County Court Judgments, financial vulnerability and spatial inequality in England

A population-aware spatial analysis of cumulative registered consumer CCJs

Keyu Chen

CASA0010: MSc Dissertation
MSc Urban Spatial Science
Supervisor: Dr Andrew MacLachlan
Word Count: 18,984

This dissertation is submitted in part fulfilment of the requirements for the MSc Urban Spatial Science in the Centre for Advanced Spatial Analysis, The Bartlett Faculty of the Built Environment, University College London

August 2026

Abstract

This dissertation examines the spatial distribution of cumulative registered consumer County Court Judgments (CCJs) across England and evaluates whether deprivation alone is sufficient to identify places with unusually high formal debt burdens. The analysis combines 4,401,837 registered judgments observed between April 2020 and April 2026 with an exact Census 2021 adult population denominator for 33,754 Lower Layer Super Output Areas and aggregates the results to 296 Local Authority Districts. Conventional choropleth mapping is compared with an adjacency-aware Dorling population cartogram so that relative CCJ intensity and the absolute scale of potential service demand can be interpreted together. A negative-binomial expected-count model then estimates the CCJ burden associated with adult population, neighbourhood deprivation, urban-rural status and Region. Its geographical transferability is assessed through complete-LAD holdout and 10-km spatially buffered cross-validation before observed and predicted counts are compared. England recorded an overall cumulative rate of approximately 98.4 CCJs per 1,000 adults. The most deprived decile recorded 215.9 CCJs per 1,000 adults, around seven times the rate in the least deprived decile. Urban areas had a higher average burden, although the proportional deprivation gradient was steeper in rural areas. Predictive performance remained similar under both validation designs, supporting use of the model as a local benchmark. Nevertheless, 64 local authorities recorded at least 10% more CCJs than expected under both designs and 87 recorded at least 10% fewer, while the remaining prediction errors were spatially clustered. The findings show that deprivation is central to the national geography of registered CCJs but does not fully explain local outcomes. Place-based debt policy should therefore combine deprivation, observed CCJ rates, absolute case volumes and departures from socioeconomic expectation.

Contents

List of Figures **4**
List of Tables **4**
1. Introduction **5**
1.1 Background 5
1.2 Research aim, question and objectives 8
2. Literature Review **9**
2.1 CCJs and financial vulnerability 10
2.2 Socioeconomic contexts and pathways associated with CCJs 12
2.2.1 Income, deprivation and financial buffers 12
2.2.2 Employment insecurity and income shocks 14
2.2.3 Housing costs, tenure and essential expenditure 16
2.2.4 Health, disability and adverse life events 17
2.2.5 Household and demographic inequalities 19
2.3 Spatial inequalities and place-based debt vulnerability in England 21
2.4 Mapping and analysing spatially uneven debt outcomes 24
2.4.1 Counts and population-standardised rates 25
2.4.2 Choropleth maps, area-size bias and population cartograms 26
2.4.3 From descriptive mapping to count modelling 28
2.4.4 Spatial dependence and geographical model evaluation 29
2.4.5 Observed-to-expected comparisons and place-based departure 32
2.5 Conclusion 33
3. Methodology **35**
3.1 Research design and analytical framework 35
3.2 Data and variable construction 36
3.2.1 CCJ outcome and adult population denominator 36
3.2.2 Socioeconomic and geographical variables 37
3.2.3 Data integration and temporal alignment 37
3.3 Measuring and mapping CCJ burden 38
3.4 Expected-count modelling 39
3.4.1 Baseline negative-binomial model 39
3.4.2 Statistical inference and diagnostics 40
3.4.3 Urban-rural interaction 40
3.5 Out-of-sample and spatial validation 41
3.5.1 LAD-grouped and spatially buffered cross-validation 41
3.5.2 Residual spatial autocorrelation 41
3.6 Observed-to-expected local comparison 42
3.7 Sensitivity, reproducibility and ethics 42
4. Results **43**
4.1 The observed socioeconomic geography of registered CCJs 43
4.2 Estimating the CCJ burden expected from socioeconomic context 48
4.3 Testing the expected-count benchmark outside the estimation sample 50
4.4 Observed CCJs versus model-expected CCJs 52
4.5 Spatial structure in the observed-to-expected departures 55
4.6 Summary of the empirical findings 57
5. Discussion **59**
5.1 From deprivation to local variation in formal debt outcomes 59
5.2 Local departures and their policy implications 63
5.3 Limitations and further research 70
6. Conclusion **75**
References **80**
Appendices **86**
Appendix A. Model validation and sensitivity 86
Appendix B. Cartogram validation 87
Appendix C. Complete Local Authority District results 88

List of Figures

Figure 3.1. Analytical workflow ... 36
Figure 4.1. Population-weighted cumulative registered CCJ rate by IMD decile ... 44
Figure 4.2. Population-weighted cumulative registered CCJ rates in urban and rural LSOAs ... 45
Figure 4.3. Population-weighted cumulative registered CCJ rates across English Regions ... 46
Figure 4.4. Conventional LAD choropleth and adjacency-aware Dorling population cartogram ... 47
Figure 4.5. Observed and out-of-LAD predicted cumulative CCJ rates ... 50
Figure 4.6. Predictive performance under LAD-grouped and spatially buffered validation ... 51
Figure 4.7. Observed and model-expected CCJ counts across Local Authority Districts ... 53
Figure 4.8. LSOA observed-to-expected CCJ burden under complete-LAD holdout ... 56
Figure 4.9. Local Authority District observed-to-expected CCJ burden ... 56
Figure A.1. IMD association under alternative spatial uncertainty corrections ... 86

List of Tables

Table 3.1. Temporal and analytical roles of the principal data sources ... 38
Table 4.1. Headline descriptive characteristics of the analytical sample ... 46
Table 4.2. Poisson and negative-binomial model diagnostics ... 48
Table 4.3. Baseline and urban-rural interaction model results ... 49
Table 4.4. Cross-validation performance of the deprivation benchmark ... 51
Table 4.5. Selected LAD departures from the deprivation benchmark ... 54
Table A.1. Spatial uncertainty sensitivity of the IMD association ... 86
Table A.2. Complete-LAD grouped cross-validation fold audit ... 86
Table A.3. Sensitivity of robust observed-to-expected departures to the threshold ... 87
Table B.1. Selected validation measures for the adjacency-aware Dorling cartogram ... 87
Table C.1. Complete LAD observed-to-expected results under both validation designs ... 88

1. Introduction

1.1 Background

A County Court Judgment (CCJ) is a formal civil judgment issued through the court system in England and Wales in relation to a monetary claim. It records a legal determination that money is owed and normally specifies the amount, repayment arrangements and payment deadline. A CCJ is therefore distinct from both a criminal conviction and an ordinary record of borrowing. The use of credit does not necessarily indicate financial difficulty, since many households borrow while continuing to meet their repayment obligations. By contrast, a CCJ represents a more formal stage of debt distress in which a monetary claim has progressed into court action and resulted in a legally recognised repayment obligation. Unless it is paid in full within one month or subsequently set aside, a registered judgment normally remains on the Register of Judgments, Orders and Fines for six years, during which it may affect access to credit and other financial services (GOV.UK, n.d.). Registry Trust Ltd. (2025), the official operator of the Register, consequently describes CCJ data as both a lagging and a potential leading indicator of financial difficulty and financial exclusion: judgments reflect circumstances in which debt has already escalated to formal enforcement, while the resulting record may contribute to later difficulties in accessing affordable credit or housing. The Consumer Data Research Centre (CDRC, 2021) similarly identifies geographically aggregated CCJ data as a potentially important area-level indicator of financial health.

CCJs arise within a broader context of household financial pressure. In January 2024, the Financial Conduct Authority estimated that 14% of UK adults felt heavily burdened by domestic bills and credit commitments, 11% had missed at least one bill or credit payment during the preceding six months, and 28% were either not coping financially or finding it difficult to cope (Financial Conduct Authority, 2024). These pressures are not geographically uniform. Fair4All Finance (2024) identified 47 UK local authorities in which more than half of adults were estimated to be living in financially vulnerable circumstances, with London and the North East recording the highest regional proportions, at 46% in each. Evidence from London further illustrates substantial inequality within apparently prosperous regions. Analysis conducted by LSE CASE and StepChange estimated that approximately 13% of adults in London were highly over-indebted, compared with around 10% across the UK, while the corresponding proportion reached 19% in the five most deprived London boroughs but fell to 6% in the five least deprived boroughs (Karagiannaki, 2024; Karagiannaki, 2025). Taken together, this evidence indicates that formal debt distress should not be understood solely as an individual financial outcome. It is situated within geographically uneven conditions of income, employment, housing costs, financial resilience and access to affordable financial services.

This geographical inequality creates both a measurement problem and a cartographic problem. Absolute CCJ counts are influenced by the size of the population exposed to the possibility of receiving a judgment. A densely populated local authority may record a large number of CCJs without having an unusually high population-standardised burden, whereas a less populous area may record fewer judgments but a substantially higher rate relative to its adult population. Comparisons between places therefore require both absolute totals and an appropriate population denominator. Statistical standardisation alone does not fully resolve the problem of spatial communication. Conventional choropleth maps display values within administrative polygons whose physical areas vary substantially. Large and frequently less densely populated areas consequently occupy more visual space, while small, densely populated urban authorities may be difficult to distinguish at the national scale. Empirical cartographic research describes this phenomenon as area-size bias: small polygons, including those containing extreme values, are more likely to be overlooked than geographically larger units (Schiewe, 2019). This problem is particularly important in London and other densely populated urban areas, where substantial populations are represented within geographically compact administrative units. As a result, places containing large numbers of residents and potentially substantial demand for debt advice, legal support or preventive intervention may receive disproportionately little visual attention, while geographically extensive but less populous areas dominate the display. Population cartograms address this imbalance by reallocating visual space according to population rather than land area (Dorling, 1996). When presented alongside a conventional choropleth, they help distinguish the relative intensity of registered judgments from the scale of the population potentially requiring support.

Existing evidence therefore establishes the value of CCJs as an area-level indicator of formal debt distress, but also reveals limitations in how their geographical distribution is commonly measured, represented and interpreted. Mapping high CCJ rates can identify places with elevated burdens, but it does not establish why these patterns occur or whether they are unusual given the socioeconomic conditions of those places. Neighbourhood deprivation is likely to be an important correlate of CCJ burden because it captures multiple dimensions of disadvantage, including income, employment, health, education, crime, housing barriers and the living environment. However, demonstrating an association between deprivation and CCJs would provide only a partial explanation. The more policy-relevant questions concern the magnitude of the deprivation gradient, whether departures from the socioeconomic benchmark remain spatially clustered after population, urban-rural status and Region are taken into account, and which local authorities experience CCJ burdens substantially higher or lower than expected.

There is consequently a need for an integrated spatial framework that combines four forms of evidence. First, absolute CCJ totals and adult-population-standardised rates should be distinguished because they represent different dimensions of local need. Second, conventional administrative maps should be compared with a population-sensitive representation so that geographically small but populous places are not visually marginalised. Third, the relationship between deprivation and CCJ burden should be evaluated using an appropriate count model and validation procedures that account for geographical separation. Finally, observed CCJ burdens should be compared with deprivation-based expectations to identify places that may otherwise be overlooked by resource-allocation systems based primarily on deprivation.

1.2 Research aim, question and objectives

To address this gap, this dissertation develops and applies an integrated, population-aware spatial framework to examine cumulative registered consumer CCJs across England. The analysis covers approximately 4.4 million registered judgments recorded between 1 April 2020 and 1 April 2026 across 33,754 Lower Layer Super Output Areas (LSOAs) and 296 Local Authority Districts (LADs). It combines population-standardised mapping with a deprivation benchmark, spatially separated validation and local-authority-level observed-to-expected comparisons.

The principal research question is:

How can a population-aware spatial analysis improve the identification and interpretation of cumulative registered consumer CCJ burden across England?

This question is addressed through four objectives. First, to construct statistically comparable measures of cumulative registered CCJ burden using an exact Census 2021 adult population denominator for residents aged 18 years and over. Second, to examine how the visibility and interpretation of local CCJ burdens differ between conventional administrative-boundary choropleth maps and an adjacency-aware Dorling population cartogram. Third, to estimate the area-level association between neighbourhood deprivation and cumulative registered CCJ burden using an expected-count model and to assess whether that relationship transfers to geographically unseen areas. Fourth, to compare observed and cross-fitted expected CCJ counts in order to identify Local Authority Districts whose registered burdens are consistently higher or lower than their socioeconomic context would predict, and to examine whether the deprivation-CCJ relationship differs between urban and rural areas.

The study evaluates the strength and spatial consistency of area-level associations and develops a transparent framework for identifying places that warrant further local investigation or comparative analysis. The framework distinguishes high absolute CCJ volume from high population-standardised burden and, through observed-to-expected comparison, identifies authorities whose registered judgment counts remain unusually high or low relative to their socioeconomic circumstances.

2. Literature Review

This chapter situates County Court Judgments (CCJs) within the connected literatures on financial vulnerability, problem debt and spatial inequality. It begins by explaining why a CCJ can be understood as a formal manifestation of financial vulnerability. It then develops the socioeconomic argument in stages: limited income constrains repayment capacity; inadequate savings weaken households' ability to absorb shocks; employment disruption destabilises income; housing and essential expenditure reduce budgetary flexibility; and health and household circumstances shape both resources and needs. Because these conditions are geographically concentrated, the discussion then moves from households to places and reviews the spatial distribution of debt vulnerability in England. Finally, it examines how existing cartographic and statistical research has represented population-related outcomes, explained event counts and identified geographical departures from expected patterns. Together, these literatures provide a coherent foundation for analysing where CCJs have accumulated, how closely that accumulation is associated with deprivation and why some places depart from the national relationship.

2.1 CCJs and financial vulnerability

A consumer County Court Judgment is a civil-court determination that an individual or organisation owes money to a claimant. It records the amount owed and the arrangements or deadline for payment. Registry Trust maintains the statutory Register of Judgments, Orders and Fines for England and Wales on behalf of the Ministry of Justice. CCJs therefore provide an administrative record of monetary obligations that have progressed beyond ordinary borrowing and initial repayment difficulty into a formal legal outcome (GOV.UK, n.d.; Registry Trust, 2025).

This legal definition identifies what a CCJ records, but the debt literature is needed to explain its socioeconomic meaning. Borrowing is not inherently evidence of financial difficulty: credit can support housing purchase, investment and short-term consumption smoothing when repayments remain affordable. The more relevant distinction is between holding debt and losing the capacity to service it. D'Alessio and Iezzi (2013) show that over-indebtedness is consequently measured through indicators such as arrears, debt-service burdens and reported repayment difficulty rather than debt ownership alone. Hood, Joyce and Sturrock (2018) reinforce this distinction empirically. Although unsecured borrowing occurs across the income distribution, arrears and heavy repayment burdens are substantially more concentrated among lower-income households. Debt becomes a marker of vulnerability when repayment obligations exceed the resources available to meet them.

The concept of financial vulnerability broadens this argument from current repayment difficulty to households' capacity to withstand and recover from financial pressure. Fernández-López et al. (2024) show that the literature commonly connects vulnerability with limited resilience, exposure to shocks and restricted recovery capacity. The Financial Conduct Authority (2021) gives this concept a more operational structure by identifying four overlapping drivers: poor health, adverse life events, low financial resilience and limited capability. These drivers explain how an obligation that was previously manageable can become unaffordable. A loss of employment may reduce income and savings; illness may simultaneously restrict earnings and increase expenditure; and relationship breakdown may alter both household resources and financial responsibilities.

CCJs occupy a clear position within this process because they record the point at which unresolved repayment difficulty becomes legally formalised. Unless cancelled following full payment within one month, a CCJ normally remains on the register for six years and may affect subsequent lending decisions (GOV.UK, n.d.). Registry Trust (2025) therefore connects judgment data to two stages of vulnerability: a judgment reflects an already realised repayment breakdown, while its effect on access to mainstream credit can extend that vulnerability into the future. The legal outcome and the financial consequence are thus connected. A CCJ records severe repayment difficulty and may also reduce the range of affordable financial options available during recovery.

The literature consequently provides a clear conceptual chain: limited household resilience increases exposure to repayment difficulty; unresolved repayment difficulty can progress into a court judgment; and a registered judgment may deepen subsequent financial exclusion. The geographical distribution of CCJs can therefore reveal where formal debt distress has accumulated. To understand why this accumulation differs between communities, it is necessary to examine the socioeconomic conditions that shape repayment capacity before legal action occurs.

2.2 Socioeconomic contexts and pathways associated with CCJs

The socioeconomic literature does not identify a single route into debt distress. Instead, it describes a connected process in which limited resources make households vulnerable, financial shocks trigger repayment difficulties and fixed expenditure determines how quickly those difficulties become persistent. Income establishes the basic capacity to repay, but income alone provides an incomplete account. Savings determine resilience, employment determines stability, housing determines unavoidable expenditure, and health and household structure influence both resources and needs. The following sections trace this process from underlying financial capacity to the wider social conditions within which debt problems develop.

2.2.1 Income, deprivation and financial buffers

The starting point is the strong income gradient in repayment difficulty. Hood, Joyce and Sturrock (2018) provide a clear measure of its scale: 16 per cent of households in the lowest income decile were behind on bills or debt repayments, compared with 1 per cent in the highest decile. Approximately one quarter of the poorest tenth were either in arrears, spending more than one quarter of disposable income on debt servicing, or experiencing both conditions. Bridges and Disney (2004) reach a consistent conclusion using the UK Survey of Low Income Families, finding that arrears were heavily concentrated among families with restricted incomes. Read together, these studies establish the basic distributional relationship: as the resources available after essential expenditure decline, the same repayment commitment absorbs a larger proportion of the household budget.

Cross-sectional evidence establishes the income gradient, while longitudinal research explains how it can become persistent. Using several waves of British household data, Kempson, McKay and Willitts (2004) distinguish families that temporarily entered arrears from those that remained in financial difficulty over several years. Persistent arrears were particularly common among families receiving means-tested benefits, lone parents and households without savings accounts. Rather than presenting another static association between income and debt, these findings show that sustained resource constraints reduce households' capacity to clear arrears once they have entered them. Carter and Hill-Dixon (2022) extend this conclusion across a wider range of household obligations in their review of poverty and social exclusion in Wales. They show that high housing and energy costs can force low-income households to borrow or miss payments, while the resulting debt repayments and arrears further reduce the resources available for essential bills, thereby deepening financial insecurity.

Household resilience depends not only on current income but also on the liquid resources available when that income is interrupted. Lusardi, Schneider and Tufano (2011) measure immediate financial fragility through households' ability to raise emergency funds. Their finding that some moderate-income households could not meet an unexpected expense shows that annual income can conceal a lack of short-term liquidity. McKnight and Rucci (2020) develop this argument by measuring savings relative to monthly income, thereby examining how long households can continue meeting their obligations without regular earnings. Boileau, Cribb and Wernham (2023) test this mechanism during an actual employment shock. Among people whose employment was disrupted during the pandemic, those without financial wealth were more likely to enter arrears, while limited savings provided only temporary protection before being depleted. The evidence therefore identifies a specific mechanism: income finances routine payments, liquid assets bridge temporary income interruptions, and arrears become more likely when the disruption lasts longer than the available financial buffer.

The literature therefore moves from an income gradient to a broader account of accumulated disadvantage. Regular income provides the resources required for routine repayments, while savings determine how long those repayments can continue after an income shock. Poverty also increases exposure to several forms of essential-cost arrears at the same time. At the neighbourhood level, these overlapping conditions are captured by the English Index of Multiple Deprivation, which combines income, employment, education, health, crime, barriers to housing and services, and the living environment (McLennan et al., 2019). IMD gives greatest combined weight to income and employment while also representing the wider conditions that shape household needs and opportunities. It therefore provides an area-level measure of the socioeconomic environment within which repayment capacity is formed. The next stage of the argument concerns employment because income and savings become most vulnerable when the regular flow of earnings is interrupted.

2.2.2 Employment insecurity and income shocks

Whereas low income and limited savings describe underlying vulnerability, employment disruption often provides the event that activates it. Kempson, McKay and Willitts (2004) identify movement out of employment as an important trigger for entering arrears, while Bridges and Disney (2004) find that employment status helps explain differences in repayment difficulty among otherwise low-income families. These studies complement the evidence reviewed above: restricted income creates a narrow financial margin, and loss of employment removes part or all of that margin. Debt commitments arranged during employment may therefore become unaffordable without any increase in the amount borrowed.

More recent linked-data research traces this transition more precisely. Bogiatzis-Gibbons and O'Brien (2024) combine longitudinal Understanding Society records with monthly credit-file data, allowing repayment behaviour to be observed before and after a change in employment.

Consumers entering unemployment were approximately 1.9 times as likely to fall behind on credit payments as otherwise similar consumers who remained employed. Consumers who left paid employment because of long-term sickness or disability were approximately 2.7 times as likely to enter arrears, a larger increase than that associated with job loss for other reasons. By showing that poor health can lead to withdrawal from paid employment and that this loss of earnings substantially increases the risk of arrears, the study identifies employment exit as a specific pathway through which health affects repayment capacity.

Delestre and Waters (2026) explain the budgetary mechanism behind this deterioration. Using UK bank-account data, they find that newly unemployed benefit claimants experienced an average monthly income reduction of approximately £1,200, while their expenditure fell by only around £550. The difference shows that households cannot reduce established expenditure as quickly as earnings disappear. They must instead draw on savings, overdrafts or other resources to maintain consumption and payments. When read alongside Boileau, Cribb and Wernham (2023), the sequence becomes clearer: job loss creates an immediate income gap, while the presence or absence of financial assets determines how long the gap can be managed before arrears arise.

Employment shocks also connect household vulnerability to place. Spatial analysis locates these household-level triggers within local labour markets, showing why income shocks are more frequent and harder to absorb in areas characterised by low pay, insecure employment and limited re-employment opportunities. Narayan (2020) associates elevated problem-debt indicators in several British cities with weak earnings growth, welfare pressures and limited household resilience. Areas dependent on low-paid, seasonal or insecure employment expose a larger share of residents to unstable earnings, while diversified labour markets provide more opportunities for recovery. Employment insecurity therefore transforms the income gradient into a geographically uneven risk. The severity of that risk then depends on how much of the household budget is already committed to housing and other essential costs.

2.2.3 Housing costs, tenure and essential expenditure

Income shocks become especially damaging when a large share of household expenditure cannot be reduced quickly. Housing is central because rent and mortgage payments are contractual costs that recur each month and cannot usually be adjusted immediately after earnings fall. Cribb, Wernham and Xu (2023) show that poorer households devote a substantially larger proportion of their income to housing than richer households. Once housing costs are deducted, the gap between the resources available to poorer and richer households for other necessities is wider than comparisons based on income before housing costs suggest. Their analysis therefore shows why nominal income alone cannot describe the resources actually available for debt repayment.

StepChange (2023) shows how this pressure differs between tenures. Private renters in its study spent an average of 37 per cent of their income on rent, compared with 29 per cent among social renters and 27 per cent among mortgagors. Two thirds of surveyed private renters struggled to afford their rent, while housing support frequently failed to cover the full payment. When housing costs already absorb a large share of income, little remains for food, energy and existing debt repayments. Even a modest fall in earnings or rise in essential costs may then force a household to postpone one payment in order to meet another, increasing the risk of arrears.

Tenure also affects the form in which debt pressure appears. Bridges and Disney (2004) identify marked differences between rent and mortgage arrears among low-income families, demonstrating that households in different tenures face different contractual obligations and financial protections. The Money and Pensions Service (2023) reports that missed payments extended across credit cards, utilities, Council Tax or rates, loans, rent and mortgages. This pattern shows that housing payment difficulties frequently form part of broader financial strain involving several essential bills and credit commitments. Carter and Hill-Dixon (2022) place these arrears within a wider account of poverty and social exclusion in which household debt, housing costs and energy costs reinforce one another. Taken together, the evidence shows that housing tenure shapes the type and level of housing payments that households must meet, while pressure from energy bills, Council Tax and credit commitments determines whether difficulty with one payment spreads into multiple arrears.

This interaction also explains why the geography of debt cannot be inferred from income alone. In high-rent cities, middle-income households may experience repayment pressure because housing costs leave them with substantially less disposable income than their earnings initially suggest. Conversely, disadvantaged towns may combine lower rents with low wages, poor housing quality, fuel poverty and Council Tax arrears, while rural households may face additional transport and energy costs. Local housing and service markets therefore shape the expenditure side of financial vulnerability, just as labour markets shape income. The remaining capacity to manage these pressures is further influenced by health because illness can simultaneously reduce earnings, increase necessary expenditure and make financial administration more difficult.

2.2.4 Health, disability and adverse life events

Health connects the income and expenditure sides of financial vulnerability. Illness and disability may restrict employment and reduce earnings while simultaneously increasing expenditure on heating, transport, care and specialist goods. The FCA (2021) therefore positions poor health alongside adverse life events, low resilience and limited capability within a single framework of vulnerability. Bogiatzis-Gibbons and O’Brien (2024) provide direct evidence of this pathway. Consumers who left paid employment because of long-term sickness or disability were approximately 2.7 times as likely to fall behind on credit payments as otherwise similar consumers who remained employed. By linking poor health to withdrawal from paid employment and the resulting increase in arrears, the study shows how health affects repayment capacity through employment and income.

A second body of research examines the relationship from the perspective of mental health. Jenkins et al. (2008), using a national British psychiatric survey, find that debt remained strongly associated with common mental disorder after income and other socioeconomic characteristics were taken into account. The association between low income and mental disorder was substantially reduced after adjustment for debt, identifying debt-related financial hardship as one mechanism connecting economic disadvantage with mental health. Meltzer et al. (2013) reproduce this association in a separate nationally representative English sample and across measures of depression, anxiety and other common mental disorders. Their findings extend Jenkins et al. by showing that the relationship is consistent across different survey samples and measures of mental health.

While these national household surveys establish and reproduce the individual-level association, systematic reviews examine whether the same pattern is found across different populations, research designs and forms of debt. Fitch et al. (2011) find that financial difficulty can intensify psychological distress, while mental-health problems can impede financial management and communication with creditors. Richardson, Elliott and Roberts (2013), synthesising 52 studies, report particularly strong associations between unsecured debt and depression. Turunen and Hiilamo (2014) reach a comparable conclusion across 33 studies, linking unpaid debts with depression, suicidal behaviour and poorer subjective health. These reviews show that the association extends across a broad evidence base. Sweet et al. (2013) then add a balance-sheet dimension by showing that the severity of psychological distress is associated not only with the amount of debt but with debt relative to the assets available to repay it. High debt accompanied by few assets was associated with greater perceived stress and more depressive symptoms.

Taken together, the evidence supports a feedback mechanism between health and debt. Illness or disability may reduce earnings and increase necessary expenditure, thereby increasing reliance on credit and the risk of missed payments. Once arrears develop, the associated financial stress may worsen mental health. Fitch et al. (2011) further show that deteriorating mental health can impair financial management and communication with creditors, making existing arrears more difficult to resolve. The initial health shock may therefore create repayment difficulties that subsequently intensify the conditions preventing the household from recovering financially.

2.2.5 Household and demographic inequalities

Household composition changes the meaning of a given income because households differ in both the number of people supported and the costs they must meet. Kempson, McKay and Willitts (2004) find that families with children were more likely to use credit and experience repayment difficulty than households without children, with lone parents particularly exposed to long-term arrears. Bridges and Disney (2004) sharpen this comparison by reporting that more than 40 per cent of lone parents and approximately 30 per cent of low-income couples with children were behind on household utility or service bills. The progression from Kempson et al. to Bridges and Disney therefore moves from identifying family type as a source of vulnerability to quantifying the especially large burden faced by single-adult families with children.

ONS (2016) places these findings within the wider distribution of household liabilities. Households with dependent children were among the groups most likely to hold financial liabilities, while couples with dependent children recorded particularly high debt relative to income. This wider evidence complements the arrears studies: family costs increase the use of credit across several household types, but the absence of a second potential earner and the concentration of childcare responsibilities make lone parents especially vulnerable to repayment problems.

Age, employment and tenure then influence how these family pressures develop over the life course. McKnight and Rucci (2020) find lower financial resilience among younger households, renters, unemployed people and households in the lowest income groups. FCA Financial Lives evidence similarly shows that low financial resilience is concentrated among people experiencing low income, disability, poor health and major life events (FCA, 2024). These characteristics affect financial resilience through several connected pathways. Younger renters have generally had less time and fewer opportunities to accumulate savings and other assets, while unemployment directly interrupts household income. Disability may simultaneously restrict earning capacity and increase unavoidable living costs. Caring and other family responsibilities may further limit a household's ability to increase working hours or reduce expenditure quickly when financial circumstances deteriorate.

Research in London shows how these economic conditions intersect with ethnicity and neighbourhood deprivation. Karagiannaki (2024), using Understanding Society and StepChange client data, finds that more than 35 per cent of London lone parents were highly over-indebted and in urgent need of debt advice. The study also identifies elevated over-indebtedness among several ethnic-minority groups. Karagiannaki (2025) develops this analysis by examining ethnicity together with local deprivation. The study shows that ethnic inequalities in over-indebtedness are structured through unequal exposure to poverty, insecure employment, housing pressure, low wealth and neighbourhood deprivation. This conclusion directly supports a place-based interpretation of CCJs because geographically concentrated judgment burdens may reflect the local accumulation of socioeconomic disadvantages that are distributed unevenly across population groups.

Taken together, the literature identifies a connected system rather than a list of independent risk factors. These factors operate together through the household budget. Regular income provides the resources required for routine repayments, while savings determine how long those repayments can continue after an income shock. Employment stability affects the continuity of household income, and housing and other essential costs determine how much of that income remains available for debt repayment. Health influences earning capacity, necessary expenditure and the ability to manage financial affairs. Household composition further determines how many people and caring needs must be supported from the same pool of resources. Because these conditions are socially patterned and geographically concentrated, the next section moves from individual and household mechanisms to the places in which they accumulate.

2.3 Spatial inequalities and place-based debt vulnerability in England

The household pathways reviewed above become spatial inequalities because employment, housing, health, wealth and access to services are unevenly distributed between places. Local conditions shape both household income and the costs that must be met from that income. Local labour markets influence whether residents can obtain stable and adequately paid employment, while housing markets affect the rents they face and the tenure options available to them. Transport and energy systems determine part of the cost of meeting everyday needs, and the availability of mainstream financial services and debt advice affects whether households can obtain affordable credit and timely support. Differences between places therefore influence both the likelihood of financial difficulty and the resources available to resolve it.

The economic-geography literature first developed this argument through the concept of financial exclusion. Leyshon and Thrift (1995) argue that exclusion from mainstream finance arises from the interaction between limited household resources and the geographical organisation of financial institutions. When mainstream financial services withdraw from particular places, residents already facing economic disadvantage encounter greater difficulty in accessing suitable financial products. Financial exclusion can therefore reinforce existing spatial inequality by concentrating restricted financial access in communities that already have fewer economic resources. Research subsequently moved from this general account to the direct measurement of changes in local financial provision. Leyshon, French and Signoretta (2008) found that bank and building-society branch closures between 1995 and 2003 were disproportionately concentrated in poorer areas, showing that communities with fewer household resources also experienced a greater loss of local mainstream financial infrastructure.

Serious debt outcomes are also unevenly distributed geographically. Individual insolvency rates vary persistently across English regions and local authorities, indicating that formal repayment failure is more heavily concentrated in some places than in others. The North East recorded the highest regional rate in England in 2025 (Insolvency Service, 2026). International credit-file research supports the wider importance of place. Keys et al. (2022) find that debt in collection, credit-card delinquency and personal bankruptcy display persistent regional variation in the United States after accounting for individual characteristics. Together, this evidence indicates that financial distress reflects durable differences in local economic and institutional environments.

Research using CCJs provides the most direct British evidence for the present topic. Narayan (2020) found that cities in northern England and Wales generally carried higher levels of debt relative to income, while high population-standardised CCJ rates were concentrated in places such as Ipswich, Liverpool, Hull, Sunderland and Blackpool. The report relates this geography of problem debt to squeezed pay, weak productivity growth, welfare cuts and more aggressive debt collection. Its city-level comparison also reveals substantial variation within broad regions. York, for example, recorded a much smaller increase in problem debt than many other northern cities. Formal debt burdens therefore reflect the particular economic circumstances of individual cities as well as broader regional inequalities.

Magrini and Sells (2021) extend this city-level analysis by examining how the financial effects of the COVID-19 pandemic varied across British cities and neighbourhoods. Their use of comparable debt and savings indicators shows that a common national shock produced markedly different local consequences because households and local economies entered the pandemic with unequal financial resources and recovered at different rates.

Evidence at local-authority and borough level reveals substantial variation hidden within broad regional averages. Two studies examine this issue at different spatial scales: Fair4All Finance (2024) maps financial vulnerability across UK local authorities, while Karagiannaki (2024) analyses how over-indebtedness varies with deprivation within London. Fair4All Finance identifies 47 UK local authorities in which more than half of adults were estimated to be financially vulnerable, including authorities in both London and the North East. Karagiannaki shows that over-indebtedness within London was approximately three times as prevalent in the five most deprived boroughs as in the five least deprived. These findings show that high regional prosperity can coexist with severe financial vulnerability in particular local authorities and boroughs. Regional averages can therefore conceal the places where repayment pressure and the need for support are most concentrated.

Rural communities contribute another dimension to this uneven geography. Rural England (2016) found that only a small proportion of identified debt-advice providers were located in rural settlements. Subsequent research connects rural financial hardship with transport costs, digital exclusion, benefit delays, food insecurity and mental-health pressure (Shucksmith et al., 2021). Dense urban areas may contain high concentrations of financial vulnerability and large service demand, while rural communities may face greater distance and access barriers despite lower population density.

The literature therefore points to three spatial dimensions of formal debt distress. Relative intensity concerns how frequently judgments occur in relation to the population. Absolute volume concerns the number of cases that advice and legal services may need to address. Contextual departure concerns why places with similar deprivation can experience different debt outcomes. These questions cannot be answered through a single indicator or map. They require methods that distinguish population from land area, relative burden from total demand and observed outcomes from those normally associated with socioeconomic conditions.

2.4 Mapping and analysing spatially uneven debt outcomes

Once debt vulnerability is understood as spatially structured, its representation becomes part of the analysis. Different mapping approaches reveal different aspects of the same spatial outcome. A map of raw totals shows where the largest number of events is concentrated, whereas a population-standardised rate map shows where the burden is greatest relative to the population exposed. A population cartogram changes the visual weight assigned to each place so that densely populated areas receive greater prominence. Model-based mapping adds a further analytical step by identifying places whose observed outcomes depart from those expected from their socioeconomic conditions. These methods are therefore not interchangeable visual styles. They answer successive questions about volume, intensity, visibility and explanation.

2.4.1 Counts and population-standardised rates

The first distinction is between the number of events and the rate at which they occur. This distinction is well established in spatial epidemiology, where researchers must separate the number of observed cases from the size of the population exposed to risk. Waller and Gotway (2004) explain that spatial event counts are partly determined by the size of the population exposed to the event. A populous area may therefore contain many cases without having an unusually high rate. Conversely, a smaller area may contain fewer cases but carry a much greater burden relative to its population. Building on this distinction, Elliott and Wartenberg (2004) show how population-standardised measures distinguish geographical variation in risk from variation produced by the uneven distribution of population.

Debt research adopts the same logic. Narayan (2020) compares British cities using CCJs per 100,000 adults rather than raw judgment totals, making it possible to identify cities where formal debt distress is especially intense relative to population rather than simply identifying the largest cities. Magrini and Sells (2021) apply comparable indicators across cities and neighbourhoods when examining the unequal financial effects of the pandemic. Their analysis demonstrates the value of maintaining consistent measures when comparing how a common economic shock produced different financial consequences across local economies.

Rates do not render counts redundant because the two measures address different policy questions. A high rate indicates a concentration of relative vulnerability, while a high count indicates a large potential volume of demand for debt advice, legal support and court-related services. By showing that the choice of geographical unit for public-health rate maps involves trade-offs among population comparability, spatial resolution, statistical stability and policy relevance, Boscoe and Pickle (2003) reinforce the need to match each measure to the question being asked. Population-standardised rates support comparisons of relative burden, while raw counts retain the total volume of cases required for service-capacity planning.

Once the appropriate measure has been chosen, the next issue is whether the map gives each affected population adequate visual prominence.

2.4.2 Choropleth maps, area-size bias and population cartograms

A choropleth map assigns a value or category to predefined geographical areas and displays it through colour or shading. Its main advantage is that familiar administrative boundaries remain visible, allowing statistical patterns to be linked directly to local jurisdictions. This has made choropleth mapping common in studies of disease, deprivation, elections and other area-level social outcomes (Boscoe and Pickle, 2003; Elliott and Wartenberg, 2004).

The administrative familiarity and geographical clarity of choropleth maps nevertheless come with a systematic visual limitation. Because each polygon occupies space according to land area, large rural units receive more visual attention than small urban units. Schiewe (2019) demonstrates experimentally that extreme values located in small areas are less likely to be detected than identical values located in larger areas. Schiewe (2023) develops this finding into a broader critique of area-size bias, showing that a statistically correct choropleth may still communicate a misleading hierarchy of importance because visual prominence reflects land rather than population.

To address this problem, population cartograms alter the amount of visual space allocated to each area so that geographical prominence reflects a population-related quantity rather than land area. Dorling (1995) argues that when the subject is a human population, the map base should give visual weight to people rather than hectares. Applying population cartograms to British localities, he demonstrates that transforming area size can reveal social patterns obscured on conventional maps. Dorling and Thomas (2004) subsequently compare conventional and population-based maps of UK census data and find that London, Manchester and Birmingham are difficult to distinguish on the conventional map, while sparsely populated rural areas dominate. On the population cartogram, urban populations and their socioeconomic characteristics become much more visible.

Houle et al. (2009) demonstrate that the same principle transfers to public health. Their density-equalising cartograms represent US states according to population while using colour to show obesity prevalence. The resulting maps communicate both the relative prevalence of obesity and the number of people represented by each state. This dual encoding parallels the distinction between rate and demand identified in the preceding section: colour can communicate relative intensity, while transformed area communicates population-related scale.

Cartograms nevertheless vary in how they balance statistical size, geographical recognisability and neighbourhood structure. Nusrat and Kobourov (2016) identify three principal dimensions for evaluating them: statistical accuracy, geographical accuracy and topological accuracy. Dorling cartograms use non-overlapping circles, making statistical area relatively easy to perceive, while alternative methods preserve boundaries or topology to different degrees. Roth, Woodruff and Johnson (2010) propose value-by-alpha mapping as another response, retaining geographical polygons while reducing the opacity of areas representing fewer people.

These studies show that different map types preserve different aspects of the data. Conventional choropleths retain familiar locations and administrative jurisdictions, whereas population cartograms reduce the visual dominance created by differences in land area and give densely populated places greater prominence. Alternative bivariate designs preserve more of the conventional geography while varying the degree to which population influences visual emphasis. For population-related outcomes such as CCJs, comparing conventional and transformed representations can keep small, densely populated urban areas visible without losing the wider national geography.

2.4.3 From descriptive mapping to count modelling

Mapping can identify where debt outcomes are concentrated and whether that concentration changes after population size is taken into account. Explaining why the burden differs between households or places requires a further analytical step. Debt research has commonly used regression models for this purpose, estimating how repayment difficulties vary with measured socioeconomic conditions. Bridges and Disney (2004) use multivariate regression to examine whether household arrears remain associated with income, employment, family structure and housing tenure when these characteristics are considered together. Their results show that low income is a central predictor of arrears, while employment status, household composition and tenure identify additional differences among otherwise comparable households. Karagiannaki (2024) applies a similar multivariate logic to over-indebtedness and demand for debt advice in London, examining how repayment difficulties vary with deprivation, employment insecurity, housing pressure and limited wealth.

The same analytical logic can be extended from households to geographical areas. Narayan (2020) compares British cities by relating local debt indicators to differences in income, welfare pressure and economic resilience, showing that regression-based explanation can assess whether variations between places are consistent with their socioeconomic conditions. When the outcome records how many events occur, the model must also reflect the discrete and non-negative form of the data. Count regression provides this framework by modelling event frequency while incorporating differences in the population exposed to those events. Cameron and Trivedi (1986) examine Poisson and negative-binomial models across financial count outcomes including missed credit instalments, insurance claims, takeover bids and prepaid mortgages. Poisson regression provides an initial model relating expected event counts to explanatory characteristics and, through an exposure term, to the size of the population in which those events could occur.

Poisson regression provides a useful starting point, but observed event counts often vary more widely than its assumptions allow. Zeileis, Kleiber and Jackman (2008) demonstrate how Poisson and negative-binomial models can be fitted, assessed and compared alongside hurdle and zero-inflated alternatives. Later methodological accounts by Hilbe (2011) and Cameron and Trivedi (2013) explain why the negative-binomial model is appropriate when event counts show greater variation than the Poisson model permits. By allowing the variance to exceed the mean, it can represent greater unexplained heterogeneity between observations.

Spatial epidemiology demonstrates how count models can be connected to geographical risk. Moraga (2018) models observed disease counts relative to the population at risk and area-level risk factors before mapping estimated risk. This separates variation caused by population size from variation associated with local conditions. The same statistical structure is directly relevant to CCJ data because registered judgments are non-negative event counts observed across areas with different population sizes. The methodological connection rests on this common data structure, not on treating legal judgments as equivalent to disease cases.

Income insecurity, unemployment, poor health, limited education and housing disadvantage frequently occur together within deprived neighbourhoods. A deprivation-based count model can therefore estimate the CCJ burden normally associated with this combined socioeconomic context. Comparing observed counts with modelled expectations then identifies places where CCJ burdens remain systematically higher or lower than the deprivation baseline. Mapping these differences reveals whether the unexplained component is geographically dispersed or forms a spatial pattern that requires further investigation.

2.4.4 Spatial dependence and geographical model evaluation

Regression models estimate how outcomes vary with measured characteristics. In spatial data, however, observations may also be related because neighbouring areas often share similar populations, institutions, services and economic histories. Tobler (1970) expressed this principle by proposing that geographical proximity is usually associated with greater similarity. Moran's I provides a formal means of testing whether this pattern is present by measuring whether areas with similar values are located near one another more often than would be expected under spatial randomness (Moran, 1950). A positive Moran's I indicates spatial clustering, meaning that high values tend to occur near other high values and low values near other low values.

This issue is directly relevant to debt research because repayment difficulties may cluster geographically, and the form of that clustering may differ across types of debt. Tontisirin, Anantsuksomsri and Laovakul (2024) analyse National Credit Bureau data aggregated to postal-code areas to examine debt and delinquency among older people in Thailand. They first use global Moran's I to determine whether delinquent debt is geographically clustered across the country and then use local statistics to identify where concentrations occur and how they vary by loan type. Credit-card delinquency is concentrated mainly in urban areas, particularly around the Bangkok Metropolitan Region, whereas business-related delinquent loans are more geographically dispersed. The example shows that the global measure establishes whether clustering exists, while local analysis identifies its locations and forms.

Rico, Cantarero and Puig (2021) reach a related conclusion in their analysis of Spanish bankruptcy outcomes. After mapping regional differences, they use Moran-based measures to identify persistent north–south clusters and connect them with industry, employment and regional economic conditions. Whereas Tontisirin et al. distinguish clusters by loan type, Rico et al. connect clusters to local economic structure. Together, the studies show that spatial autocorrelation is not merely a technical irregularity: it can reveal the geographical organisation of financial distress and suggest which place-based conditions require further investigation.

The same spatial dependence affects model validation. Randomly assigning neighbouring areas to different training and test samples can give a model an unrealistically easy assessment because the test areas may closely resemble areas already used for estimation. Through simulations and case studies, Roberts et al. (2017) show that this can cause predictive error to be underestimated. They recommend constructing validation samples according to the dependence structure of the data and the intended use of the model. When the objective is to predict outcomes in new places, geographically separated training and test samples provide a more realistic assessment than an unrestricted random split.

Valavi et al. (2019) translate this recommendation into a practical procedure. Their blockCV method divides observations into spatial blocks and can use buffers to prevent test locations from being placed too close to training locations. Although the method was developed for species-distribution modelling, its procedures can be applied to other forms of spatial modelling. This is directly relevant to socioeconomic geography because neighbouring areas often share demographic characteristics, services and economic histories. Spatial blocks can therefore test whether estimated relationships remain useful beyond the immediate neighbours of the areas used to fit the model.

Moran’s I and spatial validation assess two complementary aspects of model performance. Moran’s I establishes whether an outcome is geographically clustered and, when applied to model residuals, whether a spatial pattern remains unexplained after modelling. Spatial validation tests whether relationships estimated in one set of locations retain their predictive value in geographically separated locations. Used together, the two assessments distinguish unexplained spatial structure from geographical transferability. Expected counts can then be used as a socioeconomic baseline, while residual clustering and spatial-validation performance indicate how much confidence should be placed in differences between observed and expected CCJ counts.

2.4.5 Observed-to-expected comparisons and place-based departure

Observed-to-expected analysis proceeds through three connected stages. Population exposure or a fitted risk model first establishes the number of events expected in each area. The observed count is then compared with this reference to measure the direction and magnitude of departure. An observed-to-expected ratio above one indicates more events than expected, whereas a ratio below one indicates fewer. Spatial analysis can subsequently determine whether these departures occur in isolation or form a broader geographical pattern. This sequence distinguishes areas with large counts because they contain large populations from areas whose event burden is unusually high relative to an appropriate reference.

Clayton and Kaldor (1987) applied this framework to the mapping of age-standardised disease risk. Rather than mapping raw case totals, which are strongly influenced by differences in population size, they estimated relative risks from observed and expected cases and stabilised these estimates using information from the overall distribution and nearby areas. The resulting maps were therefore better able to represent geographical differences in underlying disease risk rather than simply showing where the largest numbers of cases occurred. Besag, York and Mollié (1991) developed the spatial component further by separating spatially structured variation shared by neighbouring areas from local variation specific to individual areas. This allowed observed-to-expected differences to be interpreted within their geographical context rather than treating every area's departure as an independent local outcome.

Waller and Gotway (2004) and Elliott and Wartenberg (2004) consolidate these methods within applied spatial epidemiology, while Moraga (2018) provides a contemporary small-area application. Across this literature, population exposure establishes an expected number of events, the observed-to-expected ratio measures departure from that reference, and spatial analysis determines whether departures form meaningful geographical patterns.

The same analytical distinction is relevant when formal debt outcomes are compared across places. A large total number of CCJs may arise simply because an area contains a large adult population. A high CCJ rate, by contrast, indicates a heavier burden relative to the number of adults, although much of that burden may still be consistent with the socioeconomic risks associated with severe deprivation. A model that estimates expected CCJ counts from both adult population and deprivation provides a more demanding comparison. The analysis then moves beyond asking where counts or rates are high and instead asks which places record more or fewer judgments than areas with comparable populations and levels of deprivation. In this way, the national association between deprivation and CCJs becomes a benchmark against which local departures can be identified.

Deprivation and observed-to-expected departure describe two different dimensions of CCJ burden. Deprivation indicates the severity of the socioeconomic disadvantage experienced by a local population. The observed-to-expected comparison shows whether the number of CCJs is unusual after population size and deprivation have been taken into account. A highly deprived local authority may record approximately the number predicted by its circumstances, or its observed burden may be substantially higher or lower. A less deprived authority may also record considerably more CCJs than expected, even if its absolute rate is not among the highest nationally. O/E should therefore be used as an analytical screening measure rather than as a fixed classification. The national model establishes a common socioeconomic benchmark, while place-based investigation can examine the mechanisms associated with particular departures.

2.5 Conclusion

Financial vulnerability can reduce households' ability to meet essential financial commitments, recover from economic shocks and retain access to affordable financial services. County Court Judgments represent a formal manifestation of this vulnerability because they record the point at which unresolved financial obligations have progressed into legal judgments. The literature indicates that this burden is unevenly distributed. Low income limits the resources available for repayment, inadequate savings weaken the capacity to absorb temporary shocks, employment disruption destabilises household income, and housing and other essential costs reduce budgetary flexibility. Poor health, disability and family responsibilities may intensify these pressures further. Because these conditions are concentrated within particular labour markets, housing systems and communities, formal debt outcomes also develop distinct geographical patterns. Evidence from British cities, London boroughs and rural communities shows that national and regional averages can conceal substantial concentrations of financial vulnerability at the local level. An England-wide spatial analysis of CCJs is therefore needed to distinguish places with high population-standardised rates from populous areas generating large absolute volumes of service demand, while also identifying places where the observed burden is substantially higher or lower than would normally be expected from local socioeconomic conditions. Existing evidence remains fragmented across geographical scales and analytical methods. Debt studies have generally focused on households, broad regions or selected cities, while conventional choropleth maps may visually underrepresent geographically small but densely populated urban authorities. Socioeconomic modelling, spatial evaluation and observed-to-expected comparisons have also rarely been integrated within a single national analysis of registered CCJs. This study addresses these gaps by combining population cartograms with small-area socioeconomic analysis. Count models estimate the CCJ burden expected from adult population and deprivation, spatial cross-validation assesses whether the estimated relationship remains applicable beyond neighbouring locations, and observed-to-expected comparisons identify local authorities whose actual burdens depart substantially from that benchmark. Together, these methods provide a framework for examining whether conventional deprivation indicators and model-based measures of excess CCJ burden identify the same places, while also selecting areas that warrant more detailed contextual and policy investigation. The following chapter describes the data and analytical procedures used to construct and evaluate this spatial framework for England.

3. Methodology

3.1 Research design and analytical framework

This study examines the spatial distribution of cumulative registered consumer County Court Judgments across England using small-area observations. The principal analytical unit is the LSOA, and the outcome is the number of registered judgments accumulated over the approximately six-year period represented by the Q1 2026 Registry Trust extract. The analysis describes and models area-level differences in formal debt burden and compares the number observed in each place with the number expected from its population and socioeconomic context. Its purpose is to estimate geographical associations and identify local departures rather than individual causal effects.

The analytical framework is organised around a model-based comparison of observed and expected CCJ counts. Population-standardised maps first show where cumulative burden is concentrated relative to the adult population. An expected-count model then estimates the number of judgments associated with each LSOA’s population, deprivation, urban-rural classification and Region. Cross-validation evaluates whether this benchmark remains informative for complete local authorities and geographically separated areas excluded from estimation. Finally, observed and cross-fitted expected counts are aggregated to LADs so that local burdens can be compared with a common national socioeconomic reference.

The framework uses three geographical levels together with one settlement classification, each linked to a specific stage of the empirical analysis. LSOA21 is the neighbourhood-level unit used to calculate rates, fit the count models and examine residual spatial autocorrelation. LAD24 defines the groups withheld during complete-authority cross-validation and provides the administrative scale at which observed and out-of-fold expected counts are aggregated for local comparison. English Regions enter the model as fixed effects to account for broad geographical differences. The 2021 Rural-Urban Classification distinguishes settlement contexts and supports both descriptive comparison and the interaction analysis of whether the deprivation gradient differs between urban and rural LSOAs.

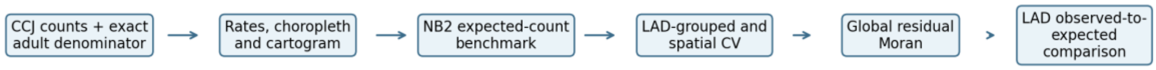


Figure 3.1. Analytical workflow. The analysis moves from population-standardised measurement to expected-count modelling, spatial validation and LAD observed-to-expected comparison.

3.2 Data and variable construction

3.2.1 CCJ outcome and adult population denominator

The outcome data were obtained from Registry Trust's Q1 2026 consumer CCJ extract. Registry Trust maintains the statutory Register of Judgments, Orders and Fines for England and Wales. Because registered judgments remain on the register for six years unless cancelled, the Q1 2026 extract was interpreted as a cumulative registered burden covering approximately April 2020 to March 2026. For each LSOA, the outcome was the number of registered consumer CCJs present in the extract during that six-year register window.

CCJ counts were standardised using the resident adult population. The denominator was reconstructed from Census 2021 data by summing the population aged 20 and over from

TS007A and adding exact single-year ages 18 and 19 from RM200. This produced an exact LSOA-level denominator for residents aged 18 years and over.

The reconstructed adult population was 44,715,472 across all 33,755 English LSOAs. One LSOA lacked a valid observed CCJ count and was excluded from the analytical sample. The final analysis therefore contained 33,754 LSOAs, 44,714,530 adults and 4,401,837 registered consumer CCJs.

3.2.2 Socioeconomic and geographical variables

Neighbourhood deprivation was represented using the English Indices of Deprivation 2025. The continuous overall IMD score was retained for modelling because it preserves differences between areas that would be lost if only ranks or grouped categories were used. IMD deciles and quintiles were retained for descriptive analysis, allowing the national socioeconomic gradient in CCJ burden to be summarised without replacing the continuous measure used in the count models.

Each LSOA was linked to its 2024 Local Authority District and English Region so that the same neighbourhood observations could support validation, aggregation and broad geographical adjustment. LAD membership defined the complete authorities withheld during grouped cross-validation and the units to which observed and out-of-fold expected counts were subsequently aggregated. Region fixed effects adjusted the baseline model for broad spatial differences not captured by neighbourhood deprivation alone. The 2021 Rural-Urban Classification distinguished urban and rural LSOAs and was used both to describe settlement differences and to test whether the deprivation gradient varied between these contexts.

3.2.3 Data integration and temporal alignment

All datasets were integrated through an LSOA21 master frame. Spatial data were projected to British National Grid (EPSG:27700) before representative points, contiguity relationships and distances were calculated. Quality checks after each join assessed missing identifiers, duplicate records and mismatches between CCJ counts, population denominators, deprivation measures and geographical classifications.

The source dates differ because each dataset performs a different analytical role. The Registry Trust extract measures the cumulative stock of registered judgments remaining during approximately 2020 to 2026, Census 2021 provides a stable adult-population exposure denominator, and IMD 2025 represents relative socioeconomic conditions towards the later part of the observation period. LAD and Region codes provide the geographical framework for aggregation and validation rather than time-varying exposures. These sources can therefore be combined to compare cumulative CCJ burden with population and broad socioeconomic context across the study period, while the resulting coefficients are interpreted as area-level associations rather than same-year causal effects.

Data source	Reference period	Spatial resolution	Analytical role
Registry Trust consumer CCJ extract	Approx. April 2020-March 2026	LSOA21	Six-year cumulative registered judgment count
ONS TS007A and RM200	Census Day, 21 March 2021	LSOA21	Exact adult population denominator
English Indices of Deprivation 2025	Recent administrative reference periods	LSOA21	Principal socioeconomic explanatory variable
LAD24 and English Regions	2024 administrative framework	LSOA-to-LAD/Region linkage	Aggregation, validation and regional adjustment
2021 Rural-Urban Classification	2021 settlement framework	LSOA21	Urban-rural heterogeneity

Table 3.1. Temporal and analytical roles of the principal data sources.

3.3 Measuring and mapping CCJ burden

Two complementary measures were used to represent different dimensions of CCJ burden. Raw CCJ counts measured the absolute number of registered judgments and therefore the potential volume of local advice, legal-support and court-related demand. Population-standardised rates measured relative intensity by dividing CCJ counts by the adult population and multiplying by 1,000. Whenever LSOAs were aggregated into deprivation groups, LADs or Regions, counts and adult populations were summed before the rate was calculated, ensuring that each area contributed according to its actual population exposure.

Conventional choropleth maps displayed LSOA and LAD rates within familiar administrative boundaries. A Dorling population cartogram was also produced at LAD level to address the limited visual prominence of dense urban authorities on land-area-based maps. Each LAD was represented by a circle whose area was proportional to its adult population, while colour continued to represent the population-standardised CCJ rate. The choropleth and population cartogram were interpreted as paired representations of the same CCJ data. Their direct comparison made it possible to evaluate how the use of land area influences the geographical visibility of registered judgment burden and whether allocating visual prominence according to adult population brings densely populated urban authorities into clearer view.

The descriptive deprivation gradient was calculated by assigning LSOAs to IMD deciles and quintiles and summing CCJ counts and adult populations within each group before calculating population-weighted rates. This aggregation showed how the national burden changed across ordered levels of deprivation. Spearman's rank correlation between continuous IMD score and the LSOA CCJ rate then quantified the strength of the monotonic relationship without assuming that the association was linear.

3.4 Expected-count modelling

3.4.1 Baseline negative-binomial model

The baseline model estimated the number of CCJs expected in each LSOA from its adult-population exposure and broad socioeconomic context. The logarithm of the adult population was included as an offset so that the model compared event frequency across areas of different population sizes. A Poisson count model was first fitted as a diagnostic. Because the observed CCJ counts displayed substantial overdispersion, the final benchmark used the NB2 negative-binomial specification, which allows count variation to exceed that permitted by the Poisson model.

The baseline specification included standardised overall IMD score, urban-rural status and Region fixed effects. Continuous IMD was transformed to a mean of zero and standard deviation of one. Its exponentiated coefficient could therefore be interpreted as the incidence rate ratio associated with a one-standard-deviation increase in deprivation after settlement context and Region were taken into account. Combining these predictors with the population offset produced an expected registered CCJ count for every LSOA.

3.4.2 Statistical inference and diagnostics

Model choice was assessed using the Pearson dispersion statistic and Akaike Information Criterion. The Pearson statistic evaluated whether the observed variation in CCJ counts exceeded the mean-variance relationship assumed by the Poisson model, while AIC compared the relative fit of models estimated for the same outcome. Principal coefficient uncertainty was reported using LAD-clustered standard errors, reflecting the possibility that LSOAs within the same local authority shared unobserved conditions. Conley spatial heteroskedasticity-and-autocorrelation-consistent intervals were calculated as a spatial sensitivity check using distance cut-offs of 2 km, 5 km and 10 km.

3.4.3 Urban-rural interaction

A second NB2 model included an interaction between standardised IMD and urban-rural status to test whether the proportional association between deprivation and CCJ burden differed between settlement contexts. Because the interaction changes the meaning of the component coefficients, context-specific deprivation IRRs were calculated separately for rural and urban LSOAs from the relevant coefficient combinations. Region fixed effects and the adult-population offset were retained, ensuring that the comparison represented a difference in deprivation gradients rather than differences in population size or broad regional composition.

3.5 Out-of-sample and spatial validation

3.5.1 LAD-grouped and spatially buffered cross-validation

Cross-validation tested whether the expected-count benchmark transferred to places excluded from estimation. The first design used five folds grouped by LAD: all LSOAs within the same LAD were assigned to the same fold, so no local authority contributed observations to both the training and test data. Every LSOA therefore received an out-of-LAD prediction.

The second design imposed stricter spatial separation. LADs were organised into geographically structured folds within Regions, and training LSOAs within 10 km of any test LSOA were removed. This tested whether predictive performance depended on immediate geographical proximity. Performance was summarised using mean absolute error, root mean squared error, log-transformed rate R-squared, Spearman rank correlation and Poisson-deviance D-squared.

3.5.2 Residual spatial autocorrelation

Out-of-fold Pearson residuals were used to assess whether remaining prediction errors were spatially organised. Spatial relationships were defined on the original LSOA polygons using first-order binary rook contiguity. Global Moran's I was calculated on these residuals and evaluated using 9,999 two-sided permutations. A positive value indicated that neighbouring areas tended to depart from the expected-count benchmark in the same direction.

Global Moran's I was retained as the principal residual spatial diagnostic. The purpose of this stage was to establish whether unexplained departures remained geographically structured at the national scale. Identification of specific places was subsequently undertaken through the more stable LAD-level observed-to-expected comparison rather than through local significance testing for individual LSOAs.

3.6 Observed-to-expected local comparison

Observed and out-of-fold expected CCJ counts were aggregated from LSOAs to LADs. The LAD observed-to-expected ratio was calculated as the sum of observed CCJs divided by the sum of out-of-fold expected CCJs. A ratio above one indicated more registered judgments than predicted by the benchmark; a ratio below one indicated fewer. The corresponding excess count was calculated as observed minus expected judgments, expressed in the original number of registered CCJs.

Reporting both ratios and excess counts distinguished proportional departure from absolute scale. A modest relative excess in a populous authority may correspond to more additional judgments than a larger proportional departure in a smaller authority. To reduce dependence on a single validation design, an LAD was counted as robustly above or below expectation only when the direction and threshold were satisfied under both LAD-grouped and 10-km spatially buffered cross-validation.

A 10% departure threshold was used as the principal descriptive rule: O/E of 1.10 or higher indicated at least 10% more CCJs than expected, while O/E of 0.90 or lower indicated at least 10% fewer. This threshold was not a statistical significance test and was not interpreted as evidence of policy performance. A stricter 20% threshold was used to assess whether larger departures persisted.

3.7 Sensitivity, reproducibility and ethics

Sensitivity analysis focused on modelling and spatial decisions capable of altering substantive interpretation. Poisson and NB2 diagnostics assessed the need for a negative-binomial count model. Conley intervals were compared across 2-km, 5-km and 10-km bandwidths. Spatial cross-validation was checked across buffer distances, with 10 km retained as the principal design. For LAD observed-to-expected analysis, the 10% screening threshold was compared with a stricter 20% threshold.

The study used aggregated or de-identified small-area counts and contained no names, addresses or direct personal identifiers, which minimised direct identification risk. The principal ethical concern arose from interpretation because area-level findings could stigmatise places or be misread as evidence about individual residents. Observed-to-expected departures were therefore treated as area-level screening signals rather than measures of individual debt outcomes, local-authority performance or policy causation.

4. Results

The analytical sample contained 33,754 Lower Layer Super Output Areas across 296 Local Authority Districts in England. Across these areas, 4,401,837 registered consumer County Court Judgments were recorded over the approximately six-year period represented by the Q1 2026 register snapshot. Relative to the adult population denominator used in the analysis, this corresponded to a national cumulative burden of approximately 98.44 registered CCJs per 1,000 adults. One English LSOA was excluded because its observed CCJ count was missing or suppressed.

4.1 The observed socioeconomic geography of registered CCJs

Registered CCJs were strongly concentrated in socioeconomically disadvantaged areas. The cumulative CCJ rate declined consistently across the IMD distribution, from 216.31 per 1,000 adults in the most deprived decile to 30.82 in the least deprived decile. The most deprived tenth of English neighbourhoods therefore recorded a cumulative CCJ rate approximately 7.02 times that of the least deprived tenth. This was not a contrast produced only by a small number of extreme neighbourhoods. The most deprived quintile contained approximately one fifth of the adult population but accounted for more than one third of all registered judgments, while the Spearman correlation between overall IMD score and the LSOA CCJ rate was approximately 0.863.

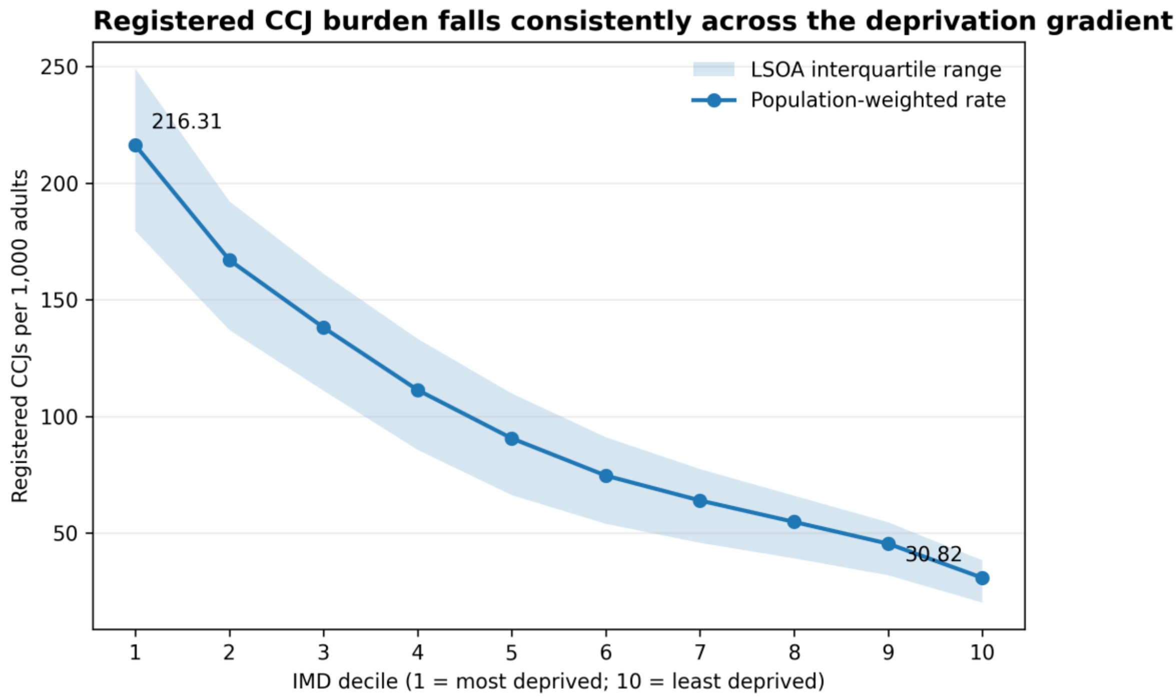


Figure 4.1. Population-weighted cumulative registered CCJ rate by IMD decile. Decile 1 represents the most deprived 10% of English LSOAs and decile 10 the least deprived 10%.

CCJ rates rose consistently with deprivation across England, establishing a strong national socioeconomic gradient. At the same time, the distribution of rates within each deprivation group remained wide, showing that LSOAs with similar levels of deprivation did not necessarily experience the same registered CCJ burden. The descriptive results therefore identify deprivation as a major correlate of national variation while also demonstrating substantial local differences around that relationship.

A further geographical contrast was evident between urban and rural England. Urban LSOAs recorded a cumulative rate of approximately 106.7 CCJs per 1,000 adults, compared with approximately 58.2 in rural LSOAs, producing an unadjusted urban-to-rural ratio of around

1.83. Regional differences were also marked, with the North East recording the highest population-weighted regional rate at approximately 128 CCJs per 1,000 adults and the South West the lowest at approximately 73.

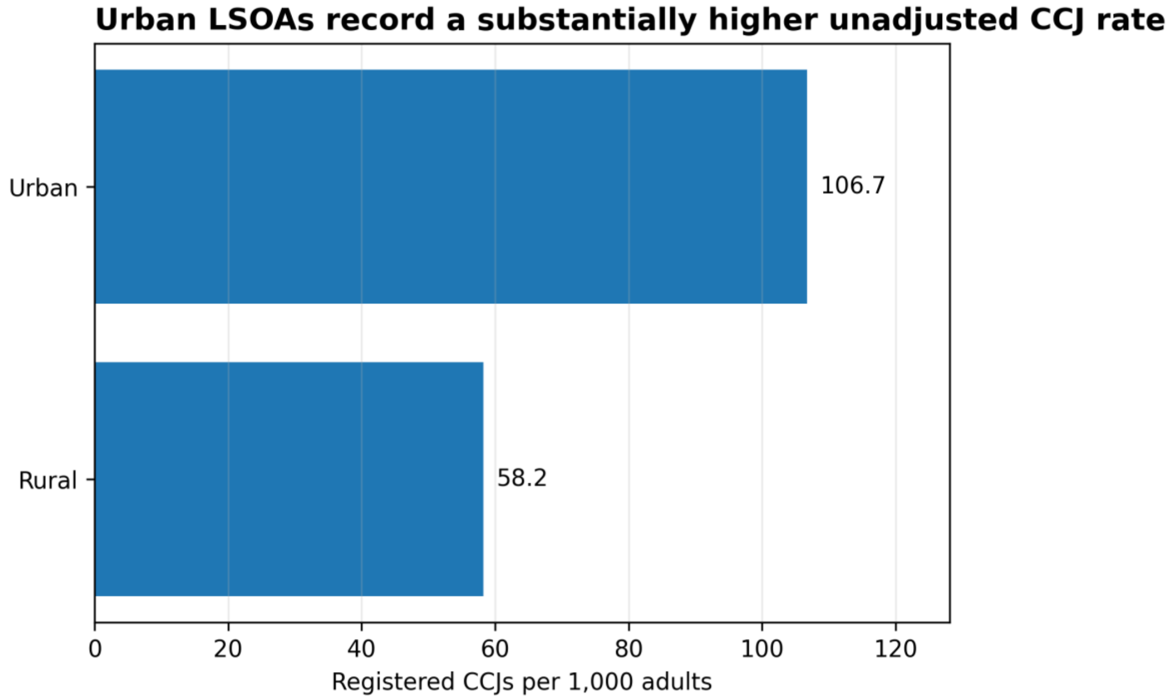


Figure 4.2. Population-weighted cumulative registered CCJ rates in urban and rural LSOAs. These unadjusted rates do not separate deprivation, regional composition or other differences between urban and rural England.

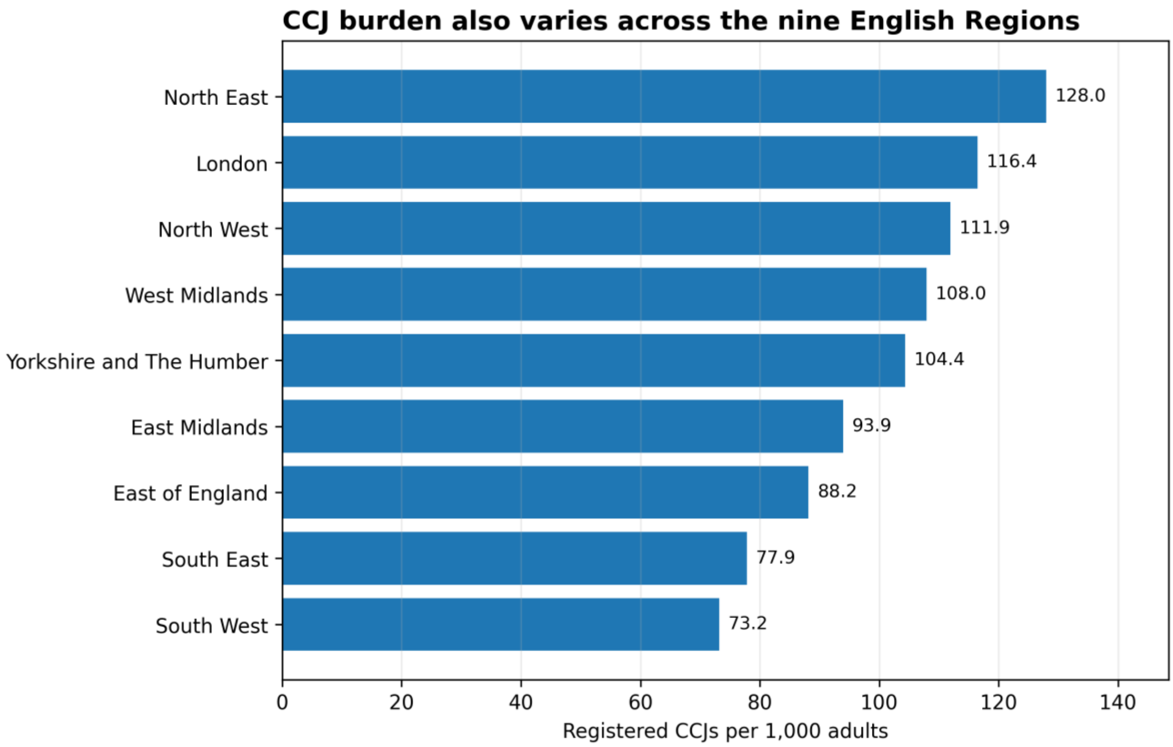


Figure 4.3. Population-weighted cumulative registered CCJ rates across the nine English Regions. Regions are ordered from highest to lowest observed rate.

Measure	Result
Analytical LSOAs	33,754
Local Authority Districts	296
Registered consumer CCJs	4,401,837
Adults aged 18+ in analytical LSOAs	44,714,530
England cumulative CCJ rate	98.44 per 1,000 adults
Most-deprived IMD decile	216.31 per 1,000 adults
Least-deprived IMD decile	30.82 per 1,000 adults
Most/least-deprived decile ratio	7.02
Urban rate	106.7 per 1,000 adults
Rural rate	58.2 per 1,000 adults

Table 4.1. Headline descriptive characteristics of the analytical sample.

The effect of map design is visible when the same LAD-level CCJ rates are displayed in two forms using identical quintile classes (Figure 4.4). In the conventional choropleth, physical land area determines visual prominence. North Yorkshire and Cornwall therefore occupy large portions of the map despite cumulative rates of 61.66 and 88.86 CCJs per 1,000 adults and totals of 30,936 and 41,368 judgments, respectively. By comparison, the much higher rates in the compact authorities of Barking and Dagenham (211.50), Middlesbrough (198.69) and Luton (168.92) are confined to relatively small polygons.

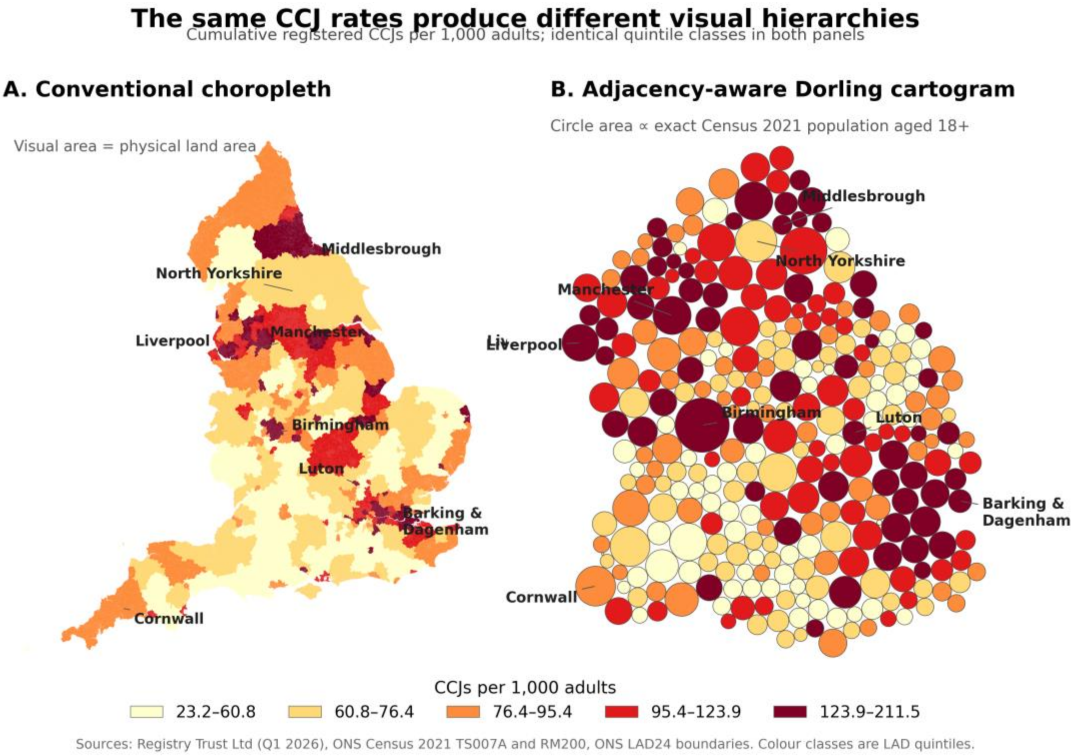


Figure 4.4. Conventional LAD choropleth and adjacency-aware Dorling population cartogram of cumulative registered CCJ burden. Both panels use identical quintile classes for registered CCJs per 1,000 adults. In panel A, visual area is physical land area; in panel B, circle area is proportional to the exact Census 2021 population aged 18 and over.

The Dorling cartogram changes that visual hierarchy without changing either the underlying CCJ values or their colour classification. Circle area is proportional to the exact adult population, so Birmingham (857,393 adults; 137,763 CCJs), Manchester (425,007; 67,145), Liverpool (393,320; 54,059) and the London boroughs collectively become more prominent, whereas the land-area dominance of North Yorkshire and Cornwall is reduced. Colour continues to represent the population-standardised rate, allowing population scale and relative CCJ intensity to be read together.

The transformed layout contained no overlapping circle pairs. Its pairwise distances remained strongly correlated with those of the conventional geography (Spearman's $\rho = 0.869$), and 78.0% of LADs that shared a boundary in the original map remained among the eight nearest neighbours in the cartogram. The transformation therefore altered visual weight substantially while retaining sufficient relative geography for national and regional interpretation.

These descriptive results show where high CCJ burdens were concentrated, but they do not establish how much of the observed burden was unusual once the socioeconomic composition of each place was taken into account. A high rate in a highly deprived urban area may be largely consistent with the rate normally observed in areas with similar characteristics. Conversely, a place with a less extreme raw rate may still record substantially more CCJs than would normally be expected from its population and socioeconomic profile. The distinction between observed burden and burden relative to expectation therefore required an area-specific expected-count model.

4.2 Estimating the CCJ burden expected from socioeconomic context

The count distribution showed substantial overdispersion. For the specification containing overall IMD, urban-rural status and Region fixed effects, the Poisson model produced a Pearson dispersion statistic of approximately 16.38. The corresponding NB2 negative-binomial model reduced the dispersion statistic to 1.008, while AIC fell from approximately 763,595 to 345,475. The NB2 model therefore provided a substantially more appropriate representation of variation in registered CCJ counts, and the Poisson specification was retained only as an overdispersion diagnostic.

Model diagnostic	Poisson	NB2
AIC	763,595	345,475
Pearson dispersion	16.38	1.008
Estimated theta	-	7.445

Table 4.2. Poisson and negative-binomial model diagnostics.

Within the retained model, a one-standard-deviation increase in overall IMD score was associated with an incidence rate ratio of 1.714. Holding urban-rural status and Region constant, the expected cumulative CCJ rate was therefore approximately 71.4% higher for an LSOA one standard deviation higher on the deprivation scale. The LAD-clustered 95% confidence interval was 1.675-1.754, while the corresponding 10-km Conley spatial-HAC interval was 1.678-1.751. The near-identical intervals indicate that the central deprivation relationship was not materially altered when geographical dependence in model errors was treated differently.

After deprivation and Region were taken into account, urban LSOAs retained an expected CCJ rate approximately 1.305 times that of rural LSOAs. This adjusted difference was considerably smaller than the unadjusted urban-to-rural rate ratio of approximately 1.83, indicating that part of the observed urban excess reflected differences in deprivation and regional composition. The interaction model also showed that deprivation was positively associated with CCJ burden in both settings, but the proportional gradient was steeper in rural areas. A one-standard-deviation increase in IMD corresponded to an IRR of approximately 1.928 in rural LSOAs and 1.702 in urban LSOAs. Rural neighbourhoods therefore had a lower average burden, but the proportional difference between their less and more deprived communities was greater than the corresponding difference within urban England.

Relationship	**IRR**	**95% CI**
Overall IMD, per 1 SD	1.714	1.675-1.754
Urban versus rural	1.305	1.264-1.348
IMD effect within rural LSOAs	1.928	1.862-1.997
IMD effect within urban LSOAs	1.702	1.662-1.742

Table 4.3. Baseline and urban-rural interaction model results.

The main function of this model was to convert the national socioeconomic relationship into an expected CCJ count for individual areas. For each LSOA, the expected value represented the number of registered judgments predicted for an area with its adult population, deprivation level, urban-rural status and Region if it followed the relationship estimated from the training data. The regression coefficients therefore established the structure of the benchmark; the substantive comparison depended on how the observed counts related to these expected values.

4.3 Testing the expected-count benchmark outside the estimation sample

Five-fold LAD-grouped cross-validation generated expected counts while withholding complete local authorities from model estimation. All LSOAs within the same LAD were assigned to one fold, and each test LAD was predicted using a model fitted only to LSOAs from the remaining authorities. Every analytical LSOA therefore received an out-of-LAD prediction, preventing observations from the same local authority from appearing in both the training and test data.

Under this validation design, the baseline model achieved a mean absolute error of approximately 29.8 CCJs per 1,000 adults and an RMSE of approximately 49.0. The log-transformed rate R-squared was approximately 0.66, the Spearman correlation between observed and predicted rates was approximately 0.88, and Poisson-deviance D-squared was approximately 0.66.

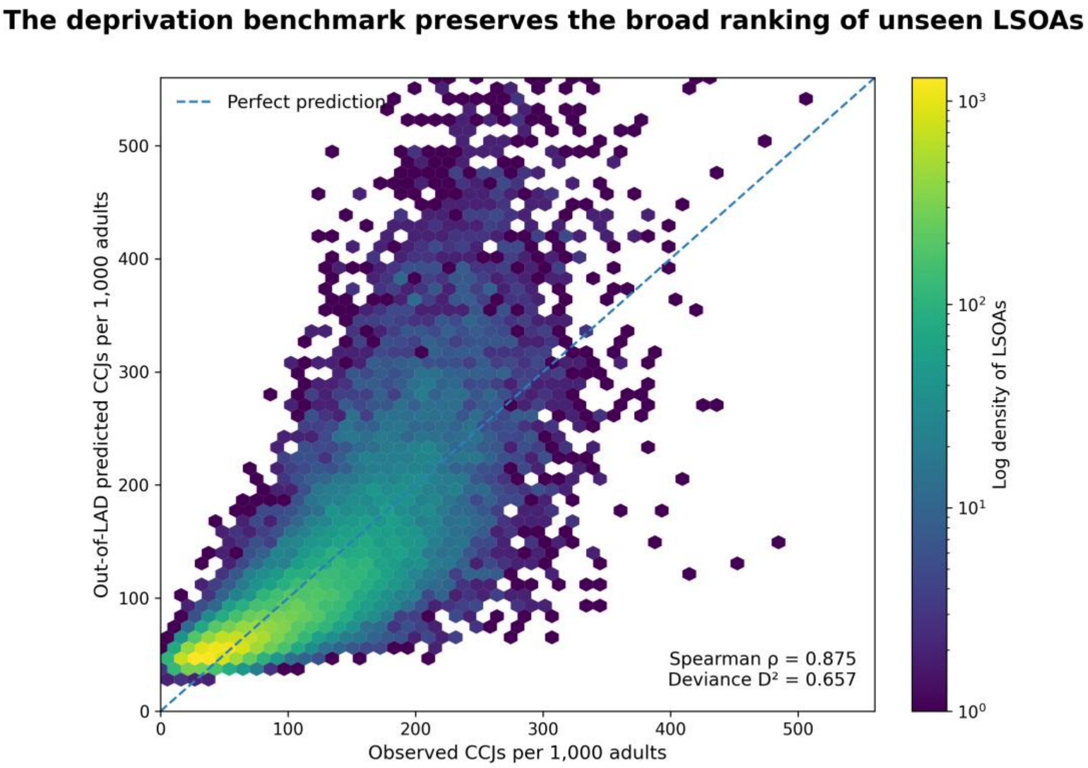


Figure 4.5. Observed and out-of-LAD predicted cumulative CCJ rates. Predictions for every LSOA were generated by a model in which its complete LAD had been excluded from estimation.

The Spearman correlation of approximately 0.88 shows that the model preserved much of the relative ordering of local CCJ rates when applied to authorities excluded from estimation. The MAE and RMSE nevertheless show that appreciable errors remained in the exact burden predicted for individual areas. The benchmark therefore reproduced the broad national distribution of CCJs without reproducing every local outcome.

A stricter validation design tested whether this predictive performance depended on geographically nearby training observations. When test areas were spatially separated and training LSOAs within a 10-km buffer were excluded, Poisson-deviance D-squared declined only from approximately 0.657 to 0.650, while the Spearman correlation declined from approximately 0.875 to 0.866. MAE increased only slightly, from approximately 29.84 to 30.07 CCJs per 1,000 adults.

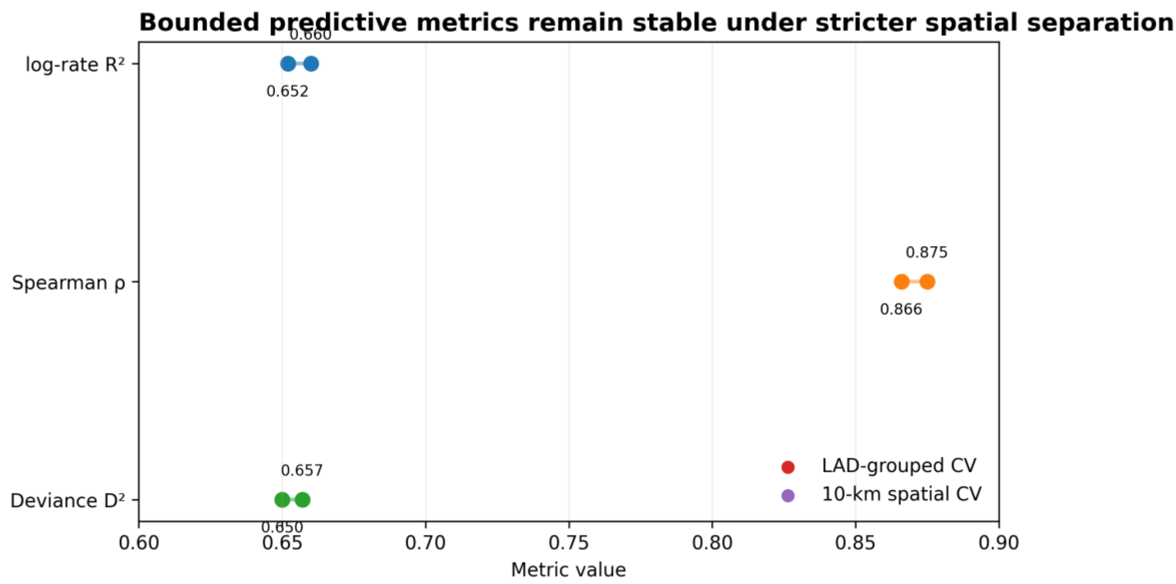


Figure 4.6. Predictive performance under LAD-grouped and 10-km spatially buffered cross-validation.

Validation design	**MAE**	**RMSE**	**log(1+rate) R2**	**Spearman rho**	**Deviance D2**
LAD-grouped five-fold CV	29.84	49.04	0.660	0.875	0.657
Region-stratified spatial CV, 10-km buffer	30.07	48.47	0.652	0.866	0.650

Table 4.4. Cross-validation performance of the deprivation benchmark.

The limited deterioration under spatial separation indicates that the expected-count model was not dependent primarily on neighbouring training observations containing nearly identical geographical information. The expected values could therefore be used to distinguish two components of local CCJ burden: the part broadly consistent with national socioeconomic structure, and the remaining difference between that expectation and the actual number of registered judgments.

4.4 Observed CCJs versus model-expected CCJs

Observed and cross-fitted expected counts were aggregated from LSOAs to LADs. The resulting observed-to-expected ratio provided a direct comparison between the number of CCJs actually registered and the number predicted from the socioeconomic benchmark. A ratio of one indicated close agreement with expectation; a ratio above one indicated more registered CCJs than predicted; and a ratio below one indicated fewer.

This comparison produced a different geography from either the raw CCJ rate or the deprivation distribution. A high observed CCJ rate and a high observed-to-expected ratio were not equivalent. The first identified places with a large absolute registered burden. The second identified places whose burden was unusually high relative to the level normally associated with their population and socioeconomic circumstances.

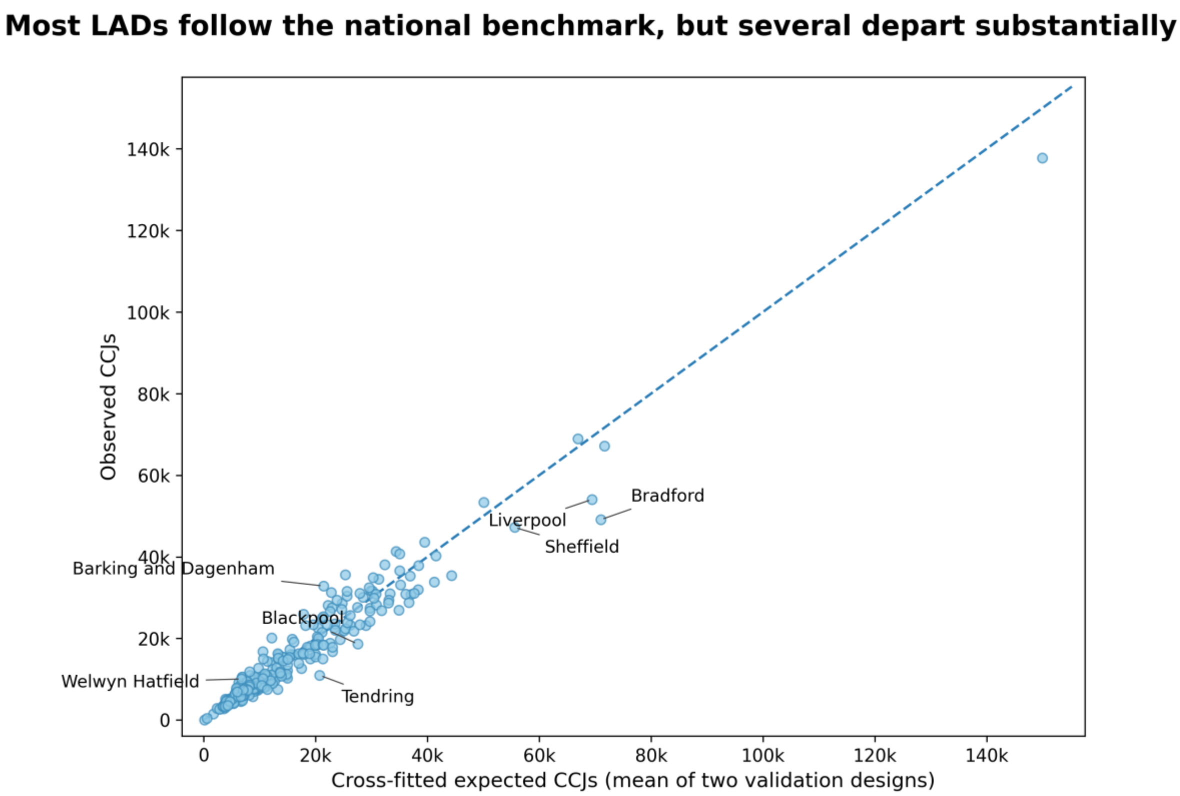


Figure 4.7. Observed and model-expected registered CCJ counts across Local Authority Districts. Authorities above the diagonal recorded more CCJs than the socioeconomic model predicted; authorities below it recorded fewer.

To identify departures that were not produced by marginal variation in a single fitted model, an LAD had to retain the same direction and threshold under both LAD-grouped and 10-km spatially separated validation. Under this rule, 64 of the 296 LADs recorded at least 10% more CCJs than expected, while 87 recorded at least 10% fewer. At the stricter 20% threshold, 29 LADs remained consistently above expectation and 28 remained consistently below. Many local authorities therefore experienced registered judgment burdens that differed materially from the level predicted by the national socioeconomic relationship.

LAD	Region	Observed rate per 1,000 adults	O/E range across validation designs	Conservative excess or shortfall
Barking and Dagenham	London	211.50	1.510-1.558	+11,096
Welwyn Hatfield	East of England	107.00	1.466-1.522	+3,197
Sheffield	Yorkshire and The Humber	107.34	0.828-0.882	-6,324
Blackpool	North West	164.61	0.665-0.688	-8,442
Tendring	East of England	89.63	0.520-0.537	-9,431
Liverpool	North West	137.44	0.780-0.789	-14,414

LAD	Region	Observed rate per 1,000 adults	O/E range across validation designs	Conservative excess or shortfall
Bradford	Yorkshire and The Humber	120.70	0.681-0.702	-20,862

Table 4.5. Selected LAD departures from the deprivation benchmark.

Barking and Dagenham illustrates the distinction between a high absolute burden and a burden that remained excessive after socioeconomic adjustment. Its observed cumulative rate was 211.50 registered CCJs per 1,000 adults, placing it among the highest-rate authorities in England. Even after the model generated a relatively high expected burden for an urban London authority with substantial deprivation, its actual count remained approximately 51.0%-55.8% above the cross-fitted expectation. This corresponded to at least 11,096 more registered judgments than the model benchmark predicted.

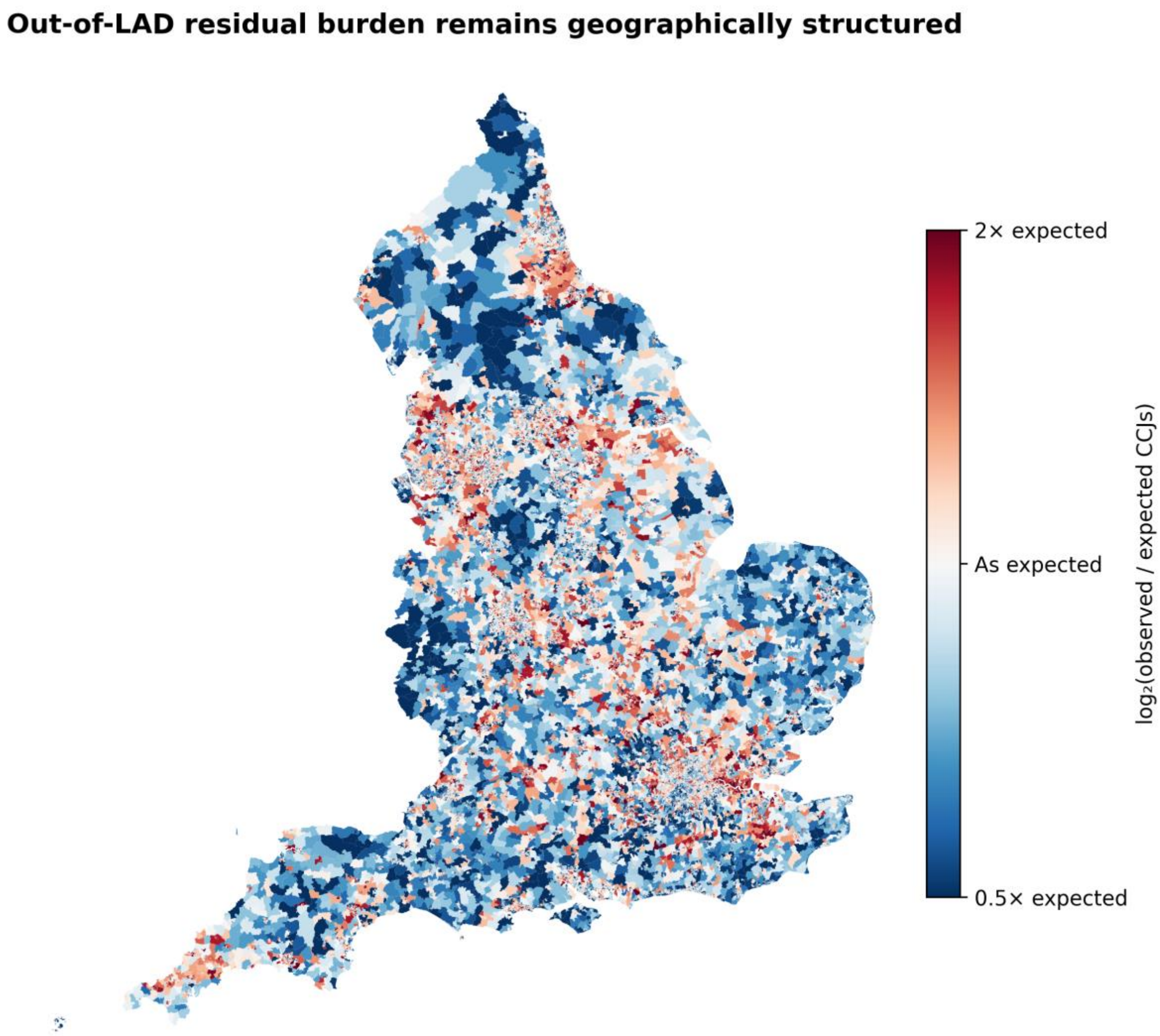
Welwyn Hatfield displayed a different form of positive departure. Its average socioeconomic position was not among the most deprived in England, but its observed CCJ count remained approximately 46.6%-52.2% above the cross-fitted expectation, representing at least 3,197 judgments above the benchmark. Unlike Barking and Dagenham, the significance of this result lies less in an exceptionally high raw rate than in the magnitude of the difference between what was observed and what its socioeconomic characteristics predicted.

The opposite pattern occurred in several relatively deprived authorities. Tendring, Blackpool, Liverpool, Bradford and Sheffield all recorded fewer CCJs than the deprivation benchmark predicted. This does not indicate that these authorities had low absolute levels of registered financial difficulty. Rather, their observed judgment burdens were lower than those generally predicted for places with comparable socioeconomic conditions. Bradford illustrates this distinction particularly clearly: its observed cumulative CCJ rate was approximately 120.7 per 1,000 adults, but its observed-to-expected ratio was approximately 0.68.

Taken together, deprivation, observed CCJ burden and excess or shortfall relative to expectation describe three related but distinct dimensions of spatial inequality. The authorities with the highest deprivation scores were not necessarily those with the largest positive observed-to-expected departures, and high absolute CCJ rates could coexist with either positive or negative departures from the socioeconomic benchmark.

4.5 Spatial structure in the observed-to-expected departures

The remaining departures were not randomly distributed across neighbouring areas. Global Moran's I, calculated from out-of-fold Pearson residuals on the original LSOA geography, was approximately 0.384. A two-sided test based on 9,999 permutations produced p = 0.0001, providing strong evidence of positive residual spatial autocorrelation.



Expected counts are generated by the baseline NB2 model under complete-LAD holdout.

Figure 4.8. LSOA-level observed-to-expected CCJ burden under complete-LAD holdout. Red areas recorded more CCJs than predicted and blue areas fewer.

Positive spatial autocorrelation indicates that prediction errors were geographically clustered. LSOAs recording more CCJs than expected tended to be located near other positive departures, while areas recording fewer than expected tended to occur near other negative departures. The remaining errors therefore represented a geographically organised pattern rather than isolated observations lying above or below the fitted relationship.

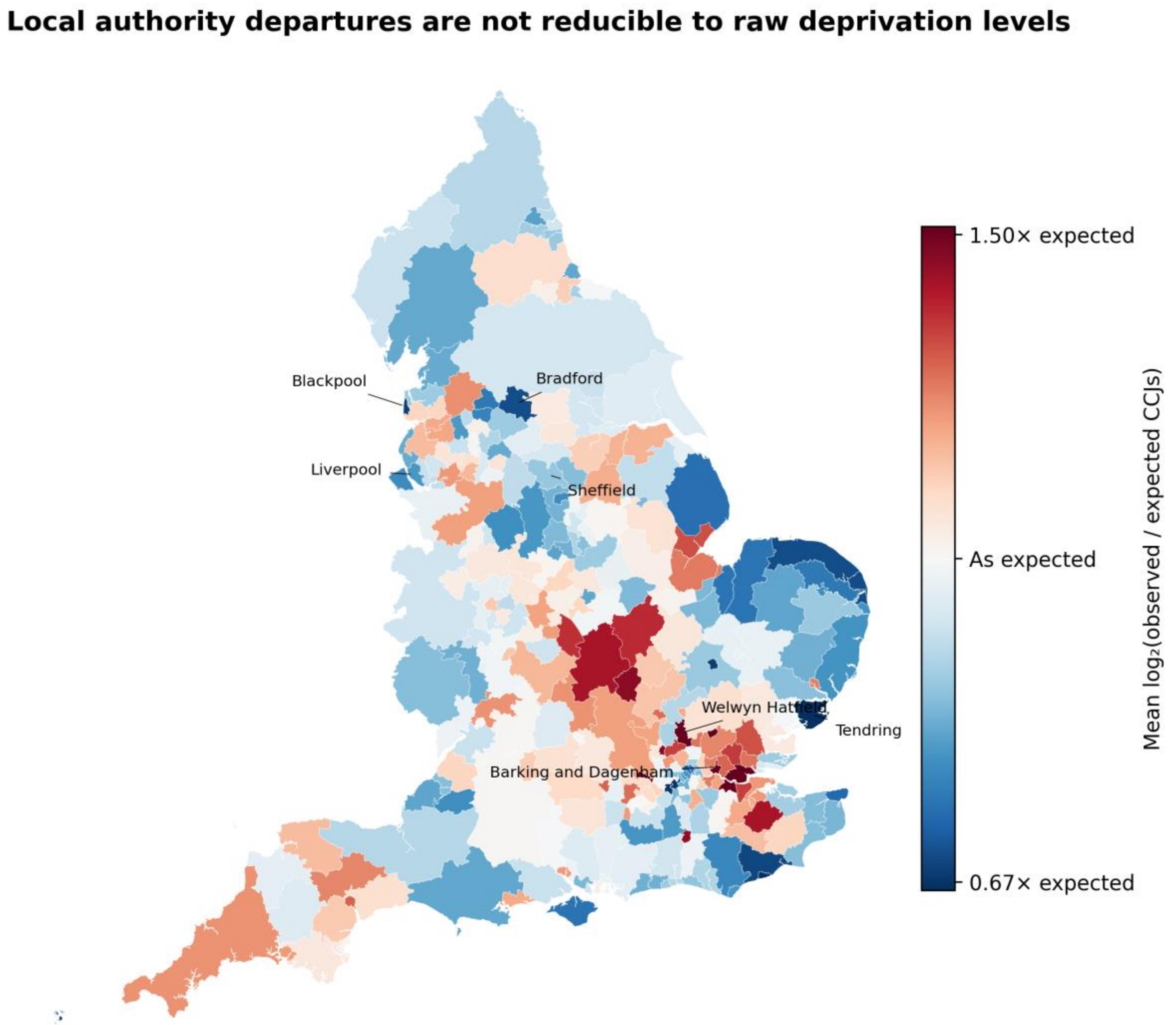


Figure 4.9. Local Authority District observed-to-expected registered CCJ burden. Values above one indicate more observed CCJs than predicted by the deprivation benchmark; values below one indicate fewer.

The residual results clarify both the explanatory reach and the limits of the expected-count model. The model reproduced a substantial part of the national distribution of CCJs, but the differences it did not explain remained geographically clustered. These residual departures therefore cannot be interpreted simply as independent statistical noise around the national deprivation relationship.

This remaining spatial pattern represents a different dimension from the original deprivation geography. Deprivation maps show where structural socioeconomic disadvantage is concentrated, whereas residual maps show where observed CCJ burden is higher or lower than expected for the population and socioeconomic conditions included in the model. The two measures consequently answer different spatial questions, even where the same areas appear prominently in both.

4.6 Summary of the empirical findings

Registered CCJ rates rose sharply with deprivation across England, but similarly deprived areas did not always record the same burden. The negative-binomial model converted the relationship between population exposure, deprivation, settlement type and Region into a consistent local comparison benchmark. Its similar performance under complete-LAD and geographically separated validation showed that this benchmark retained predictive value outside the areas used for estimation.

Comparing observed counts with these cross-fitted predictions revealed local differences that were concealed by deprivation levels or population-standardised rates alone. Substantial numbers of LADs consistently recorded more or fewer CCJs than their socioeconomic characteristics predicted, and these departures remained spatially autocorrelated. Barking and Dagenham combined severe deprivation and a high absolute burden with a further excess above expectation. Welwyn Hatfield recorded a pronounced excess despite not belonging to the most deprived group. Bradford and Tendring, by contrast, recorded fewer judgments than expected despite substantial deprivation and formal debt burden. These cases demonstrate that deprivation, absolute burden and departure from expectation do not necessarily coincide.

The empirical results therefore identify two connected spatial patterns. The first is a broad national gradient in which registered CCJ burden rises strongly with deprivation. The second consists of local departures from the burden expected after population size and socioeconomic context have been considered. Conventional deprivation maps reveal the first pattern but cannot identify the second. The observed-to-expected comparison provides the basis for examining why areas with apparently comparable structural conditions produce different registered CCJ outcomes.

5. Discussion

Across England, registered consumer County Court Judgments are distributed along a pronounced socioeconomic gradient. The cumulative CCJ rate in the most deprived tenth of neighbourhoods was approximately seven times that in the least deprived tenth, while deprivation remained strongly associated with expected judgment counts after population exposure, urban-rural status and Region were taken into account. Yet deprivation did not translate into the same formal debt outcome everywhere. A model estimated from the national relationship retained similar predictive performance when transferred to geographically separated areas, but substantial differences between observed and expected counts remained within individual local authorities. Those differences were also spatially organised, with neighbouring areas tending to depart from expectation in similar directions. Registered CCJs therefore reflect both the structural conditions that make financial difficulty more common and the local circumstances that influence how that difficulty develops into formal judgment.

5.1 From deprivation to local variation in formal debt outcomes

The steep deprivation gradient is consistent with the wider evidence on household repayment difficulty. Low income reduces the amount available after essential expenditure, while limited savings leave households with fewer resources when employment is interrupted or an unexpected cost occurs. Housing, energy and other recurrent commitments make that adjustment more difficult because much of this expenditure cannot be reduced immediately when income falls. Where financially constrained households are more concentrated, unresolved payment problems are consequently more likely to persist until they become registered judgments. The accumulation of CCJs in deprived neighbourhoods can therefore be interpreted as an area-level concentration of the household financial pressures identified in previous UK research (Hood, Joyce and Sturrock, 2018).

The distinction between indebtedness and formal judgment is important because credit can remain manageable where households retain sufficient income or assets to maintain repayments. A CCJ represents a later stage, after an obligation has remained unresolved and a claimant has pursued court action. The most deprived decile recorded 216.31 CCJs per 1,000 adults, compared with 30.82 in the least deprived decile, while a one-standard-deviation increase in IMD corresponded to an approximately 71.4% higher expected cumulative rate after settlement type and Region were held constant. These results are consistent with a sequence in which limited household resources make an initial missed payment harder to resolve, allow the obligation to remain outstanding and increase the likelihood that it progresses to formal judgment.

The urban-rural results add a further geographical distinction to this national gradient. Urban LSOAs recorded the higher average burden and retained an adjusted CCJ rate approximately 1.305 times that of rural LSOAs after deprivation and Region were considered. The proportional association with deprivation was nevertheless steeper in rural areas, where a one-standard-deviation increase in IMD corresponded to an IRR of approximately 1.93, compared with 1.70 in urban areas. Deprivation is therefore associated with higher CCJ burden in both settings, but the relationship differs in form. Urban neighbourhoods experience the higher average burden, while differences between less and more deprived communities are proportionally sharper within rural England.

The paired maps show that population standardisation and cartographic representation address different problems. Dividing counts by the adult population makes LAD rates comparable, but a conventional choropleth still gives greater visual weight to physically extensive authorities. Figure 4.4 shows the consequence: North Yorkshire and Cornwall dominate the display through land area, while compact authorities containing some of the largest totals or highest rates remain comparatively small. The reduced visibility of high CCJ rates in geographically compact authorities is consistent with Schiewe's (2019, 2023) finding that extreme values shown in small polygons attract less attention and that visual prominence in choropleth maps can reflect land area more strongly than the population or social outcome being mapped.

The Dorling cartogram addresses this mismatch by changing the visual denominator from hectares to adults. Circle area represents the population exposed to judgment risk, while colour retains the population-standardised CCJ rate. Reading the two encodings together distinguishes where judgments are most frequent relative to population from where the absolute volume of potential advice or legal-support demand is greatest. The increased visibility of Birmingham, Manchester, Liverpool and the London boroughs is therefore a substantive consequence of representing adult population, consistent with cartographic research showing that population-based transformation can reveal urban social outcomes suppressed by land-area-based displays (Dorling, 1995, 1996; Dorling and Thomas, 2004; Houle et al., 2009).

The two maps are therefore most informative when interpreted as complementary representations. The choropleth preserves recognisable administrative boundaries and exact geographical locations, while the cartogram makes population-weighted burden more visible by accepting controlled distortion of shape and distance. The absence of circle overlap, strong preservation of pairwise distance and retention of most local neighbour relations show that the transformed layout remained geographically interpretable. Presenting the maps as a matched pair balances the locational context of conventional geography with the population emphasis of the Dorling representation, reflecting the central trade-off identified by Nusrat and Kobourov (2016).

Together, population standardisation and population-sensitive mapping clarify where relative intensity and absolute demand are concentrated, but they do not establish whether a particular local burden is unusual for its socioeconomic context. A high rate in a highly deprived authority may largely follow the national relationship, whereas a less extreme rate may be unusually high for an authority with more favourable structural conditions. An expected-count model is therefore required to compare each observed burden with a reference incorporating both adult-population exposure and the principal socioeconomic geography.

The NB2 model supplied that reference by estimating the number of judgments associated with each area's adult population, IMD, settlement type and Region. Its performance remained very similar when complete LADs were withheld and when a further 10-km buffer separated test observations from nearby training areas. Poisson-deviance D-squared changed only from approximately 0.657 to 0.650, while the Spearman correlation between observed and predicted rates changed from approximately 0.875 to 0.866. This close performance under stronger separation indicates that the national relationship retained substantial predictive value beyond the immediate neighbourhoods used for estimation.

Comparison with this reference shifts the interpretation from identifying high rates to identifying departures from a common benchmark. Under both validation designs, 64 LADs recorded at least 10% more judgments than expected and 87 recorded at least 10% fewer. Requiring agreement across the two designs gives greater weight to departures that remain visible under different forms of geographical separation. At the stricter 20% threshold, 29 authorities remained above expectation and 28 below, highlighting the larger differences within the continuous O/E distribution. In these places, observed burden presents a materially different picture from that suggested by deprivation or population-standardised rates alone.

The residual analysis shows that these unexplained departures are also related to place. The out-of-fold residuals produced a Global Moran's I of approximately 0.384 because positive departures tended to occur near other positive departures and negative departures near other negative departures. This spatial clustering is consistent with a financial geography in which household vulnerability is embedded within local labour markets, housing systems, financial-service environments and institutional arrangements. Deprivation captures the dominant national pattern, while the geographically organised residuals suggest that the pathway from financial difficulty to registered judgment also depends on local contexts not represented in the model.

5.2 Local departures and their policy implications

Observed-to-expected comparisons allow the analysis to move beyond identifying high-burden places and examine why some local authorities record more or fewer CCJs than would be expected from their population and broad socioeconomic conditions. Because the benchmark already accounts for deprivation, settlement context and Region, the remaining departure draws attention to local circumstances and institutional processes not represented by these structural measures. The four selected authorities illustrate two distinct forms of departure. Barking and Dagenham and Welwyn Hatfield recorded more CCJs than expected despite markedly different deprivation profiles, while Bradford and Tendring recorded fewer than expected despite substantial socioeconomic disadvantage.

Barking and Dagenham combines severe socioeconomic disadvantage with a further excess above an already high modelled expectation. Its cumulative rate reached 211.50 CCJs per 1,000 adults. Although the model predicted a high burden after accounting for the borough's deprivation, urban status and London location, the observed number of judgments remained approximately 51.0-55.8% above that prediction, equivalent to at least 11,096 additional registered CCJs. The result raises a more specific question: why does a larger share of financial difficulty appear to culminate in registered judgments in Barking and Dagenham than would normally be expected for a similarly deprived urban London authority?

Housing affordability offers one route through which this additional pressure may arise. Barking and Dagenham's developing Housing Strategy identifies affordability, high rents, house prices and living costs among the major concerns raised by residents and stakeholders (London Borough of Barking and Dagenham, 2026). IMD captures broad neighbourhood disadvantage but does not directly measure the disposable income left after households meet the housing costs prevailing in a particular local market. Where housing and other essential expenditure absorb a larger proportion of already restricted resources, a fall in earnings or an unexpected bill can remove the remaining repayment margin more quickly. The borough's high expected CCJ burden may therefore be further intensified by local expenditure pressures that are only partially represented within the national deprivation benchmark.

Local debt-support services and changes in household liabilities provide two relevant but contrasting parts of this context. Residents can obtain free specialist assistance through Barking and Dagenham Money, Debt Free Advice and other services covering credit commitments, household bills, rent and Council Tax arrears (London Borough of Barking and Dagenham, n.d.). These services may help resolve some financial problems before legal action begins, but their availability does not show whether capacity is sufficient for local demand or whether households receive assistance early enough. At the same time, the 2025/26 Council Tax Support scheme reduced the maximum working-age award from 85% to 63%, increasing Council Tax liabilities for some low-income households (London Borough of Barking and Dagenham, 2025). This recent change cannot explain the cumulative six-year excess, although it illustrates how additional liabilities may intensify pressure where disposable income is already limited. The positive O/E result therefore identifies the need to examine the scale and timing of service use, local living costs, creditor composition and the practices through which unpaid debts proceed to judgment.

Welwyn Hatfield reaches a similar positive O/E result from a markedly different socioeconomic position. Because the district is considerably less deprived on average than Barking and Dagenham, the model predicted a substantially lower CCJ burden. Nevertheless, its observed count remained approximately 46.6-52.2% above expectation, even though its cumulative rate of around 107 CCJs per 1,000 adults was not among the highest nationally. This result suggests that financial pressures not fully captured by average neighbourhood deprivation may be contributing to the district’s CCJ burden.

Housing affordability is particularly relevant to this difference. Welwyn Hatfield's published evidence estimates an annual net need for 818 affordable homes, with 51% of newly arising need requiring traditional social rented provision (Welwyn Hatfield Borough Council, n.d.-a). The council also provides Housing Payments where Housing Benefit or the housing element of Universal Credit does not meet actual accommodation costs, including support for rent shortfalls and, in some circumstances, rent arrears (Welwyn Hatfield Borough Council, n.d.-b). These provisions reflect a local housing market in which households can experience substantial expenditure pressure despite living in an authority whose overall deprivation profile is comparatively favourable. A household need not reside in one of England's most deprived districts to have little income remaining for unsecured credit or other obligations once rent or mortgage costs have been met. Housing affordability consequently provides a route through which realised financial pressure can exceed the burden implied by IMD alone.

To understand whether such pressures are addressed before they result in formal judgments, it is also necessary to consider the forms of early support available within the district. Eligible low-income households may receive Council Tax Support of up to 75%, while residents experiencing payment difficulties can request alternative Council Tax arrangements and obtain independent advice through Citizens Advice (Welwyn Hatfield Borough Council, n.d.-c; Welwyn Hatfield Borough Council, n.d.-d). These mechanisms may resolve some arrears before they deteriorate further, but they do not remove the housing and household-cost pressures from which the arrears originate. Welwyn Hatfield therefore illustrates how comparatively favourable aggregate deprivation can coexist with housing-related financial vulnerability that is less visible in the overall IMD position.

Bradford’s cumulative rate of approximately 120.7 CCJs per 1,000 adults confirms that the district continues to experience a substantial formal debt burden. However, the model predicted an even higher number of judgments after accounting for its severe deprivation. Its negative O/E departure therefore does not indicate low financial need. Instead, it shows that Bradford recorded fewer CCJs than would normally be expected for a similarly disadvantaged area. This shifts attention from the underlying vulnerability already represented in the model to local processes that may affect whether arrears eventually reach the courts.

Bradford's Anti-Poverty Strategy places financial inclusion alongside employment, housing, health and support for vulnerable groups, combining immediate assistance with longer-term attempts to prevent households from falling further into poverty. It is explicitly organised through partnerships between public agencies, voluntary organisations, businesses and communities rather than through a single council service (Bradford Council, 2022). This broader approach is reflected in Council Tax recovery, where the council commits to early engagement, referral to independent accredited debt advice, negotiation of affordable repayment arrangements and temporary suspension of action where time is required to construct a sustainable payment plan (Bradford Council, n.d.).

Bradford’s advice and recovery arrangements are relevant to this interpretation because they operate between the emergence of financial difficulty and the use of stronger enforcement measures. Debt advice can increase benefit take-up, support affordable repayment arrangements and help households enter appropriate debt solutions. Earlier contact may also prevent additional charges and enforcement costs from accumulating. Although Council Tax recovery follows a different legal route from the consumer CCJs examined here, Bradford's approach remains relevant because early identification, referral to advice and negotiated repayment may also prevent other unpaid obligations from progressing towards court action. The district's below-expected O/E is consistent with the possibility that these practices, together with other features of the local institutional environment, reduce the proportion of unresolved financial difficulties that ultimately become registered consumer judgments. This interpretation helps explain how Bradford can continue to experience substantial financial vulnerability while recording fewer CCJs than would normally be expected from its deprivation.

Tendring provides a second below-expected case in a different type of local setting. The district contains areas of marked deprivation and continuing financial hardship, but its cumulative rate was approximately 89.6 CCJs per 1,000 adults and its cross-fitted O/E remained close to one half. Given the socioeconomic conditions already included in the model, a substantially higher number of judgments would ordinarily have been expected. The size of this shortfall directs attention to the local processes that may prevent some financial difficulties from reaching formal judgment.

Unlike policies introduced only at the end of the observation window, Tendring's local advice infrastructure was present throughout most of the period represented by the CCJ extract. By early 2025, the district council reported that it had funded an information and advice service through Citizens Advice Tendring for approximately thirteen years, with the service covering debt management, benefits, housing and related problems (Tendring District Council, 2025). Tendring also directs residents towards free debt advice, income-maximisation support and formal options such as Debt Management Plans and Breathing Space (Tendring District Council, n.d.).

Although the available aggregate data do not quantify how many Tendring residents avoided a judgment through these routes or isolate the specific effect of debt-advice provision, the district's below-expected O/E is consistent with a local context in which some financial difficulties are addressed before they progress to formal judgment. Tendring may therefore continue to experience substantial underlying financial vulnerability while producing fewer registered CCJs than would normally be expected from its socioeconomic conditions. The case demonstrates that severe deprivation does not always translate into a corresponding level of formal debt judgments and that local advice provision and debt-resolution arrangements may influence this relationship.

Viewed together, the four local cases move the discussion from individual circumstances to a broader comparison of how local authorities depart from the same national benchmark. Barking and Dagenham combines severe deprivation with an additional excess of registered judgments, while Welwyn Hatfield demonstrates that substantial repayment pressure can arise in a district whose overall deprivation is less severe. Bradford and Tendring present the opposite pattern. Both continue to experience considerable socioeconomic disadvantage, yet their registered CCJ burdens remain below the levels predicted by the national model. Their local advice and repayment arrangements may provide opportunities to address financial problems before stronger enforcement becomes necessary. These contrasts indicate that structural disadvantage establishes the underlying risk of financial difficulty but does not determine how frequently that difficulty culminates in a registered judgment. Household expenditure pressures, creditor decisions, access to timely advice and sustainable repayment or debt-resolution arrangements may all influence whether unresolved liabilities eventually reach court.

These contrasting cases also demonstrate why no single spatial indicator can fully represent local debt-related need. IMD identifies places in which the socioeconomic conditions associated with financial vulnerability are concentrated. CCJ counts measure the absolute volume of registered judgments and indicate the potential scale of demand for advice and legal support. Population-standardised rates show how frequently judgments occur relative to the adult population. O/E adds a further dimension by showing whether the observed burden is higher or lower than would normally be expected after population size and broad socioeconomic conditions have been considered. Interpreted together, these indicators identify different aspects of local need and help determine which part of the local debt pathway requires closer examination.

Once these indicators are interpreted together, the resulting framework can be connected to the place-based approach already used in national debt-support planning. The Money and Pensions Service publishes lower-tier local-authority estimates of the proportion of residents who need debt advice, revealing substantial geographical differences in underlying demand (Money and Pensions Service, 2024). O/E can add information about the extent to which this underlying need has developed into registered court judgments. Where high estimated advice need coincides with a positive CCJ departure, attention can be directed towards the timing and capacity of advice provision, housing and essential-cost pressures, creditor composition and the likelihood that arrears proceed to legal action. Where high advice need coexists with a negative departure, the comparison may indicate that debt composition, negotiated repayment or early intervention is altering the proportion of difficulties that reach judgment.

However, identifying where debt-advice need coincides with an unusual CCJ burden addresses only part of the local debt pathway. A fuller interpretation must also consider the institutional decisions through which arrears progress towards stronger enforcement. Government guidance on Council Tax collection emphasises early communication, cooperation with independent advisers, affordable repayment arrangements and proportionate enforcement (Ministry of Housing, Communities and Local Government, 2021). Although Council Tax recovery follows a different legal route from consumer CCJs, these principles illustrate how institutional decisions can influence what happens after a household first misses a payment. Similar financial difficulties may produce different formal outcomes depending on how quickly the debtor is contacted, whether an affordable agreement is reached and whether the creditor proceeds with legal action.

These decisions are made at different stages by several institutions, placing local CCJ outcomes within a wider system of responsibility. Local authorities can influence debt-advice provision, Council Tax Support, discretionary hardship assistance, housing support and the recovery of debts owed directly to them. The wider formation of consumer CCJs is also shaped by national welfare and consumer-credit policies, court procedures and the litigation decisions of private creditors. Bradford's Anti-Poverty Strategy recognises this division by noting that several major economic and welfare mechanisms remain outside local control (Bradford Council, 2022). A persistent positive O/E should therefore be treated as a signal for examining the complete local debt pathway rather than as a direct measure of local-government performance.

5.3 Limitations and further research

The policy and institutional interpretations developed above must first be considered in light of what the Registry Trust data actually measure. The Q1 2026 extract contains judgments that remained on the register at that time and therefore represents an approximately six-year cumulative burden covering 2020 to 2026, rather than a series of annual incidence rates. The dataset records judgment events rather than unique individuals, so the same person may appear more than once. An area with 100 CCJs per 1,000 adults therefore cannot be interpreted as showing that 10% of its adult population received a judgment. Registered CCJs also capture only one form of financial difficulty because arrears repaid, renegotiated or managed through other solutions do not appear unless they result in a registered judgment.

In addition to recording cumulative judgment events rather than unique debtors, the data combine judgments accumulated under substantially changing economic conditions. Judgments accumulated during the pandemic, subsequent labour-market adjustments and the sharp increase in household living costs. However, the adult-population denominator comes from Census 2021, while IMD 2025 represents socioeconomic conditions towards the end of the observation window. The benchmark therefore compares cumulative CCJ burden with the broad population and deprivation context of the period, but it does not match each judgment to the economic conditions that existed when the underlying debt first became unmanageable. The analysis can identify geographical associations across the period, but it cannot establish whether a particular change in deprivation, housing costs or local support preceded a later change in registrations.

The temporal limitations of the data are accompanied by a further interpretive constraint arising from the geographical scale of the analysis. IMD describes neighbourhood conditions rather than the individual circumstances of the people whose debts resulted in judgments. A deprived LSOA may contain residents with very different incomes, savings, housing tenures and exposure to financial shocks, while a relatively affluent LSOA may still contain highly vulnerable households. The strong association between IMD and CCJ burden therefore describes the kinds of neighbourhoods in which judgments accumulate rather than the probability that a particular resident receives a CCJ. This distinction becomes even more important when LSOA expectations are aggregated to LADs because each authority contains considerable internal socioeconomic variation.

Even within the selected geographical framework, the interpretation of local departures depends on which structural conditions are included in the expected-count model. Applying the same limited set of variables across England provides a transparent benchmark based on adult population, overall IMD, urban-rural status and Region. The consequence of this parsimonious specification is that many potentially relevant local processes remain outside the model. Residual spatial autocorrelation indicates that unexplained differences are geographically clustered, but it does not identify whether they arise from housing costs, labour-market structures, household wealth, access to advice, creditor composition or enforcement practices. A positive O/E therefore shows that observed judgments exceeded the specified socioeconomic benchmark without identifying which unmeasured local factor produced the excess.

The importance of these omitted local processes becomes particularly clear when the absence of creditor and debt-type information is considered. Authorities with similar levels of household financial pressure may differ in the liabilities that fall into arrears, the creditors pursuing them, the availability of negotiated repayment and the likelihood that unresolved debts proceed to court. Without this information, an above-expected burden may reflect either a greater volume of underlying financial difficulty or a higher proportion of comparable difficulties progressing to judgment. Similarly, a below-expected burden indicates fewer registered judgments than predicted, but it does not by itself show that local advice or repayment arrangements prevented them. The absence of these intermediate measures limits the extent to which the pathways suggested by the local cases can be distinguished.

Because these data limitations restrict how precisely individual departures can be explained, the O/E bands are most appropriately used as screening tools for identifying cases that warrant closer attention. The 10% threshold identifies authorities whose burden differs materially from expectation, while the 20% threshold focuses attention on larger departures.

Requiring the direction to remain consistent under both LAD-grouped and spatially buffered prediction reduces dependence on a single validation design. However, O/E is continuous, and authorities immediately above and below a threshold may remain substantively similar. The magnitude of the ratio and its consistency across predictions are therefore more informative than membership of a particular category.

The preceding limitations point directly to the additional data required to distinguish temporal changes from the household, creditor and institutional processes underlying local departures. Annual or quarterly registration dates would separate persistent departures from short-lived responses to economic shocks. Information on creditor category and debt type would show which liabilities contribute most strongly to local variation. Judgment value and subsequent satisfaction or removal from the register would distinguish the initial legal outcome from the debtor's later ability to resolve the obligation. These additions would also allow changes in local policies and services to be aligned with the periods in which they operated.

These additional data would be especially informative when applied to the four contrasting authorities examined in this discussion. Comparing Barking and Dagenham with Welwyn Hatfield could establish whether their positive departures involve similar debt types despite their different deprivation profiles, or whether different local pressures produce similar O/E outcomes. Bradford and Tendring could be compared to assess how creditor composition, long-standing advice provision and repayment arrangements relate to judgment burdens below those predicted by deprivation. Combining these data would allow the analysis to move beyond identifying geographical departures and examine the household, market and institutional processes associated with them.

Taken together, the empirical findings and the limitations of the available data support a qualified conclusion about the role of deprivation in shaping CCJ geography. Deprivation remains central to the distribution of registered CCJs, but it does not fully account for differences between places. The expected-count model establishes the burden normally associated with population size and broad socioeconomic conditions, while O/E identifies authorities whose observed outcomes depart from that benchmark. These departures connect the national pattern of socioeconomic inequality with local processes through which unresolved financial difficulties either progress to registered court judgments or are addressed before reaching that stage.

6. Conclusion

Financial difficulty is unevenly distributed across England, but the geography of formal debt cannot be understood simply by identifying where the greatest number of County Court Judgments is recorded. Areas differ substantially in population size, socioeconomic conditions and settlement context, while conventional administrative maps can further distort the visual importance of densely populated urban areas relative to geographically extensive rural authorities. More importantly, a high CCJ burden does not carry the same meaning everywhere. In a highly deprived area, a large number of judgments may be broadly consistent with the level of financial vulnerability already implied by its socioeconomic conditions; elsewhere, a more moderate observed rate may nevertheless represent an unusually high burden relative to what would normally be expected. Understanding the geography of CCJs therefore requires a distinction between where formal debt is concentrated and where formal debt outcomes depart from the structural conditions in which they occur.

Using approximately 4.4 million registered consumer CCJs accumulated across England between 2020 and 2026, this dissertation developed a population-aware spatial framework to make that distinction. Exact Census 2021 adult populations were used to construct comparable local rates, while conventional choropleth mapping was complemented by an adjacency-aware Dorling population cartogram. The statistical analysis then translated the national relationship between deprivation and registered CCJs into expected local counts, adjusting for population exposure, urban–rural status and Region. Because expected values are only useful if they remain informative beyond the places from which they are estimated, the benchmark was evaluated using both complete-LAD holdout and geographically buffered cross-validation before observed and expected counts were compared at local-authority level.

Applying this framework first revealed that the national distribution of registered CCJs was strongly structured by socioeconomic inequality. The most deprived tenth of English neighbourhoods recorded a cumulative CCJ rate approximately seven times that of the least deprived tenth, and deprivation remained strongly associated with expected judgment burden after wider geographical context was taken into account. Urban areas experienced higher average CCJ rates, although the proportional deprivation gradient was steeper within rural neighbourhoods. These findings place registered CCJs within the wider geography of financial vulnerability. Where households have fewer resources with which to absorb income disruption, housing costs and other essential commitments, unresolved repayment difficulties are more likely to accumulate into formal legal outcomes. The urban-rural difference also shows that this relationship is expressed through different local contexts rather than through a completely uniform national process.

The cartographic comparison added a further dimension to this inequality. Large urban populations and major concentrations of registered judgments can occupy only small areas on conventional administrative maps. Birmingham, Manchester and Liverpool, for example, contained some of the largest absolute CCJ totals in England despite occupying much less geographical space than extensive rural authorities. Similarly, geographically compact authorities such as Barking and Dagenham, Middlesbrough and Luton recorded some of the highest cumulative rates but appear as relatively small polygons on a national choropleth. The population cartogram reduced this imbalance by assigning visual area according to adult population while retaining CCJ rate through colour. It therefore did not replace conventional geography, but allowed the same distribution to be viewed from a second perspective in which people rather than hectares determined visual prominence. The resulting comparison demonstrates why the representation of population-based social outcomes is itself part of their interpretation.

The expected-count model then made it possible to determine whether this national relationship could provide a reliable benchmark for local comparison. Predictive performance remained similar when complete local authorities were excluded from estimation and when nearby training observations were additionally removed. This consistency indicates that the relationship between deprivation and CCJ burden remained informative beyond the areas used to estimate it. Having established the geographical transferability of the benchmark, observed counts could be compared with the corresponding predictions. Under both validation designs, 64 local authorities recorded at least 10% more judgments than expected, while 87 recorded at least 10% fewer. Substantial differences remained when the threshold was increased to 20%, showing that the results were not confined to marginal departures. The remaining prediction errors were also spatially clustered, indicating that neighbouring areas often departed from expectation in similar directions.

These local departures show that deprivation establishes the underlying level of financial vulnerability but does not fully determine how often unresolved financial difficulty becomes a registered judgment. Barking and Dagenham combined severe disadvantage with a burden substantially above an already high expectation, while Welwyn Hatfield showed that a large positive departure can also occur where overall deprivation is less severe. Bradford and Tendring presented the opposite relationship because substantial disadvantage remained while registered judgments accumulated less frequently than the benchmark anticipated. After repayment problems arise, their progression towards court action may be shaped by housing and essential expenditure, household financial reserves, timely advice, sustainable repayment arrangements, creditor behaviour and the institutional handling of arrears. Areas with similar deprivation may therefore produce different formal debt outcomes because these intermediate conditions and processes also vary geographically.

Because structural need and realised legal outcomes do not always coincide, debt policy requires indicators that capture different dimensions of local burden. IMD identifies places in which the socioeconomic conditions associated with financial vulnerability are concentrated. Raw CCJ counts show where the greatest absolute volume of registered judgments occurs and indicate the potential scale of service demand. Population-standardised rates measure how frequently judgments occur relative to the adult population. Observed-to-expected comparisons identify places where the actual legal burden is unusually high or low after population size and broad socioeconomic conditions have been considered. Used together with existing measures of debt-advice need, these indicators can distinguish areas where high CCJ burden broadly corresponds to severe deprivation from areas where progression into registered judgment is unusually frequent. They can also identify below-expected areas in which substantial underlying need coexists with fewer formal judgments than predicted.

These interpretations and policy applications must be qualified by two principal data limitations. First, the register records a cumulative stock of judgments rather than a sequence of annual or quarterly outcomes, limiting the ability to distinguish persistent local differences from temporary responses to economic shocks. Second, the data contain no information on individual debtors, creditor categories or the liabilities underlying each judgment, restricting analysis of the processes through which financial difficulty becomes formal enforcement. The expected-count model should therefore be understood as a consistent reference based on broad socioeconomic conditions rather than a complete explanation of CCJ formation. More detailed temporal and case-level data would strengthen the framework. Annual or quarterly records could identify when local departures emerged and whether they persisted, while information on creditors, debt types, judgment values and subsequent satisfaction could clarify which liabilities and enforcement processes produced them. Repeated O/E estimates could then be compared with contemporaneous changes in housing conditions, debt-advice provision, welfare support and recovery practices.

The study therefore makes three connected contributions to understanding the geography of registered CCJs. First, the paired use of conventional maps and a population cartogram distinguishes relative CCJ intensity from the absolute volume of potential service demand while improving the visibility of densely populated urban authorities. Second, the expected-count model converts the national association between deprivation and CCJ burden into a geographically validated benchmark for comparing local authorities. Third, observed-to-expected comparisons identify places whose registered judgment burdens cannot be understood from deprivation levels or raw CCJ rates alone. Together, these elements show that deprivation is necessary for explaining the national concentration of CCJs but is insufficient for explaining all local outcomes. The resulting framework moves the analysis from identifying where formal debt burden is high to examining why areas with comparable structural conditions may experience different levels of registered judgment.

References

Akaike, H. (1974) 'A new look at the statistical model identification', IEEE Transactions on Automatic Control, 19(6), pp. 716-723. https://doi.org/10.1109/TAC.1974.1100705

Besag, J., York, J. and Mollié, A. (1991) 'Bayesian image restoration, with two applications in spatial statistics', Annals of the Institute of Statistical Mathematics, 43, pp. 1-20. https://doi.org/10.1007/BF00116466

Bogiatzis-Gibbons, D. and O'Brien, C. (2024) Employment shocks and financial difficulty: Understanding how leaving paid employment affects ability to meet credit repayments. London: Financial Conduct Authority. Available at: https://www.fca.org.uk/publications/research-notes/employment-shocks-financial-difficulty-paid-employment-credit-repayments (Accessed: 30 July 2026).

Boileau, B., Cribb, J. and Wernham, T. (2023) Characteristics and consequences of families with low levels of financial wealth. London: Institute for Fiscal Studies. https://doi.org/10.1920/re.ifs.2022.0259

Boscoe, F.P. and Pickle, L.W. (2003) 'Choosing geographic units for choropleth rate maps, with an emphasis on public health applications', Cartography and Geographic Information Science, 30(3), pp. 237-248. https://doi.org/10.1559/152304003100011171

Bradford Council (2022) Anti-Poverty Strategy 2022-2027. Bradford: City of Bradford Metropolitan District Council. Available at: https://www.bradford.gov.uk/your-council/policies/anti-poverty-strategy/ (Accessed: 29 July 2026).

Bradford Council (n.d.) Council Tax Collection Commitment. Bradford: City of Bradford Metropolitan District Council. Available at: https://www.bradford.gov.uk/council-tax/problems-paying-your-bill/council-tax-collection-commitment/ (Accessed: 29 July 2026).

Brewer, C.A. (2016) Designing Better Maps: A Guide for GIS Users. 2nd edn. Redlands, CA: Esri Press.

Bridges, S. and Disney, R. (2004) 'Use of credit and arrears on debt among low-income families in the United Kingdom', Fiscal Studies, 25(1), pp. 1-25.

Cameron, A.C. and Miller, D.L. (2015) 'A practitioner's guide to cluster-robust inference', Journal of Human Resources, 50(2), pp. 317-372.

Cameron, A.C. and Trivedi, P.K. (1986) 'Econometric models based on count data: comparisons and applications of some estimators and tests', Journal of Applied Econometrics, 1(1), pp. 29-53.

Cameron, A.C. and Trivedi, P.K. (2013) Regression Analysis of Count Data. 2nd edn. Cambridge: Cambridge University Press.

Carter, I. and Hill-Dixon, A. (2022) Review of poverty and social exclusion in Wales. Cardiff: Wales Centre for Public Policy. Available at: https://wcpp.org.uk/report/review-of-poverty-and-social-exclusion-in-wales/ (Accessed: 30 July 2026).

Clayton, D. and Kaldor, J. (1987) 'Empirical Bayes estimates of age-standardized relative risks for use in disease mapping', Biometrics, 43(3), pp. 671-681.

Conley, T.G. (1999) ‘GMM estimation with cross sectional dependence’, Journal of Econometrics, 92(1), pp. 1-45.

Consumer Data Research Centre (2021) ‘Data News: County Court Judgements (new dataset available and potential project ideas)’, 8 November. Available at: https://www.cdrc.ac.uk/data-news-county-court-judgements-new-dataset-available/ (Accessed: 30 July 2026).

Cribb, J., Wernham, T. and Xu, X. (2023) Housing costs and income inequality in the UK. London: Institute for Fiscal Studies. https://doi.org/10.1920/re.ifs.2023.0288

Delestre, I. and Waters, T. (2026) Evidence on income shocks and household finances. London: Institute for Fiscal Studies.

Dorling, D. (1995) ‘The visualization of local urban change across Britain’, Environment and Planning B: Planning and Design, 22(3), pp. 269-290. https://doi.org/10.1068/b220269

Dorling, D. (1996) Area Cartograms: Their Use and Creation. Concepts and Techniques in Modern Geography No. 59. Norwich: GeoBooks.

Dorling, D. and Thomas, B. (2004) People and Places: A 2001 Census Atlas of the UK. Bristol: Policy Press. https://doi.org/10.56687/9781847421494

D’Alessio, G. and Iezzi, S. (2013) Household over-indebtedness: definition and measurement with Italian data. Bank of Italy Occasional Papers No. 149. Rome: Bank of Italy.

Elliott, J. and Roberts, R. (2013) ‘Balancing population and geography in area cartograms’, Cartographic Journal, 50(1), pp. 34-46.

Elliott, P. and Wartenberg, D. (2004) ‘Spatial epidemiology: current approaches and future challenges’, Environmental Health Perspectives, 112(9), pp. 998-1006.

Fair4All Finance (2024) Financial inclusion and vulnerability at local authority level. London: Fair4All Finance.

Fernández-López, S., Álvarez-Espiño, M., Rey-Ares, L. and Castro-González, S. (2024) ‘Consumer financial vulnerability: review, synthesis, and future research agenda’, Journal of Economic Surveys, 38, pp. 1045-1084. https://doi.org/10.1111/joes.12573

Financial Conduct Authority (2021) Financial Lives Survey. London: FCA.

Financial Conduct Authority (2024) Financial Lives cost of living (January 2024) recontact survey: Summary. London: FCA. Available at: https://www.fca.org.uk/publications/financial-lives/jan-2024-recontact-survey-summary (Accessed: 30 July 2026).

Fitch, C., Hamilton, S., Bassett, P. and Davey, R. (2011) ‘The relationship between personal debt and mental health: a systematic review’, Mental Health Review Journal, 16(4), pp. 153-166.

GOV.UK (n.d.) County court judgments for debt: CCJs and your credit rating. Available at: https://www.gov.uk/county-court-judgments-ccj-for-debt/ccjs-and-your-credit-rating (Accessed: 30 July 2026).

Hilbe, J.M. (2011) Negative Binomial Regression. 2nd edn. Cambridge: Cambridge University Press.

Hood, A., Joyce, R. and Sturrock, D. (2018) Problem debt and low-income households. London: Institute for Fiscal Studies.

Houle, B., Holt, J., Gillespie, C., Freedman, D.S. and Reyes, M. (2009) 'Use of density-equalizing cartograms to visualize trends and disparities in state-specific prevalence of obesity: 1996-2006', American Journal of Public Health, 99(2), pp. 308-312. https://doi.org/10.2105/AJPH.2008.138750

Inoue, R. (2011) 'A new construction method for circle cartograms', Cartography and Geographic Information Science, 38(2), pp. 146-152.

Insolvency Service (2026) Individual insolvencies by location, age and gender, England and Wales, 2025. London: The Insolvency Service. Available at: https://www.gov.uk/government/statistics/individual-insolvencies-by-location-age-and-gender-england-and-wales-2025 (Accessed: 30 July 2026).

Jenkins, R., Bhugra, D., Bebbington, P. et al. (2008) 'Debt, income and mental disorder in the general population', Psychological Medicine, 38(10), pp. 1485-1493.

Karagiannaki, E. (2024) Financial insecurity and debt in London. London: Centre for Analysis of Social Exclusion.

Karagiannaki, E. (2025) Debt, ethnicity and local area deprivation in London. CASEreport 161. London: Centre for Analysis of Social Exclusion, London School of Economics and Political Science. Available at: https://sticerd.lse.ac.uk/CASE/_NEW/PUBLICATIONS/abstract/?index=11645 (Accessed: 30 July 2026).

Kempson, E., McKay, S. and Willitts, M. (2004) Characteristics of Families in Debt and the Nature of Indebtedness. London: Department for Work and Pensions.

Keys, B.J., Mahoney, N. and Yang, H. (2022) 'What determines consumer financial distress? Place- and person-based factors', Review of Financial Studies, 35(1), pp. 42-69. https://doi.org/10.1093/rfs/hhac025

Kwon, J., Kline, D. and Hepler, S.A. (2023) 'A spatio-temporal hierarchical model to account for temporal misalignment in areal data', Spatial Statistics, 53.

Leyshon, A. and Thrift, N. (1995) 'Geographies of financial exclusion: financial abandonment in Britain and the United States', Transactions of the Institute of British Geographers, 20(3), pp. 312-341.

Leyshon, A., French, S. and Signoretta, P. (2008) 'Financial exclusion and the geography of bank and building society branch closure in Britain', Transactions of the Institute of British Geographers, 33(4), pp. 447-465. https://doi.org/10.1111/j.1475-5661.2008.00323.x

London Borough of Barking and Dagenham (2025) Council Tax Support. London: London Borough of Barking and Dagenham. Available at: https://www.lbbd.gov.uk/benefits-and-support/council-tax-support (Accessed: 29 July 2026).

London Borough of Barking and Dagenham (2026) Housing Strategy 2026 to 31. London: London Borough of Barking and Dagenham. Available at: https://www.lbbd.gov.uk/housing/housing-strategy-2026-31 (Accessed: 29 July 2026).

London Borough of Barking and Dagenham (n.d.) Help with debt. London: London Borough of Barking and Dagenham. Available at: https://www.lbbd.gov.uk/money-and-debt/help-debt (Accessed: 29 July 2026).

Lusardi, A., Schneider, D. and Tufano, P. (2011) 'Financially fragile households: evidence and implications', Brookings Papers on Economic Activity, Spring, pp. 83-134.

Magrini, E. and Sells, T. (2021) An uneven recovery? How Covid-debt and Covid-saving will shape post-pandemic cities. London: Centre for Cities.

McKnight, A. and Rucci, M. (2020) The financial resilience of households in the UK. London: Centre for Analysis of Social Exclusion.

McLennan, D., Noble, S., Noble, M., Plunkett, E., Wright, G. and Gutacker, N. (2019) The English Indices of Deprivation 2019: Technical Report. London: Ministry of Housing, Communities and Local Government.

Meltzer, H., Bebbington, P., Brugha, T., Farrell, M. and Jenkins, R. (2013) 'The relationship between personal debt and specific common mental disorders', European Journal of Public Health, 23(1), pp. 108-113. https://doi.org/10.1093/eurpub/cks021

Ministry of Housing, Communities and Local Government (2021) Council tax collection: best practice guidance for local authorities. London: MHCLG. Available at: https://www.gov.uk/government/publications/council-tax-collection-best-practice-guidance-for-local-authorities (Accessed: 29 July 2026).

Ministry of Housing, Communities and Local Government (2025) English Indices of Deprivation 2025: Technical Report. London: MHCLG.

Money and Pensions Service (2023) 'One in three people have missed payments on vital bills already this year', 6 November. Available at: https://maps.org.uk/en/media-centre/press-releases/2023/one-in-three-missed-payments-on-vital-bills-already (Accessed: 30 July 2026).

Money and Pensions Service (2024) Need for debt advice 2023: estimates for UK constituencies and local authorities. London: Money and Pensions Service. Available at: https://maps.org.uk/en/publications/research/2024/need-for-debt-advice-2023-estimates-for-uk-constituencies-and-local-authorities (Accessed: 29 July 2026).

Moraga, P. (2018) 'Small area disease risk estimation and visualization using R', R Journal, 10(1), pp. 495-506.

Moran, P.A.P. (1950) 'Notes on continuous stochastic phenomena', Biometrika, 37(1/2), pp. 17-23.

Narayan, A. (2020) Mapping County Court Judgments and problem debt in British cities. London: Centre for Cities.

Nethery, R.C. et al. (2021) 'Estimating population health effects of environmental exposures using small-area data', Epidemiology, 32(3), pp. 360-369.

Nguipdop-Djomo, P. et al. (2020) 'Socioeconomic deprivation and tuberculosis in England: an ecological analysis of notifications, 2008-2012', Epidemiology and Infection, 148.

Nusrat, S. and Kobourov, S. (2016) 'The state of the art in cartograms', Computer Graphics Forum, 35(3), pp. 619-642.

Nusrat, S., Alam, M.J., Scheidegger, C. and Kobourov, S. (2018) 'Cartogram visualization for bivariate geo-statistical data', IEEE Transactions on Visualization and Computer Graphics, 24(10), pp. 2675-2688.

Office for National Statistics (2016) Wealth in Great Britain Wave 4: 2012 to 2014. Newport: ONS.

Office for National Statistics (2023a) TS007A: Age by five-year age bands, Census 2021. Available at: https://www.nomisweb.co.uk/

Office for National Statistics (2023b) RM200: Sex by single year of age, Census 2021. Available at: https://www.nomisweb.co.uk/

Office for National Statistics (2026) 2021 Rural Urban Classification. Newport: ONS.

Registry Trust Ltd (2025) Decoding debt: unpacking the landscape of monetary judgments. London: Registry Trust.

Registry Trust Ltd (2026) Consumer County Court Judgment Register extract, Q1 2026. Secure aggregated dataset.

Richardson, T., Elliott, P. and Roberts, R. (2013) ‘The relationship between personal unsecured debt and mental and physical health: a systematic review and meta-analysis’, Clinical Psychology Review, 33(8), pp. 1148-1162. https://doi.org/10.1016/j.cpr.2013.08.009

Rico, M., Cantarero, S. and Puig, F. (2021) ‘Regional disparities and spatial dependence of bankruptcy in Spain’, Mathematics, 9(9), 960. https://doi.org/10.3390/math9090960

Roberts, D.R. et al. (2017) ‘Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure’, Ecography, 40(8), pp. 913-929.

Roth, R.E., Woodruff, A.W. and Johnson, Z.F. (2010) ‘Value-by-alpha maps: an alternative technique to the cartogram’, Cartographic Journal, 47(2), pp. 130-140. https://doi.org/10.1179/000870409X12488753453372

Rural England (2016) State of Rural Services. London: Rural England.

Schiewe, J. (2019) ‘Empirical studies on the visual perception of spatial patterns in choropleth maps’, KN Journal of Cartography and Geographic Information, 69(3), pp. 217-228. https://doi.org/10.1007/s42489-019-00026-y

Schiewe, J. (2023) ‘“Sponge Maps”: using the concept of value by area maps for avoiding the area size bias in choropleth maps’, KN Journal of Cartography and Geographic Information, 73(1), pp. 51-65. https://doi.org/10.1007/s42489-022-00127-1

Shucksmith, M., Chapman, P., Glass, J. and Atterton, J. (2021) Rural Lives: understanding financial hardship and vulnerability in rural areas. Rural Lives. Available at: https://eprints.ncl.ac.uk/289091 (Accessed: 30 July 2026).

StepChange (2023) Statistics Yearbook 2023. Leeds: StepChange Debt Charity.

Sweet, E., Nandi, A., Adam, E.K. and McDade, T.W. (2013) ‘The high price of debt: household financial debt and its impact on mental and physical health’, Social Science & Medicine, 91, pp. 94-100. https://doi.org/10.1016/j.socscimed.2013.05.009

Tendring District Council (2025) Council approves £72,000 grant to keep advice service running while review is launched. Clacton-on-Sea: Tendring District Council. Available at: https://www.tendringdc.gov.uk/news/council-approves-ps72-000-grant-to-keep-advice-service-running-while-review-is-launched (Accessed: 29 July 2026).

Tendring District Council (n.d.) Debt Help. Clacton-on-Sea: Tendring District Council. Available at: https://www.tendringdc.gov.uk/sub-content-pages/debt-help (Accessed: 29 July 2026).

Tobler, W.R. (1970) ‘A computer movie simulating urban growth in the Detroit region’, Economic Geography, 46(Supplement), pp. 234-240.

Tontisirin, N., Anantsuksomsri, S. and Laovakul, D. (2024) ‘Spatial-temporal distribution of debt and delinquency of the elderly in Thailand: perspectives from the National Credit Bureau data’, PLOS ONE, 19(7), e0306626. https://doi.org/10.1371/journal.pone.0306626

Turunen, E. and Hiilamo, H. (2014) ‘Health effects of indebtedness: a systematic review’, BMC Public Health, 14, 489.

Valavi, R., Elith, J., Lahoz-Monfort, J.J. and Guillera-Arroita, G. (2019) ‘blockCV: an R package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models’, Methods in Ecology and Evolution, 10(2), pp. 225-232.

Ver Hoef, J.M. and Boveng, P.L. (2007) ‘Quasi-Poisson vs. negative binomial regression: how should we model overdispersed count data?’, Ecology, 88(11), pp. 2766-2772.

Waller, L.A. and Gotway, C.A. (2004) Applied Spatial Statistics for Public Health Data. Hoboken, NJ: Wiley.

Welwyn Hatfield Borough Council (n.d.-a) Affordable Housing and housing developments. Welwyn Garden City: Welwyn Hatfield Borough Council. Available at: https://www.welhat.gov.uk/housing-garages/housing-developments/2 (Accessed: 29 July 2026).

Welwyn Hatfield Borough Council (n.d.-b) Housing Payment and Council Tax Support Hardship Relief Form. Welwyn Garden City: Welwyn Hatfield Borough Council. Available at: https://www.welhat.gov.uk/discretionary-form (Accessed: 29 July 2026).

Welwyn Hatfield Borough Council (n.d.-c) Benefits and other help if you are on a low income. Welwyn Garden City: Welwyn Hatfield Borough Council. Available at: https://www.welhat.gov.uk/benefit/help (Accessed: 29 July 2026).

Welwyn Hatfield Borough Council (n.d.-d) Make an arrangement to pay Council Tax. Welwyn Garden City: Welwyn Hatfield Borough Council. Available at: https://www.welhat.gov.uk/council-tax/make-arrangement-pay-council-tax (Accessed: 29 July 2026).

Zeileis, A., Kleiber, C. and Jackman, S. (2008) ‘Regression models for count data in R’, Journal of Statistical Software, 27(8), pp. 1-25. https://doi.org/10.18637/jss.v027.i08

Appendices

The appendices provide supporting diagnostics and complete local-authority results for the analyses reported in Chapters 3 and 4. They are included to make the validation, cartographic assessment and observed-to-expected comparisons transparent without interrupting the main argument.

Appendix A. Model validation and sensitivity

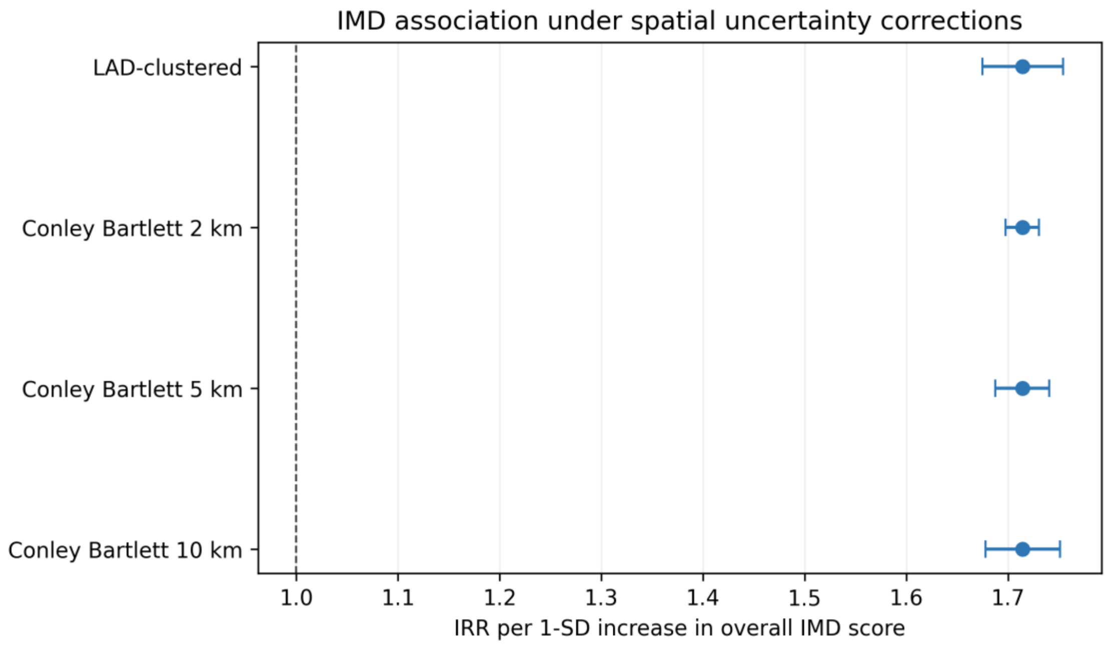


Figure A.1. Incidence-rate ratio for a one-standard-deviation increase in overall IMD score under LAD-clustered and Conley spatial uncertainty corrections. Points show identical coefficient estimates and bars show 95% confidence intervals.

Table A.1. Spatial uncertainty sensitivity of the overall IMD association.

Uncertainty specification	IRR	95% CI	p-value
LAD-clustered	1.714	1.675-1.754	<0.001
Conley Bartlett 2 km	1.714	1.698-1.731	<0.001
Conley Bartlett 5 km	1.714	1.688-1.741	<0.001
Conley Bartlett 10 km	1.714	1.678-1.751	<0.001

Table A.2. Complete-LAD grouped cross-validation fold audit.

Fold	Train LSOAs	Test LSOAs	Train LADs	Test LADs	LAD overlap	Training rate per 1,000
1	27,626	6,128	236	60	0	99.45
2	26,712	7,042	237	59	0	100.78

Fold	Train LSOAs	Test LSOAs	Train LADs	Test LADs	LAD overlap	Training rate per 1,000
3	26,882	6,872	237	59	0	95.42
4	27,509	6,245	237	59	0	99.74
5	26,287	7,467	237	59	0	96.74

Table A.3. Sensitivity of robust observed-to-expected departures to the selected threshold.

O/E departure threshold	Above expectation (LADs)	Below expectation (LADs)
5%	88	124
10%	64	87
20%	29	28

Appendix B. Cartogram validation

The selected diagnostics below quantify the principal trade-offs discussed in Sections 3.3 and 4.1. The final layout eliminated material circle overlap, preserved the overall distance structure and retained most original adjacencies within the local cartogram neighbourhood.

Table B.1. Selected validation measures for the adjacency-aware Dorling population cartogram.

Validation measure	Result
Overlapping circle pairs above 1 m	0
Maximum overlap	0.05 m
Median displacement from geographic centroid	58.70 km
All-pair distance Spearman correlation	0.869
Original adjacencies within 10% of circle contact	53.5%
Original adjacencies within 25% of circle contact	59.9%
Original adjacencies among eight nearest cartogram neighbours	78.0%
Correlation between log circle area and log population	1.000

Appendix C. Complete Local Authority District results

Table C.1 reports the observed burden and the two independently cross-fitted benchmarks for every Local Authority District. The table presents continuous O/E values rather than assigning authorities to a fixed policy typology.

Table C.1. Complete LAD observed-to-expected results under complete-LAD and 10-km spatially buffered validation.

LAD	Region	Adult population	Observed CCJs	Observed rate per 1,000	O/E LAD holdout	O/E 10-km buffer
Amber Valley	East Midlands	102,512	7,674	74.9	0.847	0.819
Ashfield	East Midlands	100,095	11,105	110.9	0.945	0.903
Bassetlaw	East Midlands	94,882	10,607	111.8	1.174	1.157
Blaby	East Midlands	81,327	5,270	64.8	1.111	1.076
Bolsover	East Midlands	64,662	6,663	103.0	0.989	0.994
Boston	East Midlands	56,001	8,445	150.8	1.304	1.314
Broxtowe	East Midlands	90,505	6,056	66.9	0.889	0.863
Charnwood	East Midlands	149,247	10,658	71.4	1.032	1.026
Chesterfield	East Midlands	83,931	7,583	90.3	0.770	0.776
Derby	East Midlands	202,782	23,142	114.1	0.825	0.775
Derbyshire Dales	East Midlands	59,495	2,810	47.2	0.791	0.785
East Lindsey	East Midlands	118,693	10,788	90.9	0.729	0.735
Erewash	East Midlands	91,077	7,738	85.0	0.836	0.807
Gedling	East Midlands	93,935	6,928	73.8	1.002	0.958
Harborough	East Midlands	77,935	4,029	51.7	1.008	0.979
High Peak	East Midlands	73,703	5,406	73.3	0.914	0.891
Hinckley and Bosworth	East Midlands	91,433	6,159	67.4	1.042	1.013
Leicester	East Midlands	281,469	35,460	126.0	0.813	0.789
Lincoln	East Midlands	85,080	9,452	111.1	0.810	0.819
Mansfield	East Midlands	87,887	10,859	123.6	0.967	0.966
Melton	East Midlands	41,818	2,717	65.0	0.985	0.958
Newark and Sherwood	East Midlands	99,299	8,604	86.6	1.036	0.982
North East Derbyshire	East Midlands	83,239	5,681	68.2	0.828	0.818
North Kesteven	East Midlands	95,388	6,027	63.2	1.061	1.062
North Northamptonshire	East Midlands	280,414	31,283	111.6	1.346	1.398
North West Leicestershire	East Midlands	83,798	6,431	76.7	1.109	1.077
Nottingham	East Midlands	257,653	33,843	131.4	0.848	0.797
Oadby and Wigston	East Midlands	45,856	3,345	72.9	1.012	1.006
Rushcliffe	East Midlands	95,038	4,265	44.9	0.879	0.840
Rutland	East Midlands	32,970	1,451	44.0	0.834	0.844
South Derbyshire	East Midlands	84,501	6,013	71.2	1.047	0.978
South Holland	East Midlands	77,147	7,414	96.1	1.248	1.240
South Kesteven	East Midlands	114,776	8,607	75.0	1.021	1.043
West Lindsey	East Midlands	77,033	6,474	84.0	0.901	0.907
West Northamptonshire	East Midlands	333,841	35,628	106.7	1.385	1.436
Babergh	East of England	75,249	4,251	56.5	0.830	0.851

LAD	Region	Adult population	Observed CCJs	Observed rate per 1,000	O/E LAD holdout	O/E 10-km buffer
Basildon	East of England	144,313	19,801	137.2	1.196	1.317
Bedford	East of England	143,706	14,862	103.4	1.071	1.167
Braintree	East of England	123,046	9,864	80.2	1.027	1.059
Breckland	East of England	115,008	8,175	71.1	0.809	0.796
Brentwood	East of England	61,055	5,124	83.9	1.288	1.391
Broadland	East of England	107,710	5,089	47.2	0.745	0.737
Broxbourne	East of England	77,120	8,065	104.6	1.236	1.275
Cambridge	East of England	122,214	5,750	47.0	0.656	0.663
Castle Point	East of England	72,367	5,910	81.7	0.893	0.979
Central Bedfordshire	East of England	230,400	17,271	75.0	1.083	1.168
Chelmsford	East of England	143,580	12,709	88.5	1.283	1.324
Colchester	East of England	152,182	12,801	84.1	0.971	1.004
Dacorum	East of England	120,159	10,497	87.4	1.135	1.226
East Cambridgeshire	East of England	69,424	4,031	58.1	0.981	0.952
East Hertfordshire	East of England	117,430	7,421	63.2	1.016	1.111
East Suffolk	East of England	201,436	15,518	77.0	0.807	0.750
Epping Forest	East of England	106,857	9,205	86.1	1.171	1.284
Fenland	East of England	82,780	7,874	95.1	0.822	0.837
Great Yarmouth	East of England	80,568	10,258	127.3	0.708	0.669
Harlow	East of England	70,919	10,442	147.2	1.503	1.574
Hertsmere	East of England	83,411	8,035	96.3	1.313	1.352
Huntingdonshire	East of England	144,303	9,278	64.3	1.066	1.031
Ipswich	East of England	108,380	16,242	149.9	1.240	1.224
King's Lynn and West Norfolk	East of England	125,882	9,031	71.7	0.727	0.748
Luton	East of England	166,289	28,089	168.9	1.235	1.293
Maldon	East of England	53,971	3,749	69.5	0.986	1.086
Mid Suffolk	East of England	84,044	4,414	52.5	0.806	0.832
North Hertfordshire	East of England	104,722	6,133	58.6	0.854	0.924
North Norfolk	East of England	87,202	4,757	54.6	0.699	0.683
Norwich	East of England	118,196	11,266	95.3	0.791	0.735
Peterborough	East of England	162,058	21,497	132.7	1.024	1.010
Rochford	East of England	68,714	4,007	58.3	0.826	0.903
South Cambridgeshire	East of England	126,534	5,932	46.9	0.849	0.865
South Norfolk	East of England	114,094	6,181	54.2	0.870	0.844
Southend-on-Sea	East of England	142,481	16,295	114.4	0.940	0.985
St Albans	East of England	112,107	5,775	51.5	0.846	0.918
Stevenage	East of England	69,210	6,931	100.1	1.153	1.190
Tendring	East of England	121,904	10,950	89.8	0.520	0.537
Three Rivers	East of England	72,554	4,979	68.6	1.010	1.106
Thurrock	East of England	131,817	20,124	152.7	1.630	1.694
Uttlesford	East of England	71,243	4,031	56.6	1.033	1.114
Watford	East of England	78,484	9,209	117.3	1.456	1.502
Welwyn Hatfield	East of England	94,850	10,060	106.1	1.466	1.522

LAD	Region	Adult population	Observed CCJs	Observed rate per 1,000	O/E LAD holdout	O/E 10-km buffer
West Suffolk	East of England	144,522	10,225	70.8	0.972	0.967
Barking and Dagenham	London	155,325	32,851	211.5	1.510	1.558
Barnet	London	299,935	34,970	116.6	1.176	1.138
Bexley	London	189,724	19,100	100.7	1.167	1.203
Brent	London	266,732	40,202	150.7	1.015	0.926
Bromley	London	257,346	18,372	71.4	0.847	0.867
Camden	London	173,599	15,004	86.4	0.697	0.714
City of London	London	7,927	449	56.6	0.805	0.795
Croydon	London	300,447	40,757	135.7	1.180	1.149
Ealing	London	286,658	31,989	111.6	0.855	0.816
Enfield	London	247,833	37,917	153.0	0.978	0.998
Greenwich	London	223,272	31,563	141.4	1.184	1.286
Hackney	London	203,490	26,797	131.7	0.831	0.854
Hammersmith and Fulham	London	151,261	13,923	92.0	0.875	0.774
Haringey	London	209,802	28,730	136.9	0.878	0.863
Harrow	London	202,837	23,400	115.4	1.265	1.138
Havering	London	203,489	23,166	113.8	1.253	1.302
Hillingdon	London	234,512	25,662	109.4	1.007	0.959
Hounslow	London	221,867	27,607	124.4	1.054	0.960
Islington	London	180,117	16,775	93.1	0.739	0.720
Kensington and Chelsea	London	120,382	10,797	89.7	0.814	0.747
Kingston upon Thames	London	131,589	8,516	64.7	0.865	0.791
Lambeth	London	262,921	30,880	117.4	1.068	0.945
Lewisham	London	235,785	32,442	137.6	1.106	1.091
Merton	London	168,035	14,895	88.6	1.036	0.948
Newham	London	267,294	43,595	163.1	1.078	1.132
Redbridge	London	233,624	29,368	125.7	1.183	1.287
Richmond upon Thames	London	151,307	7,538	49.8	0.685	0.650
Southwark	London	250,043	29,899	119.6	1.018	0.949
Sutton	London	160,583	11,604	72.3	0.852	0.852
Tower Hamlets	London	246,125	31,118	126.4	0.817	0.839
Waltham Forest	London	215,764	27,097	125.6	1.114	1.082
Wandsworth	London	268,149	19,753	73.7	0.854	0.770
Westminster	London	173,606	17,909	103.2	0.807	0.750
County Durham	North East	423,018	53,362	126.1	1.065	1.068
Darlington	North East	85,542	11,209	131.0	1.003	1.048
Gateshead	North East	157,654	18,429	116.9	0.885	0.846
Hartlepool	North East	72,522	12,101	166.9	0.791	0.826
Middlesbrough	North East	110,452	21,946	198.7	0.847	0.903
Newcastle upon Tyne	North East	242,522	28,802	118.8	0.802	0.771
North Tyneside	North East	167,037	16,087	96.3	0.928	0.871
Northumberland	North East	262,131	23,337	89.0	0.899	0.883
Redcar and Cleveland	North East	109,246	16,013	146.6	0.974	1.017

LAD	Region	Adult population	Observed CCJs	Observed rate per 1,000	O/E LAD holdout	O/E 10-km buffer
South Tyneside	North East	118,140	16,358	138.5	0.948	0.908
Stockton-on-Tees	North East	153,325	22,593	147.4	1.088	1.131
Sunderland	North East	220,108	30,841	140.1	0.882	0.828
Blackburn with Darwen	North West	114,980	14,998	130.4	0.771	0.806
Blackpool	North West	113,134	18,623	164.6	0.665	0.688
Bolton	North West	224,458	28,258	125.9	0.886	0.947
Burnley	North West	72,921	9,602	131.7	0.747	0.772
Bury	North West	150,002	15,378	102.5	0.992	1.023
Cheshire East	North West	320,548	25,400	79.2	1.178	1.203
Cheshire West and Chester	North West	287,637	22,639	78.7	0.967	0.979
Chorley	North West	93,809	7,702	82.1	1.152	1.204
Cumberland	North West	222,134	18,485	83.2	0.924	0.904
Fylde	North West	67,562	5,202	77.0	1.090	1.103
Halton	North West	100,942	13,575	134.5	0.912	0.905
Hyndburn	North West	63,509	8,635	136.0	0.872	0.920
Knowsley	North West	120,755	18,572	153.8	0.923	0.904
Lancaster	North West	116,820	9,563	81.9	0.800	0.808
Liverpool	North West	393,320	54,059	137.4	0.773	0.783
Manchester	North West	425,007	67,145	158.0	0.917	0.957
Oldham	North West	180,131	24,218	134.4	0.802	0.829
Pendle	North West	72,762	8,043	110.5	0.733	0.757
Preston	North West	115,150	15,443	134.1	1.077	1.091
Ribble Valley	North West	49,970	2,871	57.5	1.202	1.227
Rochdale	North West	169,105	22,390	132.4	0.856	0.915
Rossendale	North West	55,678	5,909	106.1	1.000	1.053
Salford	North West	211,256	31,647	149.8	1.051	1.073
Sefton	North West	226,262	21,816	96.4	0.808	0.818
South Ribble	North West	89,017	7,355	82.6	1.169	1.178
St. Helens	North West	146,542	18,365	125.3	0.918	0.930
Stockport	North West	232,355	20,065	86.4	0.971	0.992
Tameside	North West	179,827	23,339	129.8	1.047	1.070
Trafford	North West	180,235	15,247	84.6	1.118	1.178
Warrington	North West	167,889	16,015	95.4	1.200	1.203
West Lancashire	North West	95,709	8,544	89.3	1.128	1.124
Westmorland and Furness	North West	187,257	11,318	60.4	0.807	0.809
Wigan	North West	261,198	30,050	115.0	1.040	1.073
Wirral	North West	254,655	26,899	105.6	0.772	0.772
Wyre	North West	91,721	7,732	84.3	0.865	0.861
Adur	South East	51,518	3,380	65.6	0.906	0.874
Arun	South East	136,301	9,730	71.4	0.846	0.793
Ashford	South East	103,523	9,079	87.7	1.081	1.108
Basingstoke and Deane	South East	145,817	9,740	66.8	1.042	1.074
Bracknell Forest	South East	96,743	7,310	75.6	1.249	1.282

LAD	Region	Adult population	Observed CCJs	Observed rate per 1,000	O/E LAD holdout	O/E 10-km buffer
Brighton and Hove	South East	229,717	18,871	82.1	0.853	0.822
Buckinghamshire	South East	429,571	30,388	70.7	1.157	1.218
Canterbury	South East	129,239	9,081	70.3	0.811	0.829
Cherwell	South East	126,956	9,348	73.6	1.173	1.240
Chichester	South East	102,249	6,349	62.1	0.956	0.956
Crawley	South East	90,692	11,806	130.2	1.476	1.424
Dartford	South East	87,973	10,619	120.7	1.524	1.555
Dover	South East	93,596	7,843	83.8	0.815	0.838
East Hampshire	South East	100,777	5,327	52.9	0.963	0.968
Eastbourne	South East	82,306	7,011	85.2	0.808	0.756
Eastleigh	South East	107,351	6,637	61.8	0.972	0.982
Elmbridge	South East	105,240	5,428	51.6	0.905	0.931
Epsom and Ewell	South East	62,543	3,327	53.2	0.934	0.961
Fareham	South East	93,133	4,373	47.0	0.829	0.830
Folkestone and Hythe	South East	89,337	7,553	84.5	0.825	0.851
Gosport	South East	65,418	6,278	96.0	0.915	0.927
Gravesham	South East	81,961	10,971	133.9	1.317	1.348
Guildford	South East	114,977	5,905	51.4	0.888	0.911
Hart	South East	77,844	3,369	43.3	0.905	0.926
Hastings	South East	72,716	7,534	103.6	0.562	0.581
Havant	South East	100,137	9,857	98.4	0.979	0.982
Horsham	South East	117,190	5,709	48.7	0.937	0.911
Isle of Wight	South East	116,778	8,123	69.6	0.731	0.739
Lewes	South East	80,924	5,350	66.1	0.913	0.855
Maidstone	South East	138,212	14,990	108.5	1.417	1.405
Medway	South East	215,962	27,493	127.3	1.176	1.220
Mid Sussex	South East	119,588	6,534	54.6	0.994	0.966
Milton Keynes	South East	217,560	25,990	119.5	1.442	1.474
Mole Valley	South East	70,158	3,067	43.7	0.781	0.804
New Forest	South East	145,159	8,376	57.7	0.909	0.912
Oxford	South East	133,204	9,112	68.4	0.942	0.997
Portsmouth	South East	166,608	20,408	122.5	1.018	0.995
Reading	South East	137,782	14,416	104.6	1.249	1.291
Reigate and Banstead	South East	116,709	6,758	57.9	0.958	0.924
Rother	South East	77,619	4,524	58.3	0.678	0.692
Runnymede	South East	70,934	4,810	67.8	1.067	1.060
Rushmoor	South East	78,704	6,902	87.7	1.175	1.214
Sevenoaks	South East	93,613	6,069	64.8	0.998	1.024
Slough	South East	114,728	16,746	146.0	1.580	1.587
South Oxfordshire	South East	118,039	5,771	48.9	1.037	1.056
Southampton	South East	199,485	26,617	133.4	1.179	1.181
Spelthorne	South East	81,095	6,219	76.7	1.101	1.097
Surrey Heath	South East	71,517	3,858	53.9	1.010	0.999

LAD	Region	Adult population	Observed CCJs	Observed rate per 1,000	O/E LAD holdout	O/E 10-km buffer
Swale	South East	118,533	11,830	99.8	0.857	0.881
Tandridge	South East	68,610	3,721	54.2	0.895	0.867
Test Valley	South East	103,969	6,334	60.9	0.992	0.998
Thanet	South East	112,343	12,648	112.6	0.711	0.739
Tonbridge and Malling	South East	102,101	7,467	73.1	1.164	1.183
Tunbridge Wells	South East	89,351	6,285	70.3	1.125	1.153
Vale of White Horse	South East	109,157	5,968	54.7	1.056	1.078
Waverley	South East	99,884	4,200	42.0	0.776	0.794
Wealden	South East	130,102	6,164	47.4	0.776	0.752
West Berkshire	South East	126,700	7,701	60.8	1.069	1.098
West Oxfordshire	South East	91,241	4,420	48.4	0.924	0.973
Winchester	South East	101,522	5,204	51.3	0.933	0.937
Windsor and Maidenhead	South East	119,418	7,255	60.8	1.076	1.098
Woking	South East	80,594	5,237	65.0	0.999	1.029
Wokingham	South East	136,391	6,623	48.6	0.956	0.980
Worthing	South East	89,970	5,962	66.3	0.876	0.847
Bath and North East Somerset	South West	157,604	7,333	46.5	0.772	0.750
Bournemouth, Christchurch and Poole	South West	326,946	28,662	87.7	1.168	1.152
Bristol, City of	South West	380,609	30,762	80.8	0.852	0.810
Cheltenham	South West	95,817	6,367	66.4	1.020	0.998
Cornwall	South West	465,537	41,368	88.9	1.199	1.211
Cotswold	South West	74,472	3,602	48.4	1.010	1.001
Dorset	South West	313,450	16,085	51.3	0.799	0.814
East Devon	South West	124,318	7,369	59.3	1.057	1.082
Exeter	South West	108,989	9,224	84.6	1.233	1.258
Forest of Dean	South West	70,761	4,498	63.6	0.966	0.990
Gloucester	South West	103,928	9,730	93.6	1.006	0.988
Isles of Scilly	South West	1,724	40	23.2	0.515	0.526
Mid Devon	South West	66,275	5,065	76.4	1.216	1.241
North Devon	South West	80,015	7,040	88.0	1.123	1.149
North Somerset	South West	173,834	10,586	60.9	0.821	0.790
Plymouth	South West	213,100	24,999	117.3	1.170	1.201
Somerset	South West	461,881	29,450	63.8	0.913	0.868
South Gloucestershire	South West	231,243	14,786	63.9	1.127	1.057
South Hams	South West	73,113	3,964	54.2	1.034	1.056
Stroud	South West	97,447	5,137	52.7	0.913	0.914
Swindon	South West	181,940	15,539	85.4	1.116	1.103
Teignbridge	South West	110,667	7,893	71.3	1.105	1.132
Tewkesbury	South West	75,308	4,997	66.4	1.229	1.189
Torbay	South West	114,042	12,477	109.4	1.002	1.031
Torridge	South West	56,193	4,132	73.5	0.958	0.966
West Devon	South West	47,044	2,718	57.8	0.926	0.973

LAD	Region	Adult population	Observed CCJs	Observed rate per 1,000	O/E LAD holdout	O/E 10-km buffer
Wiltshire	South West	407,089	23,617	58.0	1.013	1.000
Birmingham	West Midlands	857,393	137,763	160.7	0.909	0.928
Bromsgrove	West Midlands	78,703	4,599	58.4	0.967	1.016
Cannock Chase	West Midlands	80,320	6,484	80.7	0.944	0.987
Coventry	West Midlands	268,731	38,036	141.5	1.174	1.177
Dudley	West Midlands	254,913	23,917	93.8	0.914	0.952
East Staffordshire	West Midlands	97,602	8,567	87.8	1.052	1.052
Herefordshire, County of	West Midlands	153,167	9,277	60.6	0.846	0.829
Lichfield	West Midlands	86,303	5,539	64.2	1.028	1.077
Malvern Hills	West Midlands	65,192	3,523	54.0	0.839	0.801
Newcastle-under-Lyme	West Midlands	100,480	8,195	81.6	1.011	1.007
North Warwickshire	West Midlands	52,517	4,703	89.6	1.166	1.196
Nuneaton and Bedworth	West Midlands	105,612	11,335	107.3	1.025	1.054
Redditch	West Midlands	68,238	6,942	101.7	1.099	1.146
Rugby	West Midlands	89,437	7,848	87.7	1.360	1.359
Sandwell	West Midlands	256,687	36,567	142.5	1.034	1.053
Shropshire	West Midlands	264,894	16,357	61.7	0.932	0.905
Solihull	West Midlands	169,334	14,498	85.6	1.020	1.035
South Staffordshire	West Midlands	91,069	5,273	57.9	0.944	0.986
Stafford	West Midlands	110,826	7,687	69.4	1.052	1.042
Staffordshire Moorlands	West Midlands	78,767	4,104	52.1	0.778	0.776
Stoke-on-Trent	West Midlands	199,902	27,388	137.0	0.927	0.917
Stratford-on-Avon	West Midlands	109,763	6,410	58.4	1.130	1.166
Tamworth	West Midlands	61,960	5,885	95.0	1.020	1.067
Telford and Wrekin	West Midlands	144,165	16,087	111.6	1.032	1.035
Walsall	West Midlands	215,823	26,751	123.9	0.883	0.919
Warwick	West Midlands	120,200	6,307	52.5	0.910	0.908
Wolverhampton	West Midlands	201,933	31,085	153.9	1.097	1.135
Worcester	West Midlands	83,340	7,511	90.1	0.972	0.960
Wychavon	West Midlands	107,852	6,954	64.5	0.995	0.977
Wyre Forest	West Midlands	82,479	7,338	89.0	0.939	0.917
Barnsley	Yorkshire and The Humber	194,468	22,024	113.3	0.931	0.945
Bradford	Yorkshire and The Humber	405,558	49,095	121.1	0.682	0.702
Calderdale	Yorkshire and The Humber	161,532	16,313	101.0	0.871	0.853
Doncaster	Yorkshire and The Humber	244,118	34,567	141.6	1.104	1.105
East Riding of Yorkshire	Yorkshire and The Humber	280,705	18,166	64.7	0.952	0.953
Kingston upon Hull, City of	Yorkshire and The Humber	207,819	33,177	159.6	0.940	0.946
Kirklees	Yorkshire and The Humber	335,145	35,321	105.4	0.948	0.969
Leeds	Yorkshire and The Humber	641,303	68,949	107.5	1.025	1.038

LAD	Region	Adult population	Observed CCJs	Observed rate per 1,000	O/E LAD holdout	O/E 10-km buffer
North East Lincolnshire	Yorkshire and The Humber	123,921	17,899	144.4	0.966	0.972
North Lincolnshire	Yorkshire and The Humber	135,617	14,166	104.5	1.152	1.167
North Yorkshire	Yorkshire and The Humber	501,722	30,936	61.7	0.919	0.941
Rotherham	Yorkshire and The Humber	209,464	23,373	111.6	0.834	0.843
Sheffield	Yorkshire and The Humber	444,049	47,214	106.3	0.824	0.877
Wakefield	Yorkshire and The Humber	279,758	31,650	113.1	1.040	1.064
York	Yorkshire and The Humber	168,063	9,094	54.1	0.911	0.888