (52.1)
	7 (most)	1283 (12.2)	108 (11.3)	102 (9.8)	136 (11.4)	244 (11.3)	394 (13.4)	299 (13.2)
Mental health	Mean (SD)	10.36 (5.927)	10.65 (7.415)	10.26 (5.558)	10.31 (6.417)	10.38 (5.801)	10.44 (5.609)	10.19 (5.057)
Income	Q1 (low)	2130 (20.2)	372 (39.1)	305 (29.2)	312 (26.2)	433 (20.1)	440 (15.0)	269 (11.9)
	Q2	2040 (19.4)	233 (24.5)	258 (24.7)	294 (24.7)	451 (20.9)	499 (17.0)	305 (13.5)
	Q3	2302 (21.8)	199 (20.9)	148 (23.8)	248 (20.9)	508 (23.5)	654 (22.4)	445 (19.6)
	Q4	2040 (19.4)	112 (11.8)	150 (14.4)	179 (15.1)	406 (18.8)	656 (23.3)	537 (23.7)
	Q5 (high)	2030 (19.3)	36 (3.8)	83 (8.0)	156 (13.1)	360 (16.7)	685 (23.3)	710 (31.3)

TABLE 1 (Continued)

Variable	Value	*N* (10,542)	Entrenched disadvantage	Fluctuating disadvantage	Below average	Shifting average	Fluctuating affluence	Stable affluence
Subjective finance	Comfortable	3559 (33.8)	166 (17.4)	214 (20.5)	300 (25.2)	666 (30.9)	1188 (40.5)	1025 (45.2)
	Doing well	3953 (37.5)	323 (33.9)	38 (37.3)	431 (36.2)	841 (39.0)	1100 (37.5)	870 (38.4)
	Getting by	2101 (19.9)	279 (29.3)	287 (27.5)	308 (25.9)	476 (22.1)	472 (16.1)	279 (12.3)
	Difficult	521 (4.9)	101 (10.6)	84 (8.0)	93 (7.8)	103 (4.8)	92 (3.1)	48 (2.1)
	Very difficult	202 (1.9)	49 (5.1)	35 (3.4)	33 (2.8)	33 (1.5)	35 (1.2)	17 (0.8)
Benefits	No	8624 (81.8)	645 (67.8)	774 (74.1)	908 (76.4)	1749 (81.0)	2540 (86.6)	2008 (88.6)
	Yes	1918 (18.2)	307 (32.2)	270 (25.9)	281 (23.6)	409 (19.0)	394 (13.4)	258 (11.4)
Neighbourhood cohesion	Mean	27.31 (8.797)	24.7 (10.941)	24.92 (10.505)	25.8 (9.699)	27.3 (8.449)	28.25 (7.941)	29.08 (7.032)
Household space	Mean	1.45 (0.777)	1.19 (0.725)	1.26 (0.776)	1.3 (0.730)	1.41 (0.758)	1.54 (0.775)	1.63 (0.779)
Political interest	Very interested	1276 (12.1)	74 (7.8)	86 (8.2)	132 (11.1)	252 (11.7)	412 (14.0)	320 (14.1)
	Fairly interested	3995 (37.9)	235 (24.7)	322 (30.8)	371 (31.2)	812 (37.6)	1228 (41.9)	sreon1027 (45.3)
	Not very interested	3298 (31.3)	307 (32.2)	321 (30.7)	395 (33.2)	708 (32.8)	871 (29.7)	696 (30.7)
	Not interested	1973 (18.7)	336 (35.3)	315 (30.2)	291 (24.5)	386 (17.9)	423 (14.4)	223 (9.8)
Political disaffection	No	6601 (62.6)	579 (60.8)	651 (62.4)	715 (60.1)	1341 (62.1)	1837 (62.6)	1479 (65.3)
	Yes	3941 (37.4)	373 (39.2)	393 (37.6)	474 (39.9)	817 (37.9)	1097 (37.4)	787 (34.7)

Data source: UKHLS (2020).

Differences between neighbourhood types are primarily observed in the wellbeing outcomes. Across the two 'left behind' neighbourhood types, people living in *Entrenched Disadvantage* neighbourhoods reflect the wider processes of structural disadvantage in which they live (Section 5.1). They report the lowest income of the sample and are most likely to report financial difficulties and receive benefits. All health outcomes are poorer for individuals in these neighbourhood types. Politically, the group comprises the highest proportion of people who are disaffected and report low levels of interest in politics. People living in *Fluctuating Disadvantage* neighbourhoods also report having low interest in politics, are strongly urban, and have the largest variation in mental health.

Individuals in *Below Average* areas are the most likely to report being politically dissatisfied, while those in *Shifting Average* are characterised by the lowest household space. Comparatively, people living in *Fluctuating Affluence* neighbourhoods report being healthy, financially comfortable and politically interested. The privilege of *Stable Affluence* is reflected in the wellbeing outcomes, reporting the highest incomes, financial security and household space.

5.3 | Modelling associations between 'left behind' neighbourhoods and wellbeing outcomes

We now present models estimating the relationship between individual outcomes and neighbourhood context, focusing on those neighbourhood types identified as 'left behind' (Tables 2–4).

Models estimate the association between individual-level outcomes and three levels of covariates: individuals, LSOA, and the six neighbourhood types. In the fully adjusted models, most of the variance is observed at the individual level,

TABLE 2 Results of linear multilevel models.

	Mental health	Neighbourhood	Household space
LSOA Var/VPC	4.685/0.134	16.159/0.213	0.333/0.518
Trajectory Var/VPC	0.000/0.000	1.979/0.025	0.017/0.026
Regression coefficients			
Age, 18–24 ref			
25–34	0.546 (0.555)	−0.341 (0.783)	0.066 (0.064)
35–44	0.707 (0.540)	−0.123 (0.773)	0.052 (0.063)
45–54	0.771 (0.536)	−0.136 (0.767)	0.048 (0.062)
55–64	0.671 (0.540)	−0.234 (0.774)	0.042 (0.063)
Over 65	0.801 (0.567)	−0.092 (0.812)	0.066 (0.066)
Gender, female	0.170 (0.115)	0.170 (0.164)	0.011 (0.108)
Relationship, single ref			
Partnered	−0.086 (0.176)	0.520 (0.253)**	−0.024 (0.021)
Post-partnership	−0.239 (0.219)	0.261 (0.313)	−0.008 (0.025)
Ethnicity, White ref			
Black	0.066 (0.320)	−0.294 (0.460)	0.030 (0.038)
South Asian	−0.330 (0.927)	−2.704 (1.329)**	−0.011 (0.108)
Other Asian	0.276 (0.240)	0.625 (0.346)*	0.014 (0.029)
Mixed	0.077 (0.503)	−0.569 (0.719)	0.042 (0.059)
Other	1.324 (0.548)**	−0.258 (0.784)	−0.032 (0.063)
Economic activity, employed ref			
Unemployed	0.090 (0.229)	−0.161 (0.343)	−0.009 (0.034)
Retired	−0.207 (0.224)	−0.084 (0.327)	−0.025 (0.029)
Student	0.047 (0806)	−2.781 (1.194)**	−0.217 (0.110)**
Other inactive	−0.688 (0.332)**	0.214 (0.498)	0.077 (0.050)
UK born	0.204 (0.185)	−0.533 (0.264)**	0.018 (0.40)
Urban	0.277 (0.161)*	−1.156 (0.251)***	−0.068 (0.026)**

Note: Includes controls for region. LSOA=Lower Super Output Area; VPC=variance partition coefficient. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$.

TABLE 3 Results of Logit multilevel models.

	Benefits	Political disaffection
LSOA Var/VPC	1.164/0.354	0.294/0.090
Trajectory Var/VPC	0.191/0.058	0.002/0.001
Log odds		
Age, 18–24 ref		
25–34	0.262 (0.277)	−0.223 (0.208)
35–44	0.171 (0.271)	−0.119 (0.202)
45–54	0.208 (0.26)	−0.171 (0.201)
55–64	0.237 (0.271)	−0.074 (0.202)
Over 65	0.078 (0.284)	−0.063 (0.212)
Gender, female	−0.012 (0.057)	0.003 (0.044)
Relationship, single ref		
Partnered	0.048 (0.088)	−0.078 (0.066)
Post-partnership	0.226 (0.107)**	0.016 (0.082)
Ethnicity, White ref		
Black	−0.255 (0.164)	−0.227 (0.123)*
South Asian	0.352 (0.430)	−0.143 (0.353)
Other Asian	−0.035 (0.118)	−0.052 (0.090)
Mixed	0.139 (0.240)	−0.265 (0.194)
Other	−0.044 (0.268)	0.144 (0.204)
Economic activity, employed ref		
Unemployed	−0.073 (0113)	0.190 (0.082)**
Retired	0.061 (0.110)	−0.087 (0.083)
Student	−0.084 (0.382)	−0.336 (0.309)
Other inactive	−0.540 (0.177)**	0.073 (0.119)
UK born	−0.091 (0.091)	0.088 (0.070)
Urban	0.290 (0.087)***	0.057 (0.058)

Note: Includes controls for region. LSOA=Lower Super Output Area; VPC=variance partition coefficient. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$.

followed by LSOA—although all models reveal variation across the neighbourhood types except the mental health model, demonstrating the importance of individual and place factors in capturing experiences of 'left behindness'. We also control for region; however, these results are not statistically significant and are not reported here. Overall, the effects for individual outcomes (Figure 5) show the same patterns and direction of association as described in Table 2. We now explore how these outcomes vary across the neighbourhood types.

5.3.1 | Economic wellbeing

All individual economic measures show similar associations across predictors and neighbourhood types, where, unsurprisingly, relatively disadvantaged neighbourhoods also have poorer individual economic outcomes. Receiving benefits is the only economic indicator where cluster effects were not observed for all neighbourhood types, being significant only for the extremities of *Entrenched Disadvantage*, *Fluctuating Affluence* and *Stable Affluence*, accounting for 6% of variation. Economic activity, as well as urban living, is a significant predictor of higher income, better subjective finances, and benefit receipt. Income models reveal the strongest effects for neighbourhood type, with over 10% of model variance captured at this level, as represented by the VPC (reducing to 4% for subjective finance). This is likely to be partly explained by the strong influence of income within the IMD.

TABLE 4 Results of ordinal logistic multilevel models.

	Subjective health	Life satisfaction	Subjective finance	Income quintile	Political interest
LSOA Var/VPC	0.095/0.029	0.232/0.071	0.620/0.188	2.020/0.614	0.261/0.079
Trajectory Var/VPC	0.043/0.013	0.036/0.011	0.139/0.042	0.349/0.106	0.067/0.020
Thresholds	vPoor|Poor	0|1	vPoor|Poor	1|2	0|1
	−1.83 (0.145)	−1.506 (0.143)	−2.643 (0.204)	−1.746 (0.294)	−0.997 (0.162)
	Poor|Fair	1|2	Poor|Fair	2|3	1|2
	−0.093 (0.144)	−1.302 (0.143)	−1.869 (0.207)	−0.731 (0.294)	0.034 (0.162)
	Fair|Good	2|3	Fair|Good	3|4	2|3
	0.069 (0.144)	−0.968 (0.143)	−0.705 (0.205)	0.188 (0.294)	1.374 (0.163)
	Good|vGood	3|4	Good|vGood	4|5	
	1.264 (0.145	−0.666 (0.142)	0.627 (0.205)	1.258 (0.294)	
		4|5			
		−0.309 (0.142)			
		5|6			
		0.161 (0.142)			
		6|7			
		1.596 (0.143)			
Log odds, age 18–24 ref					
25–34	−0.041 (0.107)	0.030 (0.108)	−0.085 (0.123)	−0.061 (0.141)	0.039 (0.112)
35–44	−0.078 (0.104)	0.054 (0.106)	−0.171 (0.120)	−0.064 (0.137)	0.073 (0.109)
45–54	−0.023 (0.104)	0.084 (0.105)	−0.164 (0.119)	−0.043 (0.137)	0.124 (0.108)
55–64	−0.084 (0.104)	0.093 (0.106)	−0.174 (0.120)	−0.093 (0.138)	0.093 (0.109)
Over 65	−0.067 (0.109)	0.098 (0.111)	−0.126 (0.126)	−0.088 (0.145)	0.063 (0.115)
Gender, female	0.005 (0.022)	0.230 (0.023)	−0.003 (0.026)	−0.003 (0.028)	0.047 (0.023)**
Relationship, single ref					
Partnered	−0.003 (0.034)	0.017 (0.035)	0.035 (0.040)	0.050 (0.045)	0.034 (0.036)
Post-partnership	−0.020 (0.042)	0.045 (0.043)	0.024 (0.049)	0.070 (0.055)	−0.024 (0.044)
Ethnicity, White ref					
Black	0.037 (0.061)	−0.045 (0.063)	0.055 (0.073)	0.085 (0.083)	−0.082 (0.065)
South Asian	0.007 (0.181)	−0.137 (0.182)	−0.115 (0.210)	−0.080 (0.237)	0.171 (0.189)
Other Asian	0.003 (0.046)	0.091 (0.047)*	−0.039 (0.055)	−0.035 (0.065)	−0.071 (0.048)
Mixed	0.011 (0.098)	−0.033 (0.098)	−0.185 (0.112)*	−0.134 (0.128)	−0.106 (0.101)
Other	0.007 (0.106)	−0.073 (0.107)	−0.157 (0.124)	−0.126 (0.140)	−0.167 (0.111)
Economic activity, employed ref					
Unemployed	−0.009 (0.043)	0.015 (0.046)	−0.028 (0.057)	0.077 (0.080)	−0.029 (0.047)
Retired	0.017 (0.042)	−0.002 (0.044)	0.038 (0.053)	0.120 (0.067)*	−0.073 (0.046)
Student	0.015 (0.165)	−0.361 (0.181)**	−0.433 (0.191)**	0.100 (0.246)	−0.070 (0.169)
Other inactive	0.030 (0.062)	0.129 (0.067)*	0.083 (0.083)	−0.025 (0.118)	−0.021 (0.069)
UK born	−0.062 (0.035)*	−0.043 (0.036)	−0.044 (0.042)	−0.004 (0.047)	−0.052 (0.037)
Urban	−0.100 (0.030)***	−0.078 (0.033)**	−0.151 (0.043)***	−0.114 (0.062)*	−0.013 (0.034)

Note: Includes controls for region. LSOA=Lower Super Output Area; VPC=variance partition coefficient. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$.

5.3.2 | Living environment

There is less evidence of neighbourhood type effects for models of living environment, with significant variation in ‘left behind’ neighbourhoods. We observe 2.5% of the variation at this scale, for both neighbourhood cohesion and household space. Economic activity and urban living are significant predictors of both outcomes, while marital status, ethnicity and

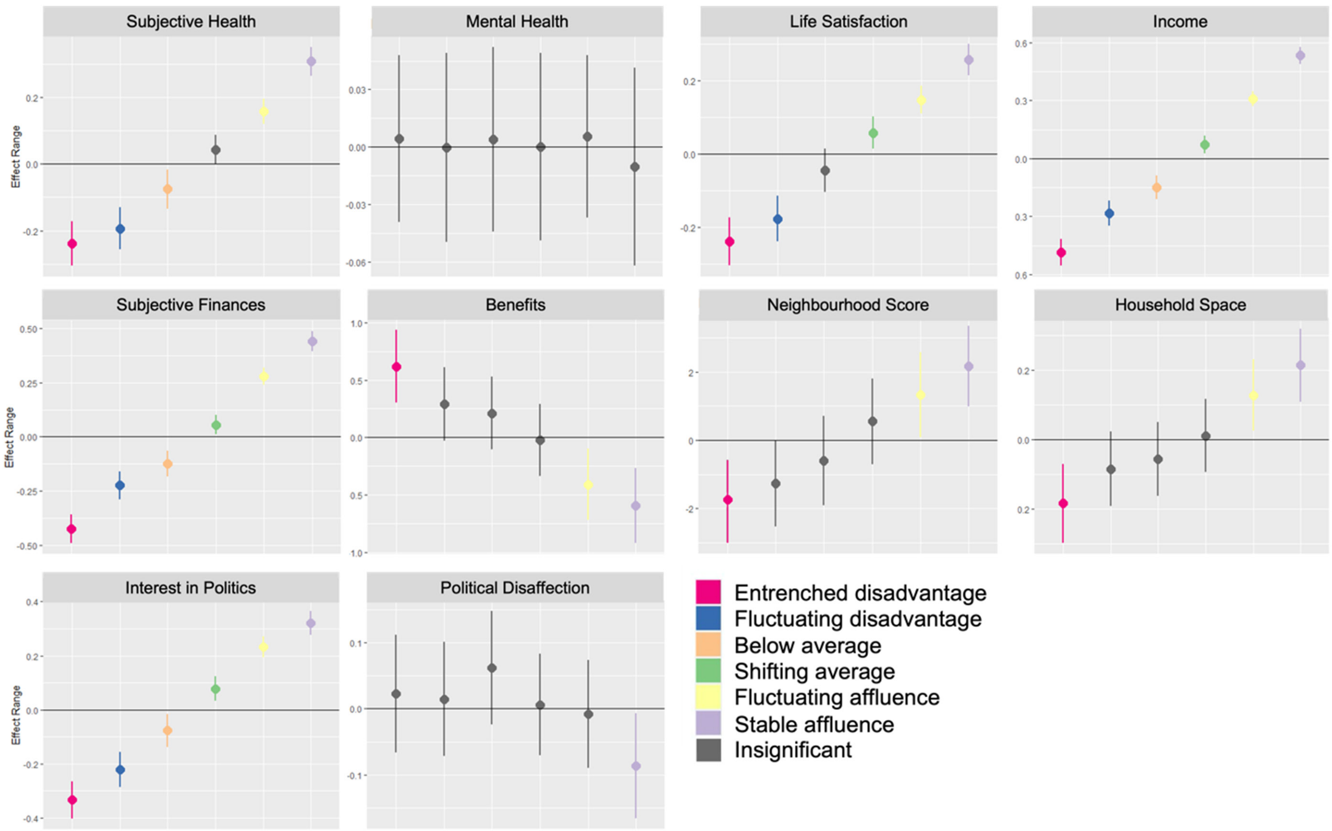

FIGURE 5 Caterpillar plots of random intercept by neighbourhood type. *Data source*: UKHLS (2020).

being UK born are associated with stronger neighbourhood cohesion. The strong association with economic indicators may explain, in part, the large amount of LSOA variation, accounting for over 50% in the household space model, the highest identified across any individual measure.

5.3.3 | Health and wellbeing

The mental health model shows no variation across neighbourhood types, implying that symptoms of mental distress only significantly differ across LSOA and individual levels. While context matters, the type of neighbourhood appears less important here. We speculate this may relate to the complexities of mental health and the medical diagnostic measure, which may not represent individual lived experiences of living in a 'left behind' neighbourhood in the same manner as more subjective, self-reported indicators applied to other models. This may be further compounded by the distribution of health services across England, where inequalities tend to cross urban–rural, ethnic and age boundaries (Gulliford et al., 2004), all of which were accounted for in our study. However, the remaining health models—subjective health and life satisfaction—reveal significant variation across almost all neighbourhood types, particularly for those identified as 'left behind'. Across neighbourhood types, health improves with affluence. Subjective health is strongly associated with being UK born and an urban resident, while ethnicity, economic activity and urban living were significant predictors of life satisfaction.

5.3.4 | Political sentiment

Political variables differ considerably in terms of neighbourhood-level and individual-level effects. While strong and significant neighbourhood type effects are observed for individuals' interest in politics, with those in 'left behind' neighbourhoods less interested, gender was the only significant individual-level predictor, which may reflect gender differences observed in studies of 'left behind' industries in economic decline or wider forms of social inequality (Abreu & Jones, 2021). Contrarily, non-statistically significant effects suggest that neighbourhood type did not appear to affect political disaffection (just 1%), although ethnicity and economic activity displayed significant associations at the individual level. This finding contradicts previous research in the UK context that establishes a strong association between voting for 'Leave' in the 2016 Brexit referendum and living in a 'left behind' area (Furlong, 2019; Jump & Michell, 2020). It may also reflect methodological differences, with previous studies predominantly focusing on area-level metrics, rather than individual attitudes (Dorling & Pritchard, 2010). Most variation occurred across individuals, with less than 10% seen at the LSOA level in both cases.

5.3.5 | Individual characteristics

Model results indicate that individuals of some ethnicities display poorer outcomes, particularly for mental ill-health, life satisfaction, subjective finance, and neighbourhood cohesion. Notably, those identifying as South Asian experience significantly lower neighbourhood cohesion, and more financial difficulty. Most minority ethnic groups did not report being more politically disaffected, again implying that, at least in this analysis, political outcomes are less straightforward than demographic assumptions around minority disengagement might suggest (Just, 2017). Relationship status was a particularly strong predictor of some of the economic and environmental measures: receiving benefits was significantly higher among separated or widowed individuals, while partnered residents reported much stronger neighbourhood cohesion, though this may be additionally related to ageing, widow benefits and single-parent households. Mixed results were observed among other predictors.

Taken together, these findings indicate individual outcomes are worse on a variety of fronts for those living in 'left behind' neighbourhoods. Health, economic and living environment measures are particularly poor for individuals living in 'left behind' neighbourhoods, suggesting that these are most strongly related to individual experiences. We also notice differences within those neighbourhoods defined as 'left behind'. While *Entrenched Disadvantage* and *Fluctuating Disadvantage* both follow similar patterns in the strength and significance of individual outcomes including subjective health, life satisfaction, and interest in politics, there is notable variation across receiving benefits, neighbourhood score, and household space, where only those living in *Entrenched Disadvantage* neighbourhoods perform significantly more poorly than the average. Individual and area-level measures and covariates therefore provide vital insight into more granular aspects of individual circumstance, highlighting the significance of experiences overlooked in area level only analyses.

6 | DISCUSSION

In characterising neighbourhoods as 'left behind' by their deprivation trajectory, we argue that temporal persistence is central to the processes via which communities are 'left behind'. We find that neighbourhoods classified as 'left behind'—those experiencing prolonged deprivation with the least potential to transition between deciles of deprivation—are highly spatially concentrated, particularly in major urban conurbations and post-industrial or coastal towns (see also Rae, 2012). Characterising how different areas fare over time through varying levels of deprivation is key to understanding the challenges faced by different communities (Patias et al., 2021).

While previous research has firmly established how deprived neighbourhoods can exacerbate poorer individual outcomes (Galster & Sharkey, 2017; Sampson, 2019), our investigation found that neighbourhoods following different trajectories may lead to differentiated individual outcomes. Notably, of our two neighbourhood types classified as 'left behind', only neighbourhoods defined by the most *Entrenched Disadvantage* had significantly poorer neighbourhood cohesion than average, while being the most likely to receive benefits. Contrarily, the general and mental health of those living in *Entrenched* or *Fluctuating Disadvantage* neighbourhoods were significantly lower than average. This demonstrates the value of insight to be gained by considering indicators of wellbeing beyond the traditionally economic.

The analysis also highlights the importance of a multiscalar approach. Crucially, particular dimensions in our multidimensional conceptualisation of 'left behind' become important at different scales. For instance, while populations are demographically similar across neighbourhood types, we observe that those in 'left behind' neighbourhoods display poorer individual health and economic outcomes. Poor experiences of the living environment (in terms of lower household space and neighbourhood cohesion) are evident in the 'left behind' neighbourhood types, but we notice most variation across individuals rather than LSOA. While those in 'left behind' neighbourhoods report being less interested in politics, strong gender differences are observed at the individual level, with women reporting significantly higher interest. Exploring these multiple facets of wellbeing expands our understanding of individual experiences of living in a 'left behind' neighbourhood, which has previously focused on economic values (MacKinnon et al., 2022).

Our findings suggest that both place *and* time matter, especially for individuals' perceptions of their living environment, including residing in an urban area and perceived neighbourhood cohesion, whereas ethnicity and economic activity are more strongly related to individual experiences. Comparatively, we observed minimal, non-statistically significant, variation across regions compared with the statistical difference in outcomes across neighbourhood types. Individual and area-level patterns of peripheralisation are likely to be of greater importance than the regional scale, despite the region assuming such importance to date in 'left behind' research (Lowe & Vinodrai, 2020; Sykes, 2018). Neighbourhoods represent the geographical scale at which people experience their daily life. As such, when designing policies to reduce the impact of prolonged disadvantage, we argue that the interactions of multiple scales should be considered. Understanding and intervention at the neighbourhood scale are vital to improve outcomes in situ, leading to aggregate impacts at a regional and national level.

Our methodological approach has several limitations. Our deprivation trajectories are based on data from three time points (2010, 2015 and 2019). Due to individual-level data availability, we were unable to measure individual outcomes at multiple time points. As such, the importance of temporal change is only reflected in the 'place' aspect of our analysis. While the English IMD allows us to quantify neighbourhoods experiencing sustained relative disadvantage, income and employment factors together contribute 45% of the total score, thereby potentially biasing the analysis towards economic inequality. Furthermore, as we are interested in 'left behind' neighbourhoods as those experiencing prolonged disadvantage, we did not include individuals who had relocated to new LSOA during the study period. While this enables us to focus on the experiences of individuals within persistently deprived neighbourhoods, we do not consider outcomes for those who have resided in different types of neighbourhoods over time. Finally, the use of survey data means that results should be interpreted with response rates and attrition in mind.

7 | CONCLUSION

In this analysis, we classified 'left behind' neighbourhood types, and examined how individuals experience these effects across England. We delineated changing trajectories of deprivation at the neighbourhood scale to identify places experiencing prolonged deprivation with limited mobility to transition out of state. Novelly, we explored variation across scales and dimensions to provide new insights into how objective and subjective wellbeing outcomes at the individual scale are shaped by living in a 'left behind' neighbourhood.

'Left behind' neighbourhood types cluster spatially, implying that local comparison between areas is relevant to individual perceptions and experiences. Crucially, however, these relationships are much more complex than those captured at a regional level. They move beyond traditional perceptions of 'left behind' areas being driven by economic disadvantage. The focus on multiple dimensions and change over time at the neighbourhood scale highlights the inter-related and place-based character of 'left behindness'.

Demonstrating the novelty of these trajectories by employing a multilevel model, the paper emphasised the importance, and interaction, of different spatial scales in understanding what it means to experience being 'left behind', and the differences between people and places. We show how people living in 'left behind' areas are likely to have differing experiences to those living elsewhere in the country, particularly in terms of health and economic wellbeing, as well as social and political attributes.

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DATA AVAILABILITY STATEMENT

Code and data to reproduce the results are available here: https://github.com/fcorowe/left_behind/.

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ENDNOTES

[1] Each IMD domain is combined into a final indices using weights, specifically 22.5% for both income and employment, 13.5% for the domains of health and disability, and education, and skills and training, and 9.3% for the domains of barriers to housing and services, crime, and living environment (DCLG, 2019).

[2] Boundaries were recalculated using the ONS look-up tables to identify the LSOA of best fit. Overall, the number of LSOA increased from 32,482 in 2001 to 32,844 in 2011.

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