Homelessness Monitor Research Programme

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HOMELESSNESS MONITOR RESEARCH PROGRAMME

TECHNICAL REPORT ON UPDATED BASELINE ESTIMATES AND SCENARIO PROJECTIONS FOR ENGLAND 2023

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Chapter 1

Introduction and Overview

This technical report is designed to accompany the 2023 edition of the Homelessness Monitor England and particularly the analyses presented in Chapter 5, which focuses on core homelessness and the forward projections which examine the potential impacts of a wide variety of policy options and scenarios. It follows similar lines to the detailed technical report which accompanied the 2020 edition of the Homelessness Monitor England (published in early 2021). The current round of the Monitor has involved a more extensive update of the core homeless estimates and the projections modelling, partly thanks to a lot of new data (e.g. 2021 Census) and having more data covering the first four years of the post-Homelessness Reduction Act (HRA) regime and its associated data system 'H-CLIC'. In addition, work had been progressing on updating and refreshing the underlying sub-regional model of the housing market in England.

The period since we first developed homeless projections in 2017 has been characterised by a succession of major 'shocks' or discontinuities, notably Brexit, the Covid pandemic, and then the Ukraine war and associated cost of living crisis. Over the same period there have also been significant political instabilities affecting the UK Government, leading to a degree of policy instability and uncertainty. This makes the task of projecting the future course of events more challenging in various respects, both because of the sheer uncertainty as well as because of the sharp short term changes in a number of the variables which drive our projection model.

The work underlying Chapter 5 of the Homelessness Monitor falls into two parts: the first is concerned with estimating, from an increasingly wide range of sources, the numerical extent of core homelessness in our base year (2022 in this case) and immediately preceding years; the second is concerned with forecasting or projecting those numbers into the future, firstly on the basis of 'existing policies' and secondly subject to a wide range of changed policies or scenarios relevant to homelessness. The first part, the estimation of current core homelessness numbers, is the focus of Chapter 2 of this Technical Report, while also supported (in respect of newer data sources) by Appendix A. The second part is developed over the following three chapters (3-5). The first of these (Ch.3) describes the underlying model of the housing system, known as the Sub-Regional Housing Market Model (SRHMM), and how this has been reviewed and updated. The second (Ch. 4) describes how we predict the different elements of core homeless, 20 years into the future, from that underlying platform. The third of these chapters (Ch.5) then describes and discusses how we have modelled and examined a range of suggested policy changes, or wider scenarios, the results of which tests were discussed in the main Homelessness Monitor (Chapter 5). The final main chapter (6) of this report reflects on the current state of play with this modelling and possible future refinements or developments.

There are four technical Appendices. Appendix A supports chapter 2 by reviewing some new data sources used this time. Appendix B lists sources for all the data used in the modelling. Appendix C presents some selected timeline graphs for key housing market and other variables generated from the baseline scenario of the SRHMM. Appendix D provides more detail on the statistical sub-models used to predict key variables, both general housing market variables and specific homelessness numbers, where these models have been revised in this round.

Chapter 2

Baseline Estimates of Core Homelessness

The concept of core homelessness

The core homelessness concept was introduced in research undertaken with Crisis in 2017, updated in 2018[1], and then subject to a further major update in the 2020 Homelessness Monitor England.[2] Its components and their definitions as applied in this study are shown in Table 1 below.

Table 1: Core Homelessness Categories and Definitions

Category	***Description***
Rough Sleeping	Sleeping in the open e.g. in streets, parks, carparks, doorways
Unconventional Accommodation	Sleeping in places/spaces not intended as normal residential accommodation, e.g. cars, vans, lorries, caravans/motor homes, tents, boats, sheds, garages, industrial/commercial premises
Hostels etc.	Communal emergency and temporary accommodation primarily targeted at homeless people including hostels, refuges and shelters[3]
Unsuitable Temporary Accommodation	Homeless households placed in temporary accommodation of certain types, viz Bed and Breakfast, Private Non-self-contained Licensed/Nightly Let, and Out of Area Placements (half in London, all elsewhere)
Sofa Surfing	Individuals or family groups staying temporarily (expecting or wanting to move) with another household, excluding nondependent children of host household and students, who are also overcrowded on the bedroom standard

The development of the core homelessness concept sought to enable a robust measurement framework that overcame limitations in traditional approaches to homelessness calibration used in the UK, and in particular on statutory homelessness statistics (tracking those seeking local authority housing assistance), and counts or estimates of rough sleeping. While both of these approaches are informative and important (and reviewed as a core part of our analysis in successive Monitors), they are also subject to shortcomings that limit their value for analytical purposes – including cross-country (including within UK) comparison, trend over time analysis and serving as a basis for projections on the possible future scale of homelessness.

[1] Bramley, G. (2017) *Homelessness Projections: Core homelessness in Great Britain. Summary Report*. London: CRISIS https://www.crisis.org.uk/media/237582/crisis_homelessness_projections_2017.pdf and Bramley, G. (2019) *Housing Supply Requirements across Great Britain for low-income households and homeless people.* Main Technical Report of Research for Crisis and the National Housing Federation.
[2] Bramley, G. (2021) *Research on Core Homelessness and Homeless Projections: Technical Report on New Baseline Estimates and Scenario Projections*. Edinburgh: Institute for Social Policy, Housing and Equalities Research, Heriot-Watt University. https://doi.org/10.17861/fex5-jg80
[3] For the purposes of these core homeless estimates and projections, 'Everyone In' accommodation in hotels and its legacy is treated as being part of 'hostels, etc.' Data for 2020 have been adjusted to reflect the fact that some of it was recorded by LAs as 'B&B' (part of 'unsuitable TA').

These limitations were reviewed more fully in chapter 5 of the 2020 edition of the Homelessness Monitor England, but include that statistics derived from statutory homelessness activity are in fact measures of 'expressed demand'. As such, they omit people whose circumstances may equate to 'homelessness' in an objective sense, but who have not (or have not yet) made an application, reflecting for example perceived or real limits to their entitlements (e.g. single people) and/or eligibility (e.g. people with No Recourse to Public Funds or limited access to benefits). On the other hand, the statutory homelessness statistics include some households who are homeless, but less acutely, because either they have not yet left their previous accommodation or they have been temporarily housed in 'suitable' accommodation. While not included in our core homelessness estimates, understanding the scale and drivers of these forms of 'other statutory homelessness' remains crucially important, not least because these they have major service planning and resource implications for local authorities. We therefore use our forecasting model to generate key numbers relating to the statutory system – homeless applications and total numbers of households in temporary accommodation – as part of the output of all scenarios.

Rough sleeping counts and estimates are one useful source of data to track trends over time in this most acute form of homelessness, and this has been enhanced since 2021 by the publication of more regular management information covering stocks and flows of both current rough sleepers and also past or potential rough sleepers placed in emergency off-street or more permanent move-on accommodation. However, both the annual count as well as these management data still suffer limitations that we seek to overcome in our approach to measuring core homelessness, including a recognised tendency to undercount or estimate levels of street homelessness, evidenced by practitioner experience, a wider international literature, and the alternative sources which we use in this study.

The range of data sources

In the current round, core homeless numbers for the base year (2022, financial year) are derived from combinations of eleven distinct sources, with three additional sources providing supporting evidence on year-to-year changes or base populations. For each of the five main components listed in Table 1 above, between five and seven distinct sources are used to arrive at a base year number. These sources were listed in Table 5.2 of the main Homelessness Monitor England 2023. In this part of the Technical Report we provide more detail on the characteristics of these sources, which together feed into a general judgement of quality and relevance which is expressed as a numerical weight specific to each source in relation to each component. Factors which feed into this judgement are set out in Table 2, and include issues of timeliness, coverage, sample size, response rates and potential bias, and relevance of questions/categories.

Some sources provide point-in-time (PIT) estimates, while others need to be translated into that common currency for core homeless estimates, drawing on evidence of durations of episodes or their inverse, annual multipliers. Similarly, when using statutory homeless administrative data (HCLIC in England), we need to apply factors to represent the proportion of different core homeless groups who apply to councils – we have good sources for this in our Destitution (DUKS) and Public Voice surveys, for example.

Some sources are for points in time one or several years before the base year. In these cases we use information from various other sources in the Table to estimate likely change factors between the dates in question. For example, for rough sleeping we use quarterly time series in the DLUHC management information, and estimates associated with the ‘Everyone In’ programme; for sofa surfing we use Labour Force survey data on relevant categories of concealed households; for hostels we use DWP Single Housing Benefit Extract (SHBE) data obtained by FOI. Cryptic notes under some of the Figures in Table 3 highlight where changes from earlier years have been allowed for, with ^ symbol indicating a rise and V indicating a fall from the last known value.

Weighting

While we give an overall quality weight to each source in the final column of Table 2, we also apply specific weights for each source used for each category of core homelessness - so for example, the Destitution (DUKS) survey is given a high overall quality/relevance weight of 5 and reasonably high relative weights in relation to rough sleeping, unconventional accommodation and hostels, but a zero weight for sofa surfing because this service user survey does not appear to capture a major part of sofa surfing. These specific weights are shown in Table 3, and they are constrained to add up to 1.00 for each column, corresponding to each category of core homelessness. So, for example, for rough sleeping a higher weight of 0.3 applies to the number derived from DUKs, moderate weights of 0.2 apply to two other national surveys (Public Voice and ONS-SLC), and lower weights of 0.1 apply to the other three sources: the annual DLUHC count/estimates, an estimate derived from HCLIC data on applicants who were previously sleeping rough or with no fixed abode, and the State of Hunger survey.

For unconventional accommodation we give highest weight to the Public Voice survey, which provides the most specific detail albeit in relation to retrospective experiences. For hostels we give the highest weight to the DWP FOI data on short term emergency and transitional accommodation (adjusted to exclude certain rehab-type facilities), a moderate weight to DUKS, and lower weights to the remaining five sources. It can be seen from the hostels etc. column that there is a reasonable degree of similarity in the numbers across the seven sources used.

For Unsuitable TA the largest weight goes to the official admin data, but we also make some reference to the DWP FOI data, the Public Voice panel and (with a low weight) the ONS SLC. For sofa surfing we rely on household surveys, regarding the EHS as the best source (weight 0.3), three other surveys as reasonable (Public Voice, ONS SLC, UKHLS), and one other new source (Crisis Opinium Panel) as usable.

The base year numbers

The results of applying these weights to the estimated numbers from the relevant sources for 2022 are shown in Table 4. In comparing these numbers with 2020, it should be borne in mind that 2020 was a year dominated by Covid and affected by the Everyone In programme, which reduced rough sleeping substantially, and sofa surfing marginally, with some offsetting increase in hostels, etc. (the category in which we placed the special emergency provision in hotels). The new results for 2022 show that, for three of the five categories, the weighted totals for 2022 are higher than the comparable totals estimated previously for 2020. These include rough sleeping, unsuitable TA and sofa surfing. It has been acknowledged by DLUHC and shown in their most recent count/estimates and management data that rough sleeping has been rising significantly in the last year, after remaining fairly low through 2021. Total and unsuitable TA have been increasing moderately in the administrative data. The increase in sofa surfing is partly affected by some technical changes in the way this is measured, particularly in our best source the EHS. We have little basis for estimating change in the unconventional accommodation category, while the hostels etc number is down somewhat thanks to the phasing out of much of the special Covid provision.

The net change in core homelessness over the two years from 2020 appears to be 19.1%, but if we take sofa surfing out of the picture the increase would be more moderate at 12.3%.

Table 2: Key Characteristics of Data Sources Potentially Usable for Estimating Base Period Core Homeless Numbers

SOURCE	*TYPE*	*YEARS AVAIL*	*COVERAGE*	*TIME ADJ to Point In Time (Annual Mult)*	*OVERLAP with HCLIC*	*RESPONSE & attrit bias*	*MOST RELEVANT CORE H'LESS CATEGORIES*	*SAMPLE SIZE*	*OVERALL QUALITY WEIGHT*
Destitution in the UK (DUKS)	Census-type survey users of crisis services	(2017)/2019/2022	Users of 'crisis services' Ltd cov of Sofasurfing Strong on NPHHP	Direct PIT + A M est's with queries	Can Quantify (specif q)	Captures under-rep gps	RS, Hostel, UTA	3700/3860	5
Public Voice Panel (Kantar)	Interview survey representative panel of UK adults	2020	Adults resid in private hhds	Quantified A Ms	Can quantify (specif q)	Best panel available	All, incl Unconv Acc	2900	3
ONS Survey of Living Conditions (SLC)	Interview survey module within EU-SILC	2018	Private hshld popn	Quantified A Ms	No	Signif attrition bias (part-panel)	All, incl U A, but UTA not clearly separable	18000	2
Rough Sleeper Count/Estimates DLUHC	Local PIT estimates: spot or wider count in some cases	Annual to 2022	Street homeless - many limitations	n/a	Unclear	See comments in 2020 Monitor	RS only	n/a	1
Rough Sleeping Management Info DLUHC	Service admin returns	Quarterly from 2020	Street homeless as above, but more detail on TA & move-on	n/a	Can quantify approx	As above	RS	n/a	2
HCLIC admin data homeless applics & temp'y accom	Statutory system admin records	Quarterly & annual 2018-22	Applicants to LA homeless or at risk (56 days)	Need A Ms to get to PIT from flow	Need external estim to gross up	Migrants with NRPF inelig; singles dis-couraged by ltd duty	UTA esp, but also RS (espScotland), (UC), (Hostel), all TA	n/a	4
DWP FOI SHBE cases in TA, SA, s t emergy	Claimants of benefit suppt with hsg costs	Selected months 2020-2022	Most TA, SA and Hostel etc residents	n/a	Should closely overlap TA	Under-repres of TA for wkg hhd; % of	Hostel, UTA, (all TA)	n/a	4

& transit accom						STEMTran unclear			
Homeless Link Support for Single Homeless Report	Indirect survey of relev services	annual -2021	Hostel etc residents, (users of dropin)	n/a	Unclear	apparently somewhat low	Hostel, etc	unclear	3
English Housing Survey (EHS)	Household survey	Annual-2019 (2021 headlines)	Private households usual residents (+ quest on temp S/S)	n/a for main ind need to assume for temp res	Can quantify (specific q)	Best general hhd survey	Sofa surfers (? TA resid)	13,330 pa	5
Scottish Household Survey (SHS)	Household survey	Annual - 2019	Private households usual residents	n/a for sofasurf; some older data from retro q's	Older retro q enabled quantif	Rel good as fresh sample unclustered	Sofa Surfers (older retro hless data ->2015	10,600 (formerly more)	4
U K Household Longitudinal Survey (UKHLS)	Household & indiv panel survey	2010-19/21	Private households usual residents	n/a	No	Serious attrition issue	Sofa Surf	c.20,000	2
State of Hunger Survey 2018 NEW	Service user survey (foodbanks)	2018	Users of foodbanks		No	Unclear	RS, Unconv, Hostel TA total	1130	2
Crisis Opinium panel survey lower income households; NEW	Interview survey quota panel of UK hshlds	2022	Households in bottom 40% of hhd income distribn (AHC)	need to use A Ms	D K (use PV)	Quota sample	RS, Unconv, Hostel, etc., Sofasurfer	2000	2
Labour Force Survey (LFS)	Household/adult survey	Quarterly long way back	Households & adults	n/a	n/a	V. large sample	Concealed, sharing (risk factors for sofasurf)	84300	2
Census 2021 NEW	100% census	2021 (also 2011)	All hhd & persons usually resident in hhd or com accom	n/a	n/a	Some doubts esp communal estabs	Crowd, concshr, (undercount?)	n/a hostels, B&B	3

Table 3 Estimated Numbers of Core Homeless Households and Weights used by Data Source and Core Homeless Category for Base Year (2022)

	CURRENT BEST ESTIMATES ENGLAND 2022 (unrounded)					*WEIGHTS*		*As used*		
Data Source	England Rough Sleep	*Unrounded* Unconvent'l	Hostel etc.	Unsuit T A	Sofa Surf	Rough Sleep	Unconv-entional	Hostel etc.	Unsuit-able T A	Sofa Surf
Destitution in the UK (DUKS)	12,575 0.87	11,139	40,230	5,730	6,344	0.3	0.2	0.2	0.00	
Public Voice Panel (Kantar)	14,549 adj to 22√	18,875 ?	54,626 adj to '22 ^√	15,001 adj to '22 ^√	145,139 adj to '22 V√	0.2	0.3	0.1	0.2	0.2
ONS Survey of Living Conditions (SLC)	12,584 adj to '22 V√	31,396 ?	29,952 adj to '22 ^√	11,618 adj to '22 ^√	121,374 adj to '22 V√	0.2	0.2	0.1	0.1	0.2
Rough Sleeper Count/Estimates DLUHC	6,204 adj to 22, ^ using Mgt Inf					0.1				
Rough Sleeping Management Info DLUHC										
HCLIC admin data homeless applics & temp'y accom	6,490 2021	10,066 ?	40,757 2021 yr end ^ in yr? x1.1	35,755 This fig Sept22 incl 'other' 27,755		0.1	0.2	0.1	0.5	
DWP FOI SHBE cases in TA, SA, s t emergy			60,394 [52,936 in '21}	24,418 exc qtr ^Exmpt				0.3	0.2	

& transit accom			[42,756 in Mar 2020						
Homeless Link Support for Single Homeless Report			32,184					0.1	
English Housing Survey (EHS)					162,668 Adj p r LFS conc				0.3
Scottish Household Survey (SHS)									
U K Household Longitudinal Survey (UKHLS)					114,511				0.2
State of Hunger Survey 2018 NEW	12,506 (2019 scaled)	13,558 2020	48,171 ^ '18-22			0.1	0.1	0.1	
Crisis Opinium panel survey lower income households; NEW	107,250	292,594	173,820	115,880	142,726	0.0	0		0.1
Labour Force Survey (LFS)									
Census 2021 NEW								0.0	

Table 4: Weighted Numbers of Core Homeless Households by Data Source and Core Homeless Category for Base Year (2022)

Data Source	WEIGHTED NUMBERS for 2022 v.1 23/03/2023					
	Rough Sleep	Unconvent'l	Hostel etc.	Unsuit T A	Sofa Surf	All Core HL
Destitution in the UK (DUKS)	3,773	2,228	8,046			
Public Voice Panel (Kantar)	2,910	5,663	5,463	3,000	29,028	
ONS Survey of Living Conditions (SLC)	2,517	6,279	2,995	1,162	24,275	
Rough Sleeper Count/Estimates DLUHC	620					
Rough Sleeping Management Info DLUHC						
HCLIC admin data homeless applics & temp'y accom	649	2,013	4,076	17,878		
DWP FOI SHBE cases in TA, SA, s t emergy & transit accom			18,118	4,884		
Homeless Link Support for Single Homeless Report			3,218			
English Housing Survey (EHS)					48,800	

Scottish Household Survey (SHS)							
U K Household Longitudinal Survey (UKHLS)					22,902		
State of Hunger Survey 2018 NEW	1,251	1,356	4,817				
Crisis Opinium panel survey lower income households; NEW	0				14,273		
Labour Force Survey (LFS)							
Census 2021 NEW							
Crisis Sofa Surfing study (Too small/purposive sample)							
WEIGHTED TOTALS	Rough Sleep	Unconvent'l	Hostel etc.	Unsuit T A	Sofa Surf	All Core HL	
No. of sources	6	5	7	4	5	11	Increase
2022	11,719	17,539	46,733	26,923	139,278	242,191	19.1%
2020 compare	9,838	17,559	49,740	22,639	103,648	203,423	*12.3%*

Note: overall percentage increase includes an element of definitional change affecting sofa surfing; the increase figure below that excludes sofa surfing.

Chapter 3

The Sub-Regional Housing Market Model

From the outset of this strand of research supported by Crisis, the approach adopted has been to build on an existing modelling framework which has been used in both this and a number of other research studies. This framework is the Sub-Regional Housing Market Model (SRHMM) which the author has developed in stages over more than a decade[4]. This new sub-regional economic model of housing markets was primarily developed and intended to inform planning decisions on housing provision in the current decentralised planning framework in England. This model built on previous work (notably Meen 2011; Leishman et al 2008, ODPM 2005, Bramley & Leishman 2005; as reviewed in Bramley 2013a) but went beyond it in terms of using a more appropriate geographical framework of sub-regional housing market areas, explicit modelling of the supply process as a function of planning, economic modelling of demographic change, and linking component models in an integrated simulation approach which takes account of spatial interaction between markets. Its outputs were initially primarily intended to provide a critical missing element in the evidence basis for localised planning decisions and an ability to assess the performance of the whole system in promoting supply and affordability. Subsequently it has been used to inform policy simulations relating to poverty, housing needs and requirements, and homelessness.

The essence of this model is to inform policy consideration in relation to planning, housing and related social policies by presenting consistent scenarios for the housing market and related systems/markets over the medium to longer term. These scenarios are driven by conditional forecasts embodying econometric functions to predict key variables (for example, housebuilding, house prices and rents, tenure shares and lettings). Key assumptions about future economic growth and financial conditions are judgemental inputs informed by independent forecasts and assessments. National population numbers are informed by official projections while sub-regional household numbers are generated by econometric functions allowing for behavioural responses in terms of movement between areas and household formation. The model predicts the evolution of levels of housing need and, since 2017, has been significantly enhanced to predict a range of numbers within the official homelessness system and core homelessness numbers in the categories defined for this study. These predictions are made for 102 subregional areas in England and another 14 areas in the other UK countries (the latter are not reported here).

This unique model is of particular value in the present context, where we are trying to predict core homelessness numbers in the near and more distant future. It is one thing to have a model which can predict a particular aspect of homelessness, such as rough sleeping, on the

[4] See in particular Bramley, G. & Watkins, D. (2016) 'Housebuilding, demographic change and affordability as outcomes of local planning decisions: exploring interactions using a sub-regional model of housing markets in England', *Progress in Planning*, 104, pp.1-35; Bramley, G. with Leishman, C., Cosgrove, P. and Watkins, D. (2016) *What Would Make a Difference? Modelling policy scenarios for tackling poverty in the UK.* https://pureapps2.hw.ac.uk/portal/files/10844984/Bramley_WhatWouldMakeaDifference_Report.pdf ; and Bramley, G. (2018) *Housing Supply Requirements across Great Britain for low income households and homeless people*. Research Report for Crisis and the National Housing Federation. Main Technical Report. Edinburgh. Heriot-Watt University. https://researchportal.hw.ac.uk/en/publications/housing-supply-requirements-across-great-britain-for-low-income-h .

basis of a number of risk and contextual factors; it is another to have a system which can 'predict the predictors' in such a model going forward over 10-20 years in a consistent fashion.

Schematic outline of sub-regional model

Figure 1 presents a schematic diagram of the sub-regional model, reproduced from the 2016 article by Bramley & Watkins (2016).

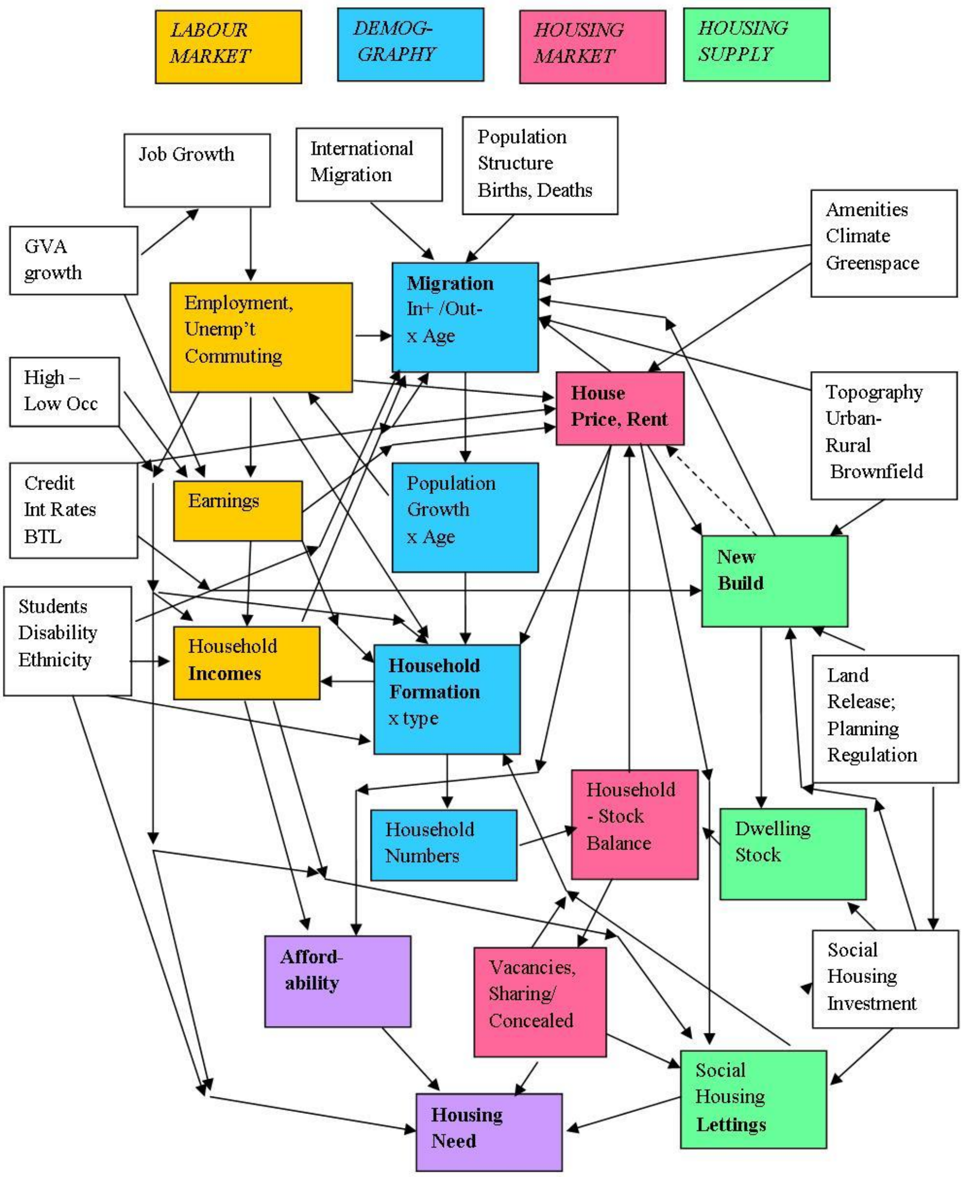

Figure 1: Schematic Representation of Sub-Regional Housing Market Simulation Model

Note: Figure 1 is reproduced from Bramley & Watkins (2016) article in *Progress in Planning*

This diagram shows four main strands colour coded as follows:

- (Orange) the labour market, including the generation of employment and unemployment rates, earnings and household incomes
- (Blue) demographics, including migration (both international and domestic), population growth, age structure, household formation and types
- (Pink) the housing market, including house prices, rents, the balance between households and dwellings, tenure, vacancies and sharing/concealed households
- (Green) housing supply, including new build completions by private and social sector, evolution of the dwelling stock, and social lettings

Exogenous variables are shown in white around the outside of the diagram. These include key assumptions about: expected short and longer term trends in economic growth (GVA & productivity), including sub-regional differences based partly on past performance; financial conditions; trends in factors like occupational mix, illness/disability, higher education, ethnicity, and so forth. Relatively simple mechanistic functions characterise the labour market strand. For example, earnings growth is driven by changes in GVA per worker, a labour market balance factor, and changes in broad occupational mix.

In the demographic strand, births, deaths and international migration are assumed to continue following recent trends, as reflected on ONS projections at national level, but subject to some additional judgements (e.g. on migration, reflecting recent events and policy positions). However local populations reflect endogenous econometric functions for gross migration flows by broad age groups, while household numbers and composition reflect the operation of econometric functions for household headship by broad age. The latter functions were recently re-estimated using data UKHLS over recent years, but the internal migration functions remain as estimated on data from the period 1997-2007. It should be noted that many of the demographic and other inputs to the model have been updated to incorporate new data from the 2021 census, including modifying certain trends based on experience over the last decade.

The housing market strand is more key to predicting outcomes relating to housing affordability, need and homelessness. A number of key functions within this strand have been re-estimated on updated data in the current round of projection, including, house prices, rents and the functions determining the tenure balance between home ownership and private renting. Also important in this strand is the turnover in the social rented sector which is the main determinant of social lettings supply, alongside new build supply. New private construction is modelled as a function of planning factors as well as market conditions, in the final (green strand). We discuss the latest versions of these key sub-models further below.

The diagram shows the balance between households and dwellings as playing a key role in the model, and this is reflected not just by the inclusion of key measures in the estimated regression models but also in additional feedback mechanisms which kick in when this balance gets out of line beyond threshold levels.

Spatial Framework

The spatial framework for the model is based on previous research into housing market areas (HMAs) in England. In a parallel project for the former National Housing and Planning Advice Unit (NHPAU) a separate research team produced a comprehensive analysis of this issue and tested a range of sets of HMA boundaries (Jones et al 2010). The set used here were selected as the most suitable 'interim' output from that project, and were based on a composite of official travel-to-work areas, modified to achieve minimum 55% self-containment in migration of 25+ age group, and subsequently tested against house price criteria (which led to little change). The version of this set of HMAs used here is that based on grouping of whole local authority districts (pre-2009), rather than the ward-based set of boundaries, in order to maximise data availability. Within England this generated 102 HMAs, ranging from 'London' (population 9.6m) to Oswestry (40,000). While this represents a consistent application of the conceptual framework underpinning HMAs, with hindsight one might have chosen to (a) break London into broad sectors while (b) combining some very small contiguous HMAs. In practice the tendency for government to encourage piecemeal local government amalgamations has weakened the fit of functional HMAs to administrative areas and made the process of updating input data from mainly LA level sources more difficult and time-consuming.

Model platform

The overall model is designed to work in an Excel spreadsheet setting, where for each of c. 150 variables values are shown for each year from 1997 (or often later, e.g. 2001 or 2011) through to 2041, with currently 2021 being the last year of actuals, 2022 the first year of predicted values. (Albeit first-year predictions are often controlled to estimated values from multiple sources in the case of key core homeless numbers for that year, or in other cases with partial controlling to previous year actuals). The overall spreadsheet approach facilitates the visual examination of the evolution of particular variables over time. Other worksheets contain control parameters for the simulations, technical parameters governing parts of the simulation, cross-sectional only variables, tables of coefficients for predictive functions, and summarised predicted values for key variables in a compact tabular format highlighting key target years (and showing differences from baseline).

The model is designed to be recursive, so that each endogenous variable is generally a function of 1-year lagged values of key drivers where these are also endogenous. No attempt is made to 'solve' simultaneous equation systems within year. This approach means that the model has what may be described as somewhat clunky dynamics in the short term, especially if exposed to large shocks. In relation to the core sub-regional housing market behaviour, additional feedback mechanisms are in place when the relationship between households and dwellings goes out of a certain range, and these help to damp out some of the clunkiness. This design decision is partly motivated to keep it simple and minimise endless problems of circularity, but also reflects an analytical philosophy regarding urban economic systems; namely that these tend to evolve in an incremental and path-dependent fashion without a short run ability to necessarily achieve equilibrium (Bramley & Watkins 2016, Bramley Simmonds & Dobson 2011, Simmonds 2010).

Econometric approaches

There are some related issues in the econometric approaches used to fit key functions to data. While attracted in theory to the possibility of applying an Instrumental Variables approach (IV, of which the most popular variant is 'Two-Stage Least Squares' or 2SLS) to certain groups of sub-models, having tried this the author remained unsatisfied with the results. The literature does indicate that a lot of care is needed in the choice of appropriate instruments and where models do not all have a very good fit this may not yield satisfactory results (Angrist & Pischke 2009, Ch.4, Angrist & Krueger 2002, Stock, Wright & Yogo 2002). In practical terms, as well, a lot of variables were available for different time periods or at different levels.

Quite a lot of functions are fitted to short annual panels of local authority (district or unitary, LAD for short) or in some cases Housing Market Area (HMA) level indicators, which can typically be updated frequently. Having most if not all variables in the models in time-varying form is advantageous and increases the credibility of models in terms of reflecting relationships which would apply when modelling change. However, the author is sceptical about the excessive reliance in a lot of econometric work on fixed effects models. In this kind of urban modelling there is a lot of relevant information in the cross-sectional dimension, while the information content of interpolated time varying factors may be limited, and 'errors in variables' (for example where data are derived from sample surveys, such as LFS/APS) can weaken the power of fixed effects models (Angrist & Pischke 2009, ch. 5: Griliches & Hausman 1986). As such, the general approach in the LA panels has been to use random effects models, but with specific dummy variables for particular years (e.g. to reflect financial crisis, the introduction of the Homelessness Reduction Act, or Covid) or particular areas (e.g. London). In a number of cases a partial adjustment framework has been used (i.e. with lagged dependent variable included) – arguably this is a robust approach which gives several benefits, including capturing much of any fixed effect relating to heterogeneity while also capturing the varying speed of response towards the longer term structural solution.

Core housing market functions

In this section we briefly discuss key features of the core housing market functions. Fuller details of key sub-models referred to here are provided in Appendix D of this report, where they have been re-estimated in this round. Otherwise, details may be found in the 2020 Technical Report (Bramley 2021, Appendix D).

The *new build* private housebuilding supply function follows similar lines to previous versions, fitted to 12 years of data at LAD level, explaining 54% of the variance, with all 12 variables having the expected direction of effect. Private completions were driven by previous completions, new permissions, existing permissions, and higher prices, but with a strong positive effect from new social completions (probably reflecting the role of s.106 planning mechanisms as well as local authority sentiment); negative influences included vacancies, higher mortgage rates, greater shares of brownfield land and small sites, and the Covid years.

Real *house prices* were modelled on a 12 year panel of housing market areas (weighted by relative size) in a partial adjustment framework in log-log form, but indicating reasonably quick adjustment and a very close fit. Key drivers included in particular household income, consistent with key literature such as Meen (2011), but also negative supply feedback via completions, vacancies and logged household-dwelling balance, and a negative 'user cost of capital' term which includes interest rates. Wealth effects represented by FTSE for London and the South appear significant, while year dummies underline the price bounces in 2010, 2020 and 2021.

Rents are probably more critical for homelessness than prices, but as expected these were related to both level and change in house prices. Again we used a lagged adjustment framework, based now partly on Zoopla data for asking rents, again over 12 years with this time the results indicating relatively sluggish adjustment of rents but an overall very close fit.

Other positive factors included earnings and younger adult populations, with negative effects from new supply and vacancies.

A simple partial adjustment model is also fitted to data on the *private rental stock share* of dwellings, this time using a 3 year lag. This indicates that private rental supply responds positively to the rental rate of return, the house price:earnings ratio (indicative of unaffordability of buying), and real stock prices (FTSE index) with negative association with mortgage interest rate, and positive dummies for London and post-2016. The 2021 Census revealed a continued expansion in private renting, notwithstanding George Osborne's tax measures in the middle of the decade. Our overall tenure balance is partly also determined by a tenure choice function fitted to UKHLS data, again aggregated to HMA level; the house price:income affordability factor also featured strongly in this.

As mentioned above, *household formation* (headship) is determined through functions fitted econometrically to data aggregated from UKHLS to HMA level, subject to adequate numbers of observations. The key age group (18-25) was re-estimated in this round and this showed a clear negative relationship with the house price/income ratio, in addition to expected demographic effects from previous household types, in-migrant flows, relationship breakdowns (positive) and students and social renting (negative). The suppression of household headship in the younger age groups has been a strong feature of the English housing market over recent years.

Predictions of *household income* were also developed from UKHLS data (2011-19) aggregated to HMA in a similar fashion; these were driven particularly by real GVA per capita, median earnings, higher social class, employment rates, and negatively by unemployment, part time working, long term sickness, single and lone parent households, and Council Tax bands (AB vs GH).

Last but not least in the set of functions representing the housing market, there is a model to predict the *net relet rate* for social housing, fitted to LAD level data over the period 2016-21 (shorter because data quality/consistency problems affect the earlier years particularly). This showed that relets were lower where/when house prices were higher or rising, rental affordability was worse, poverty and social renting more prevalent, and during Covid; and relets were higher where/when private completions were higher, vacancies higher, densities higher, and more young adult tenants in 2011. This relets variable is crucial in being able to address the needs of homeless households and prevent the build-up of unsuitable temporary accommodation.

Initial and Baseline Economic Assumptions

The model is intended to approximately track the most recent years in terms of key economic variables at national level, and then to move forward on the basis of a set of assumptions about medium to longer term trends in key economic and demographic variables. Recent economic events have been characterised by turbulence generated by external events (Brexit, Covid and Ukraine war) as well as domestic political changes, which inevitably increases uncertainty and may impart instability to the model. Nevertheless, we have attempted to capture the average or consensus view of short-to-medium term economic prospects from key official and reputable independent sources – typically taking the average across OBR, Bank of England, NIESR, and the Treasury summary of recent published forecasts. Table 3 summarises the key values derived from this exercise and shows how they compare with the model's projected scenario and a variant high growth scenario. The key values are the average performance over the period 2019-22 and the anticipated rate in the medium term (up to 2026 or 2027, typically). The model values refer to the two decades from 2021 to 2041.

Table 5: Summary table of key economic assumptions, showing model values for baseline and high growth compared with average of official and leading independent forecasts

SUMMARY TABLE	Real GDP	Productivity GVA/wkr	Inflation CPI	Unemp	Real Hhd Disp Inc	Mortgage Int Rate	Nominal House Price % pa	Real Mkt Rents
	% pa	% pa	% pa	(ILO, %)	% pa	%		% pa
From official & indep f/casts								
Recent trend (2019-27)	1.0	0.8	3.2	4.2	0.5	3.8	3.1	0.7
Prospective trend (consensus)	1.9	1.0	3.0	3.5	1.4	4.0	5.0	
From SRHMM								
Model trend/average baseline	1.9	1.4	3.3	3.1	1.4	5.0	5.0	0.6
Model trend high growth	3.0	1.6	3.3	2.2	2.7	5.0	6.4	1.4

The model values for GDP, inflation, disposable income and nominal house prices look in line with the consensus for prospective trends. The model value for productivity looks a little high in the baseline[5], although this has been adjusted following reviewer comments. The model values for ILO unemployment look a little low, especially in the high growth scenario, compared with longer term published forecasts and past experience, although labour supply might expand more with increased participation by older workers, or else productivity growth could be higher in the optimistic scenario.

Rents are more important for housing need and homelessness than house prices. Our baseline model prediction shows only modest growth in real terms for England, although the figure for London is higher, while higher economic growth would push up both price and rental inflation.

Appendix 3 shows some broad regional timelines for a number of key variables in the SRHMM baseline scenario. Different charts show varying degrees or smoothness or tendency to oscillation, reflecting the character of the SRHMM model with its many lagged response functions. Developments in the model subsequent to this round of projections have included additional functions to damp some of these tendencies.

[5] The baseline GVA and productivity growth rates at sub-regional level were derived from actual data 2011-16 and local economic forecasts for subsequent period as used in Land-Use-Transportation modelling, which then interact with assumptions about future rates of change informed by the review of independent forecasts and recent actuals.

Chapter 4

Predicting Elements of Core Homelessness

Predictive functions for homelessness

The functions used to predict elements of core homelessness fall into two main categories: (1) local authority-level aggregate models to predict stocks or flows recorded in the H-CLIC and related administrative systems; (2) micro household survey based models to predict the odds of respondents reporting experiences of core homelessness, either at the time of the survey or in the past. The former types of model are used to predict two key numbers in the mainstream statutory system – total applications and total households in TA (as a percentage of all households) – as well as one specific category of core homelessness: unsuitable temporary accommodation. Such models are also used for two specific subsets of applications (those losing a previous private tenancy, and those previously sleeping rough or with no fixed abode). Models of the second type are used mainly to predict rough sleeping, unconventional accommodation or sofa surfing, generally cases where we take an average of the predictions from several different models. However, models of type (2) generally include local authority level housing and labour market characteristics attached to the micro data for the relevant years. This reflects an important conclusion from key previous literature and reviews thereof, namely that individual level studies should take account of the interaction between individual and area-level attributes, where the latter include market processes and influences[6].

When type (2) models are used in the simulation, micro level variables are represented by HMA level equivalent variables in the same units (typically proportions), many of which may be aggregated up from LA-level panel datasets. In some cases such variables have to be interpolated between data points when not available directly on an annual basis. In this round 2021 Census data was used to update a number of such variables. A few variables in UKHLS could not be directly replicated in LA/HMA level datasets (e.g. savings, financial/debt problems, family/relatives' support); in these cases LA level values were generated by a weighted average of the pooled LA value from UKHLS sample and the value for a broad-region-LA type group, weights depending on the sample size.

Models of the first type have a long track record[7]. They provide an opportunity to include and calibrate the effects of different types of influence, including local and sub-regional market effects, demographic influences, background housing need conditions, but also certain differences in policy and practice, insofar as these are measurable. Local authorities in England operate under a common legal framework and set of duties regarding homelessness, which contrasts their situation with cities in the USA or most other countries, yet at the informal level of frontline administrative practice (often called 'gatekeeping') there has always been significant variation in practice, much of which has been difficult to capture in systematic measures or marker variables. Nevertheless, it has been possible in different

[6] See Bramley & Wood (2023 forthcoming), Johnson et al (2018) and o'Flaherty (2019, p.14).
[7] Going back at least to Bramley (2010) *Estimating Housing Need* study for DCLG and to earlier LA level cross sectional models in Bramley (1989 & 1993).

time periods to measure the extent and impact of certain types of practices, particularly in the area of homelessness prevention.

It may be argued that the most recent four-year period (2018-21) is the most relevant when modelling variables from the statutory homeless system in England, thanks to the introduction of the Homelessness Reduction Act (HRA) (which came into force in April 2018). The simultaneous introduction of the HCLIC household-level record system reinforces this, insofar as certain analyses or indicators (for example of prevention outcomes) are better able to be captured in this period. In several instances we reflect this perspective by running the relevant model for both a longer period (e.g. 2014-21) and the shorter period (2018-21) and taking the average value of the coefficients, including for variables which are only significant in one of these periods. This has the effect of giving greater weight to variables which are significant in both periods, while also recognising effects which are stronger in the recent period as well as effects that are only revealed over the longer period. It has been suggested that this is a 'non-standard' econometric technique and might be better achieved through use of dummy variables or interactions, a possibility which may be explored in future rounds.

Homeless applications

The current model for the flow of homeless applications (as a percentage of resident households) fitted over the 8 years period (2014-21) as reported in Appendix D (Table D.7) follows in the footsteps of previous models, explaining two–thirds of the variance. It highlights the effects of policy regime change (HRA from 2018), demographics, tenure (private renting and loss of private tenancies) affordability (rent-income ratio, and excess of rent over LHA), poverty, unemployment and the prevalence of destitution associated with complex need although general ill-health/disability has a negative impact. As suggested above, we take the average of the coefficients from the 8-year and 4-year models; the latter sees four variables drop out (HRA and Covid dummies, unemployment rate and excess rent), and one additional prevention measure become significant, while the other prevention measure changes sign (to the 'right'/expected negative effect).

A separate model is fitted to data for the important specific sub-flow of applicants leaving private renting due to eviction or other loss of tenancy, again at LA level over 8 years. This model has similarities but this time the demographics include Black population share and share of children, affordability reflected by rents (positive) and household income (negative), PR tenure share (positive) and change (negative), while two prevention measures both appeared to reduce this flow.

Temporary accommodation

The total level of TA is an important barometer of pressure on the local homelessness system as well as a key driver of costs. We model it as part of a stock-flow adjustment system ,with the inflow from current new applications adding to the lagged stock while social lettings and prevention into social rent serve to reduce the stock (Table D.9, Appendix D). Higher rents increase TA levels, positive dummies represent the positive impacts of HRA, Covid, and being in London, while local hostel numbers also seem to feed into total TA. This model is repeated for the shorter post-HRA period and average coefficients are taken, leading to a strengthening and broadening of the prevention impact in reducing TA. These models explain 92% and 93% of the variance respectively.

The subset stock of unsuitable TA is subjected to a similar modelling approach (Table D.10), where the existing stock is augmented from both new applications flow and increases in total TA, while being alleviated by social lettings rates and prevention efforts. Rent levels and affordability ratios, as well as the share of private renting, tend to push up levels of unsuitable TA, with similar dummy effects this time also including (provincial) core cities. Again we combine the 8 year and four year models with averaged coefficients, with the models explaining 83% and 77% of the variance.

Rough sleeping

Rough sleeping is of strong media and policy interest, but is difficult to measure reliably. For these reasons, we use three distinct models to estimate and predict levels at HMA level, with equal weight. The first of these is an aggregate LA-level flow measure from H-CLIC, with numbers adjusted to a comparable point in time stock measure by applying factors derived from surveys for duration and share of rough sleepers applying to councils, as explained in Chapter 2 (see Table D.11, Appendix D). This model is now fitted to four years of data post-HRA, using the log of half of the number of applicants previously sleeping rough plus those with no fixed abode[8].

This model shows positive effects from single person households, crime rate, complex need, excess rent over LHA, loss of private tenancy; and living in a sparsely populated area; and negative effects from general destitution, no qualifications, hostel residents, London dummy and two prevention measures. This underlines the association of rough sleeping more with complex needs and less with general poverty, while continuing the theme of problematic private renting, but this time seeing hostels as an alternative /route out rather than a route in.

The remaining two models for rough sleeping are based upon micro household surveys. The first of these is the same model as used in previous two rounds of projection, based on the Kantar Public Voice panel survey questions on retrospective experiences of homelessness in the form of rough sleeping (see 2020 Technical Report, pp 48-9 and pp 77-78). This emphasized the links to other forms of core homelessness (unconventional accommodation, emergency and temporary accommodation and sofa surfing), as well as younger age, disability, non-working/unemployment and very low income.

The third model is new to this round of projections and is based on the technique of combining the unique Destitution in the UK Survey (DUKS) of users of crisis services with a mainstream household survey (UKHLS) for the same year (2019) for a common set of variables, creating a composite data set which can be used to model rough sleeping (current/last month) as well as core homelessness as a whole, destitution and the use of food banks (the latter being the focus of a recently published article[9]). A common logistic regression model is fitted to both core homelessness and rough sleeping, as shown in Appendix D below (Table D.12), containing 25 variables of which five are LAD area-based measures and all bar 5 are significant at the 5% level in the rough sleeping model. Significant positive factors include being younger, born overseas, living as a single/nonfamily household, reporting physical or mental health problems, being on Universal Credit, experiencing eviction, or having very low

[8] This is on average equivalent to all of those sleeping rough plus 35% of those citing no fixed abode.
[9] Bramley, G., & Fitzpatrick, S. (2023) 'Capturing the neglected extremes of UK poverty: a composite modelling approach to destitution and food bank usage', *Journal of Poverty and Social Justice*, February, DOI: 1**0.1332/175982721x16649700901023**

income and savings; negative factors reducing risk included living in a couple or family households, being a home owner or social renter, having other living relatives, and higher social renting lettings locally, with this time rural showing as negative.

Brief mention should also be made here of the only statistical model developed for unconventional accommodation (spaces not intended for permanent residence). This model was based on 2020 Public Voice survey data and is discussed on pp. 79-80 of the 2020 Technical Report. In effect changes beyond the base year are mainly generated by other components of core homelessness.

Sofa Surfing

Sofa surfing is the largest category of core homelessness and as befits this status we again combine three separate models, with equal weight. All three are micro household survey based logistic regression models, which predict the current or very recent presence of sofa surfers (a subset of concealed households) in a household.

The first of these is the model based on 9 waves of UKHLS (2010-17), as reported in the 2020 Technical Report (pp. 85-86).

The second is a newly improved model based on English Housing Survey 2014-19. The key improvements are (a) to incorporate attached local authority level indicators of local demographic and market conditions and (b) to combine the main model focused on sofa surfing involving usually resident household members with a second model focused on temporary residents accommodated over the preceding year who would otherwise have been homeless. A weighted combination of the coefficients from the two models referred to in (b) above is used, where the weights reflect the respective numbers of households having the two forms of sofa surfing at a point in time, as referred to in Section 2.

The models are described in more detail in Appendix D (Table D.13), but they include demographic factors such as ages 30-65, lone parent and multi adult households, long term sickness, lower social class, social or private renting, migrant, Black or Asian ethnicity, and the excess of market rent over LHA, but with more social lettings reducing the risk.

The third model is a companion to the third rough sleeping model, being based on the composite dataset of Destitution (DUKS) and UKHLS for 2019, this time taking the overall prediction of core homelessness and applying a/the?? share of that total (57.5%) accounted for by sofa surfing nationally[10]. As shown in Table D.12, the same variables are included as in the rough sleeping model but their relative strength and significance differs somewhat, although for many variables the direction and significance of effects were similar. Only two variables showed a different direction of effect: Black ethnicity increased risk of core homelessness and using English language reduced it. Variables which were weaker and less significant in their effects on overall core homelessness than in the case of rough sleeping were the two health variables, particularly mental health. Cases where the effect on core homelessness was significant whereas it had not been for rough sleeping included relationship breakdown, LHA-rent gap, average size of houses in locality (negative), complex need band (LA level), and rural area (negative).

[10] This was judged to be probably more robust than the alternative procedure of subtracting the independently estimated numbers/rates of the other separate components of core homelessness from the predicted total.

Chapter 5

Simulating Variant Policies and Contextual Scenarios

In the work we have done since 1997 in developing and refining homeless projections, the main aim has been to create a tool which can be used to examine and assess different possible policy measures which might be implemented. This modelling tool can also be used to fulfil other policy analysis purposes, for example estimating and predicting/anticipating the scale of problem which might need to be responded to by services. However, in practice the main focus has been upon a range of discrete policy approaches or packages, and their potential efficacy in reducing core homelessness.

The policy packages exemplified in the 2023 round of projections for England were set out in Table 5.3 in the main report (p.99). In short these were labelled

1. Raise Local Housing Allowance (LHA)
2. Limit evictions
3. Enhanced prevention
4. Increased allocation of social lettings to core homeless houesholds
5. Universal Credit and related measures to tackle destitution
6. Housing First as a strategy to tackle complex need homelessness
7. Increased social housing supply
8. Higher economic growth
9. 'Levelling Up'
10. Large hike in welfare benefit allowances

It is possible to conceive of quite a wide range of ways of going about this modelling challenge, and indeed the way the model has been developed and used has illustrated quite a number of these approaches. These may be seen as drawn from generic methodologies in the policy forecasting arena.

Direct movement of households between states (from undesirable to desirable).

The direct moving of groups of households from one situation to another is exemplified in this study by the policy option 4. Above, involving additional rehousing in social rented lettings specifically for core homeless people. The presumption is that typically/in general, core homeless households (who are mainly single) do not have priority access to social rented housing), so that the institution of a formal additional element (even at a relatively moderate level, such as 20% of net lettings) would make an immediate and substantial difference. The implementation modelled is subject to logistical constraints, related to the number of lettings and the number of core homeless households, but is otherwise applied mechanistically. So for example if the predicted net social lettings were 500, up to 100 could be used to take households out of core homeless situations, roughly pro-rata their distribution across forms of core homelessness (but excluding hostels where numbers are treated as supply-determined); so that could mean 10 less rough sleepers, 10 less unconventional, 25 less unsuitable TA, and 35 less sofa surfers (depending on the local mix of need). This simple model assumes that these households helped sustain their tenancies, that they are a net addition to rehousing of core homeless, and that the other households displaced from (or delayed in) their rehousing, on other grounds (health, disability, crowding, sharing, poor house condition) do not immediately fall into (core) homelessness.

A single significant policy parameter which is reflected in the modelling.

This entails changing a specific variable which plays a role in one or several predictive functions for core homelessness. A good topical example of this is the level of the Local Housing Allowance (LHA), the focus of package 1. This measure governs the extent to which households on low income benefits (UC, HB, ESA) can expect to have their rent covered in the private rental sector. While in principle the LHA is (periodically) set at the level of the 30th percentile of local market rents (for their 'allowed' size of property), governments since around 2013 have not consistently uprated it with rent levels, or even with general inflation – currently it is frozen at October 2019 levels in the face of raging inflation. The variable which captures this is called 'exrent2' – it is the difference between the median (2-bed) market rent and the LHA (£pw @ 2006 general price level). The use of the median rather than the 30th percentile is used because it is routinely published, is not in practice much higher than the 30th percentile, and arguably a fully adequate regime would cover up to this level to allow for the fact that there might not be enough available lettings in some areas to meet need. This variable appears in a few key models, sometimes alongside other variables measuring general rental affordability: HCLIC-based model for rough sleeping/NFA; homeless applications rate (2014-21); EHS sofa surfing (temporary household members); UKHLS panel sofa surfing; and a composite (DUKS + UKHLS) model for all core homeless.

Devising indices of policy vigour or effectiveness, and testing their impact in models

Such indicators would need to display inter-LA variation, and have demonstrable beneficial effects on core homelessness outcomes in regression models. We then posit emulation of 'best practice' to bring laggards up closer to leaders. This approach is used effectively in the case of homeless prevention activity (package 3), where the new HCLIC cohort outcomes data (over 3 years) are used to generate measures such as the proportion of prevention cases accommodated in social renting/social or private renting; or the proportion of all completed cases accommodated. A number of these measures are significant predictors of lower levels of homeless applications, total TA, unsuitable TA, and homeless applications losing private tenancies. In addition the (log of the) balance between prevention and all cases also appears predictive of better outcomes, at least after the introduction of the HRA. For the policy simulation we take for each area the difference between its score and the upper quartile of all local authorities scores on the relevant indicator and multiply that by the relevant coefficients to simulate the improvement associated with a 'levelling up' of prevention performance. A possible limitation of this approach is that some authorities may face intrinsic difficulties in applying prevention to such a high level, due to their local or regional housing market circumstances – regional or peer group targets would be a more subtle version of this approach, which may be explored in future rounds. As pointed out in the main report, this is essentially about the delivery effectiveness of a given range of tools or powers which are available to local authorities; a more vigorous prevention policy might bring in other agencies by placing duties on them to act earlier to prevent homelessness, or give local authorities more financial resources to provide more effective support to households facing homelessness due to financial difficulties.

Legislative and/or administrative measures

There may be proposals for particular legislative or administrative changes which could reasonably be expected (on the basis of logic, past experience, international experience, etc) *to reduce some adverse processes* leading to core homelessness. From this we may posit a package which would lead to a substantial, but rounded, proportional reduction in that adverse process. The example of this approach is limiting evictions from private renting (package 2.). Legislation that would limit 'no-fault' evictions is currently being considered in Parliament, so this is topical. In addition, experience in the 2008-10 financial crisis showed that applying codes of practice and instituting court protocols to delay or defer evictions (where mortgages were in arrears) could substantially reduce defaults. There are also international examples of similar measures being used to prevent homelessness. In this application the scale of reduction is an arbitrary and round target of one-half, but at least this provides a clear benchmark to aim at. Under this option this 50% scale of reduction is applied directly to the predicted rate of households losing PR tenancies and applying as homeless (as predicted by the model in Table D.8, Appendix D).

Welfare benefit measures which impact on the incomes of the poorest group at high risk of homelessness

In this case we proposed (in package 5.) a mix of specific measures, based on parallel research (Fitzpatrick et al 2020), which could significantly reduce the most extreme form of poverty (destitution), which itself is quite strongly related to homelessness. These measures relate particularly to features of the UK benefit system which appear to trigger or reinforce destitution, partly on the basis of qualitative evidence generated in parallel research, although reinforced by some quantitative findings as well. We then track the impact of these measures through including factors in models which impact on measures of relevant incomes and income sources for particular groups likely to be adversely affected. Moving on to *Universal Credit* (UC) was known to be problematic because of design features including the 5-week wait, digital by default, debt deductions from payments, with both qualitative and quantitative evidence to back up this claim[11]. UC appears in certain of the statistical models including that for destitution risk, total core homelessness and (one of the models for) rough sleeping, and a further rollout of UC under 'managed migration' is expected during 2023-24. Other specific measures, such as families subject to benefit cap, have featured in some of the predictive models. Static microsimulation of changes in UC benefit rates and parameters can also generate measures of the resulting impacts on poverty and destitution. These were particularly important for package 10, which involved a large rise in personal allowances as well as the more specific measures targeting destitution.

Evidence from evaluation studies and trials of key innovations

This approach utilises evidence relating to key innovative policy packages, which approximately quantify the success rate in terms of key outcomes. The key exemplar of this is package 6, which takes the innovation of 'Housing First' (HF), which is probably the homelessness initiative which has been subject to the most rigorous trials internationally. The general consensus from these studies is that HF has a relatively high success rate in terms of tenancy sustainment, which is the key outcome mainly at issue here. The main option exemplified in this modelling was to increase the scale of HF supported in England by a factor of 3 from current levels; from evidence on the eligible population of complex need homeless cases, this level of provision would not be likely to run out of cases. A significant feature of our modelling of HF in this context was that we linked it to a progressive rundown in hostel etc. capacity, based on the recognition that a high proportion of hostel residents were potential clients for HF.

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[11] See Fitzpatrick et al (2020), *Destitution in the UK 2020* Joseph Rowntree Foundation, Bramley et al (2021) *The State of Hunger*. Trussell Trust, and Sosenko, Bramley & Bhattacharjee (2022) .

A large quantitative change in a directly relevant public programme

The obvious candidate here is a large increase in new social housing supply through new housebuilding (package 7), given that the sub-regional housing market model (SRHMM) is well-adapted to tracing the impact of such change through the housing system. The scale of increase modelled in this iteration was a 'more than doubling' (from 30,000 pa to 65,000 pa), although a larger increase could certainly be argued for in needs terms (although it might be deemed unaffordable), and the spatial distribution was based on a measure of need. In the latest implementation of this policy option, it is assumed that a modest proportion (c.10%) of additional social rented provision is targeted at longer term core homeless households, to again enable a further rundown of hostel capacity. This turns out to account for a larger part of the total impact of the policy.

Larger enhancement of welfare benefit rates

A further policy package (10) focused on welfare benefits builds on package 5.the to further change the overall income distribution in favour of the relatively and absolutely poor, through a much larger rise in the personal allowance rates in the key Universal Credit system. We quantify this through a static microsimulation using a large household survey model of the population (UKHLs), and then map the impacts down to sub-regional level and use key models to predict the impacts via key poverty measures which feature in a number of the predictive functions for homelessness. Consequential changes in the housing market and demography (e.g. household formation) are included in this scenario.

Changing regional economic performance

Positing the implementation of a successful strategy to change the absolute and relative economic performance of certain regions of the country is the focus of package 9, labelled 'Levelling Up' after the current UK government policy aspiration. We do not investigate or model in detail the mechanisms used to generate this economic boost to lagging regions, but merely try to trace the effects through the labour and housing markets of such a strategy bearing fruit. We specify a certain degree of narrowing of economic growth rates between regions, with most moving upwards and so lifting the national average performance. This is accompanied by some increase of housing supply in the regions benefitting. The model traces the myriad indirect effects of this through labour and housing markets and demographics to influence housing outcomes including core homelessness..

Changing national economic performance

Finally, and most ambitiously, in package 8 we posit the success of an overall government /national strategy to increase the economic growth (GDP total, and productivity) of the country in the medium term, and trace the effects of this through the system of markets. Most actual or potential governing parties appear to aspire to such a goal. We do not here examine or specific exactly which combination of policies would achieve this desired result. Again, the effects of this strategy work through many different channels as represented through the SRHMM, but appear on the whole, in the case of England, to bring about a significant reduction in core homelessness.

Chapter 6

Limitations and Potential Developments

The core homelessness estimates and projections have been evolving and developing since their first appearance in 2017. Over time both the baseline estimates and the forward projections have improved significantly, and incremental improvement continues. With regard to the overall modelling platform, the sub-regional housing market model (SRHMM), has a longer track record, going back to around 2009, but we do also continue to improve elements of this incrementally as the opportunities arise. However, the resources available for these development tasks are finite, and it cannot be claimed that these models are the last word in terms of econometric sophistication or the exhaustiveness of sensitivity testing.

Nevertheless, we believe this modelling suite is currently unique in the UK and with no current official or rival system which can do the same job. This is evidenced by the increasing interest in the findings of Chapter 5 in successive homelessness monitors regarding the potential impacts of suggested policy changes, and the formal and informal discussions which take place between its author and government officials.

Having, made these claims, we are open to comments and suggestions for improvement or refinement of the estimates and the forward modelling. To that end, in Spring 2023 Dr Mike Brewer, Deputy Chief Executive and Chief Economist at the Resolution Foundation provided valuable comments on chapter 5 of the (then draft) Homelessness Monitor: England 2023 and a previous draft of this technical report. Areas for potential improvement identified include the following:

- Careful examination of elements of the SRHMM which can impart some instability to short term dynamics, for example around the balance between households and dwellings; while 'thresholded' feedback factors are designed in, these have not necessarily been optimised (further work on this indicates that these problems can be minimised using feedback factors based on both levels of and changes in key variables).
- Some policy options are modelled in a cruder fashion than others – this comment might be applied to direct rehousing (allocations of social lettings) for example, prevention, and levelling up.
- Some policy options are not modelled to the fullest or most radical extent which might be conceived (for example the case in relation to prevention)
- Some functions are overdue for updating, for example internal migration models or (more readily feasible) measures of various backlog needs (this has now been implemented for the next iteration of model)
- Covid disrupted many things, not least conventional government household surveys; it would be good to work with the latest versions of these where efforts have been made to overcome fieldwork and response challenges characteristic of 2020 and 2021.

There are also opportunities for improving the way the model handles inputs and outputs in terms of their geographical framework. As local government in England seems to be in a process of rolling ad hoc amalgamations of local authorities, this is becoming a pressing issue in terms of updating of data inputs. At the same time, we anticipate a growing interest in looking at the predicted rates of homelessness at somewhat lower levels than some of our subregions, for example sectors of London or individual local authorities more generally.

There are also somewhat wider agendas which the model could contribute to, as it has in the past:

- Broader estimates of housing requirements at national and regional level, looking at overall housing supply as well as social and intermediate tenure (an update of a 2018 study is in progress at the time of writing);
- More extensive analysis of policy options around taxation of housing;
- More extensive analysis of potential reforms to and regulation of the private rental market;
- Engagement with more detailed welfare benefit changes, which are typically modelled in large scale survey datasets or micro-simulation systems.

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APPENDIX A

Details of Data Sources used to Estimate Core Homelessness

The following data sources were described in detail in the 2020 Technical Report and continue to be used in the current round of estimates

- *Destitution in the UK Survey* – previous estimates used 2019 edition, current estimates use very similar 2022 survey
- New Kantar population panel survey, *Public Voice*, 2020
- ONS *Survey of Living Conditions* (SLC) 2018
- *H-CLIC* household-level *administrative data system* used to record *statutory homelessness activity* (applications, prevention, relief, decisions, outcomes) aggregated to local authority level by year 2018-22, and associated temporary accommodation numbers, as well as comparable previous aggregated numbers from P1E returns (DLUHC)
- Homeless Link: *Support for Single Homeless People*, annual survey of hostel numbers (2021-2 edition)
- *DWP FOI datasets* on households supported through Housing Benefit in Temporary, Supported and Short Term Emergency and Transitional accommodation, by local authority at selected time points
- *English Housing Survey* (annual), primarily relevant to sofa surfing, including in this round attached data on housing and labour market conditions in local authority areas, years 2014-19 (not Covid period[12])
- *UK Household Longitudinal Survey* (alias '*Understanding Society'), again with attached local authority indicators, years 2010-19 (not Covid period[13]).
- *Rough Sleeping Counts and Local Estimates*: for reasons given in the 2020 Technical Report (pp.54-56) we use these only in modified form with limited weighting

These sources are not discussed further here. Instead we focus on a few additional data sources which have become available or come to our attention for inclusion in this round of the Monitor.

Rough Sleeping Management Information

This is additional detailed information which DLUHC has been collecting from local authorities on a monthly basis since May 2020, about the support for people sleeping rough or at risk of sleeping rough, alongside the annual rough sleeping snapshot data. On average 95% of authorities respond. It provides a 'more frequent although less robust' estimate of people sleeping rough on a single night, compared to the official RS annual snapshot statistics collated by outreach workers, local charities and community groups. In practice, the snapshot

[12] The Covid emergency and associated lockdowns had a serious impact on government household surveys, with conventional face-to-face interviewing suspended and telephone or online approaches substituted; this had a serious impact on the response rates and representativeness of these surveys in 2020—21, and to some extent into the following year(s), which tended to disproportionately affect more disadvantages groups more likely to experience homelessness.

[13] See previous footnote

figures are of similar magnitude. The management data provides more information about flows as well as stocks, and also covers immediate off-street accommodation as well as longer term move-on activity. The data is partly compiled with the assistance of organisations providing a range of services including the above types of accommodation, generally funded as part of the Government's Rough Sleeping Initiative. Local authorities make monthly online submissions of data through a system known as DELTA. Not all the people recorded in this system are necessarily recorded in the mainstream H-CLIC system relating to people apply as homeless under the HRA or previous legislation, because they may not be eligible (migrants with NRPF), have not engaged with the process, or not owed a Relief duty, or applying to a higher tier authority.

For the purposes of the current round of core homelessness estimates, we have found these data most useful for tracking trends within and between years in the key groups affected.

State of Hunger Survey

The State of Hunger survey was carried out by researchers at I-SPHERE, Heriot-Watt University, as part of a larger research project for the Trussell Trust, the UK's largest network of food banks. The relevant survey fieldwork was carried out in late 2018, and involved a self-completion survey of users of food banks in Britain, administered via tablets managed by staff or volunteers in 42 foodbanks. The survey design was intended to be representative of the population using food banks nationally, and achieved 1130 responses. From our detailed work on both this survey and the JRF Destitution in the UK Survey (DUKS) we know that there is a close relationship between destitution and food bank use - 85-95% of food bank users are destitute, and around half of destitute households have made some use of a food bank. Furthermore, common questions were asked between the DUKS survey and the State of Hunger survey, particularly on accommodation, which identified four relevant categories of current accommodation (staying at family member's or friend's house; hostel, refuge, B&B, or night shelter; sleeping rough, or other). It also asked questions about the duration of time people had slept rough. Using this information it was possible to derive estimates for hostel etc. accommodation which triangulated well with other estimates from multiple sources, for rough sleeping (within the range of other sources) and for unconventional accommodation.

Subsequently the Trussell Trust have commissioned regular surveys covering similar ground, and we anticipate making use of these in future rounds of the core homeless estimates.

Crisis Opinium Panel Survey of Lower Income Households

In the autumn of 2022 Crisis commissioned the survey organisation Opinium to conduct a panel survey of lower income households (adult members of their survey panel who were in the lower 40% of the household income distribution). 2000 interviews were conducted with adults during November 2022. While the main focus of the survey was on overall cost of living and living conditions issues, including changes in spending on housing and other essentials, debt issues, attempts to move home, and anticipated problems with housing or other essentials over the coming winter, one question (Q2) focussed particularly on a range of living conditions (essentially, categories of core homelessness) experienced in the last 2 years or ever. We were able to compare these figures and other household profile information with data from our own highly representative Public Voice survey, for the 40% lower income segment, and were able to judge that they were sufficiently representative to be usable, at least in relation to the broader category of core homelessness, namely sofa surfing. We were also able to use parameters from Public Voice to translate from 'last 2 years' to a point in time estimate, as well as from 'bottom 40%' of income distribution to all households.

Labour Force Survey

The Labour Force Survey, also often billed as the Annual Population Survey, is a large, regular and very well established survey of the UK population (in private households) which is used primarily to estimate key economic labour market statistics, particularly the ILO unemployment rate and economic activity/participation rates. It is also used to provide annual estimates (subject to sampling error) of local authority level characteristics such as the occupational class mix or the proportion of adults with high or no qualifications.

In the Homelessness Monitors we have routinely used data from this source to track trends nationally, and by region/nation, in key relevant categories of household, particularly concealed households (in three sub-groups) and sharing households, as well as in 'household representative rates', a key measure of household formation by age group. In the current context, we have used trends in the key relevant sub-groups of concealed households over time to provide an overall check and correction on data derived from UKHLS on concealed households relevant to sofa surfing, recognising that UKHLS suffers from a degree of sample attrition over time. We typically would use the LFS Quarterly household dataset, which for example in Q3 of 2022 had 31,821 households in total, of which 24,829 were in England, of which 14,612 would be households containing concealed households, and of which 5,075 would be in the categories more relevant to sofa surfing. We would also often combine two or more quarterly data points to boost sample numbers and reduce the confidence interval around any estimate.

Census 2021 (England & Wales)

The 2021 Census for England and Wales released a large number of data tables in the late autumn of 2022 through to early 2023, enabling many variables included in our local authority level panel dataset to be updated or enhanced. This included populations by age, ethnicity, migrancy, country of birth, general health, and economic activity; and households by household type and size, dwelling type, tenure, occupancy/crowding, living arrangements (e.g. divorced, separated), and so forth. This then enabled us to correct a number of the local authority level annual time series which play important roles in many of the predictive models used for housing market or homelessness variable.

Some of these time series turned out to be somewhat different from what had previously been assumed from other sources, modelled values or 'dead reckoning'. For example, the number of households in 2021 was significantly less than the numbers previously projected by ONS or within our SRHMM. Taken in conjunction with the general economic and political turbulence of the recent period, as highlighted in Chapter 1, this has led to significant differences between some numbers as previously modelled and the revised estimates and projections now in use. These factors have also imparted some disturbance and instability to parts of the SRHMM predictions which are apparent through the early to mid-2020s.

APPENDIX B

List of Data Sources used in the Modelling

Table B.1: Data Inputs and Sources for Sub-Regional Housing Market Model (SRHMM)

Item	*Definition*	*Source*
Completions	Number social and private per 100 households x Year x LAD	DCLG/MoHCLG Housing Statistics Live Tables, T.253
Migration (domestic)	Persons per 100 residents ‘in’ & ‘out’ x 4 age groups x year x LAD, adj to HMA basis using 2007 matrix	ONS Local migration estimates based on NHSCR data; ONS Components of Change in population tables.; Census 2021 (*UR-ltla+migrant_ind.xlsx*);
Household Headship	Ratio of HRP/Population x 3 age groups	BHPS analysis 1997-2003; 2001 & 2011 Census base rates 2001 & 2011x LAD; ONS 2016-based household projections..
House Price	Median and Lower quartile price all sales & by type	H M Land Registry data compiled at LAD level; ONS House Price Index
Market rents	Median market rent for 2 bedroom unit; number of lets recorded	Valuation Office Agency (VOA) local market database;
Market rents supplementary source	Zoopla listings rents and lettings data	Zoopla listing agency, sourced from Zoopla Limited, © 2022, via Economic and Social Research Council. *Zoopla Property Data,* 2022 [data collection]. University of Glasgow - Urban Big Data Centre.
Social housing stock	LA + RSL rental dwellings x Year x LAD	CLG HSSA returns; MHCLG Local Authority Housing Statistics data returns.; Census 2021 (*TenureCSV_TS054*)
Total & Private Stock	Private sector dwellings x Year x LAD	CLG HSSA returns ; MHCLG Table LT100 & LT125; MoHCLG net additions.
Earnings	Median full time earnings x LAD (residence)	ASHE (Annual Survey of Hours & Earnings)
Population	Number x Age x LAD	ONS Mid Year Estimates; ONS Population Projections 2018 & 2020; Census 2021

Net Lettings	No. of lets to new tenants by LA's & RSLs x LAD	CLG HSSA returns; MoHCLG CORE Summary Tables 2016-20
Vacancies	No. & % of dwellings by social/private x LAD	CLG HSSA returns; LA level all Vacants MHCLG Table LT615.
Household Income	Gross Income of Household from all sources £k pa x LAD	Synthetic model estimate based on UKHLS 2009-17; earlier years based on change in Regional Accounts Real Household Disposable Income series for NUTS3 regions; Recent years based in part on ONS Household Disposable Income estimates by LA
Births & Deaths	Numbers x LAD	ONS 'Components of Change' tables; ONS 2018 Population Projections.
International Migration	Number 'in' and 'out' x year x LAD	ONS local 'Components of Change' tables; ONS national half-yearly estimates: Long-term international migration, provisional - Office for National Statistics (ons.gov.uk)
Mortgage Interest Rate	Ave percentage x year	Former HM Treasury 'Pocket Databank'; UK Finance Mortgage Trends
Unemployment (asunem)	Core age (30-44) claimant unemployment % of working age, adj for definitional changes	NOMIS data compiled for MigMod study and extended for Bramley-Leishman panel model
Unemployment (ILO)	Unemployed and seeking work, % of economically active	Annual Population Survey (APS) 3-year rolling average, and 2001/2011 Censuses; post -2016 'model based' estimates of ILO unemployment by LAD (NOMIS)..
Planning permissions flow	New planning permissions granted for housing, units x LAD, as % of households	Estimated from CLG PS2 returns and Emap-Glenigan database of major sites.
Planning permissions stock	Outstanding uncompleted permissions units x LAD, as % of households	Estimated from former DOE PS3 returns, Emap-Glenigan database, PS2 returns and CLG completions data;
Small sites	Share of small sites in private housing permissions	Emap-Glenigan database, c. 2015
Housing built on previously	Annual LA level % new	MoHCLG Tables P211-213

developed land (PDL)	housing on brownfield land (PDL)	
High & low Social Class	% in higher occupational groups	Censuses 2001/2011 + Annual Population Survey Occupational Groups (pooled 3 yr ave data)
Single person, lone parent & other household types	% households single non-elderly, lone parent, etc	Censuses 2001 & 2011; LFS trends x broad age & region 1992-2008; DCLG Household projection share trends 2008-2033 and 2014-2039; Census 2021 'Household composition' table by LAD.
White British, Black, Asian, Mixed/other	% population with White-British, Black, Asian, Mixed/other ethnicities	Census 2001 & 2011; LFS trends x broad age & region1992-2008 ; Census 2021 'EthnicityXLS' table, http://10.30.155.83:10400/datasets/TS021/editions/2021/versions/1
Net Density	Dwellings per hectare of land in residential use, ward level	Census 2001, GLUD (Generalised Land Use Database) from CLG via Neighbourhood Statistics
Sparsity	Hectares per person, LAD level	Census 2001 & 2011
Students	% population f t students	Census 2001 & 2011; LFS trends x broad age & region1992-2008; Census 2021: EconomicActivityTS066-2020-1 (http://10.30.155.45:10400/datasets/TS066/editions/2021/versions/1)
IMD Low Income	IMD 2004 & periodic updates to ID2019; Low Income Score, averaged at LA level	IMD (Indices of Multiple Deprivation), derived from DWP benefits data
Distance major centre	Ave distance in km of dwellings from major retail service centre (>150k m2 floorspace)	CLG database of major retail/service centres
Children in poverty	Relative poverty rate for children after housing costs	DWP 'Children in Low Income Families: local area stastistics, UK, FY;s 2015-21. Children in low income families: local area statistics - GOV.UK (www.gov.uk)
Universal Credit	Households on UC	Derived from DWP Stat-XPplore system, monthly data by LAD.
Disability benefits	Households on ESA or PIP	Derived from DWP Stat-XPplore system, periodic data by LAD.

Greenspace	% of land area 'greenspace'	GLUD
Air	Index of Air quality/pollution	Derived for DTLR MigMod study
Climate	Index of warmer, drier, sunnier climate	Derived for DTLR MigMod study
Scenic	Index of proximity to scenic areas e.g. Nat Parks, AONB	Derived for DTLR MigMod study
Cars density	Cars per m of road length	2001 Census, GIS analysis
Sick/disabled	Limiting long term illness/disability, %	2001 & 2011 Censuses; LFS trends x broad age & region1992-2008: Census 2011 & 2021.
General health	Poor /very poor health	DCLG Indices of Deprivation ID19 3-component index
Mental health	Mental health problems	DCLG Indices of Deprivation ID19 3-component index
Relationship breakdown	Proxy based on living arrangements (sep, div, apart)	Census 2021 Living Arrangements
Destitution related composite indices	General destitution and complex need destitution rates	Composite LA-level indices for destitution affecting migrants, households with complex needs and general population; see Bramley et al (2020 & 2023) Destitution in the UK 2023: Technical Reports

Table B.2: Additional data Inputs and Sources for Homeless Projection Model and Enhancement of SRHMM to provide local level needs estimates and targets

Item	*Definition*	*Source*
Statutory Homeless annual flow numbers	Applications, Acceptances and Decisions; reasons for loss of last secure accommodation; from 2018: accommodation immediately prior to application	Local Authority Annual 'P1E' statistical returns; From 2018/19 LA annual returns based on H-CLIC individual record system under Homelessness Reduction Act
New Statutory Homelessness data post-HRA from 2018	All applications, prevention cases, relief cases, main duty cases; demographic characteristics;	From 2018/19 LA annual returns based on H-CLIC individual record system under Homelessness Reduction Act

	immediate prior accommodation; support needs; outcomes of prevention	
Temporary Accommodation	Homeless households in TA in total and in particular 'unsuitable' types (B&B, nightly non-selfcontained, out of area)	LA returns of numbers at 31 March each year. Incorporated within new H-CLIC based monitoring system post 2018; Totals estimates also confirmed from DWP FOI data, retrospective and service user surveys.
Rough Sleepers	Spot count/estimate data for autumn each year; Alternative estimates for rough sleeping and 'quasi rough sleeping'.	MHCLG .Rough Sleeping in England 2010-19.; also CHAIN data for London. Data subject to imputation for LAs without counts
Rough sleeping alternative sources	Survey of users of crisis services; Retrospective questions in household surveys; inference from admin data; ad hoc data collections.	Destitution in the UK 2022, 2019 & 2017 surveys; ONS Survey of Living Conditions 2018; Kantar Public Voice panel survey 2020; HCLIC data on homeless applicants prior accommodation rough sleeping or 'no fixed abode' (part) Scottish Household Survey 2012-15 (durations estimates); data from 'Everyone In' initiative 2020 Trussell Trust 'State of Hunger' survey (2018-19)
Hostel Residents	Occupied hostel places (category also includes shelters, refuges, and emergency hotel accommodation under Everyone In initiative 2020).	Homeless Link 'SNAP' /SSHP survey annual (to 2021); DWP Freedom of Information data from SHBE (Housing Benefit) system on all households supported in 'emergency, temporary and transitional accommodation' (relevant categories, informed by 2016 research study by Blood et al) up to 2022 Service user and retrospective surveys as above, plus Everyone In data.
Sofa surfers	Concealed singles or households wanting to move, not non-dependent children or students,	EHS and UKHLS survey estimates 2014/12-19; EHS modified based on 2017-19 data on temporary residents accommodated additional to usual

	overcrowded. EHS includes temporary residents accommodated who would otherwise have been homeless.	resident concealed households wanting to move; ONS-SLC and Public Voice retrospective survey questions; predicted rates based on logistic regression models fitted to former surveys

Note on General Surveys used for Modelling

As mentioned at the beginning of Appendix A, several large scale household surveys are used as a basis for calibrating statistical models used to predict rates of different forms of core homelessness or other related variables which feed into these predictions (e.g. incomes, poverty, evictions, etc.). These general surveys include

- UK Household Longitudinal Survey (also known as Understanding Society)
- English Housing Survey
- Labour Force Survey
- Survey of Living Conditions
- Kantar 'Public Voice' panel survey

The relevant characteristics of these surveys are discussed in detail in Appendix A of the 2021 'Technical Report' (Bramley, G., 2020 *Research on Core Homelessness and Homeless Projections: Technical Report on New Baseline Estimates and Scenario Projections*. Edinburgh: Institute for Social Policy, Housing and Equalities Research, Heriot-Watt University. https://doi.org/10.17861/fex5-jg80

Some additional surveys used in this round of the projections are discussed briefly at the beginning of Appendix A.

APPENDIX C

Timeline Graphs for Housing Market Model

In conventional economic forecasting it is normal for regular bulletins to include timeline graphs for key variables over the forecast period, often with corresponding timelines for the actual outturns over preceding time periods. We believe this is useful both to gain a picture of how key variables evolve over time in different broad regions of the country. At the same time, it provides useful diagnostic information on how the model is performing technically. In the context of these projections produced during winter of 2022-23, these charts reflect some sharp instabilities in some key variables associated with Covid and then the Ukraine and cost of living crises. These instabilities can generate some echoing fluctuations subsequently through the forecasting period, and this particular modelling framework is more subject to such fluctuations because of its recursive structure with a predominant reliance on one-year lagged relationships. Some of the patterns in the following figures show that for some variables in some regions these cyclical fluctuations can persist.

Subsequent to completing this round of the projections, and in preparing for the next rounds, we have implemented some further damping mechanisms which appear to deal with this issue more satisfactorily in key instances.

Figure C.1: New private housebuilding rate by broad region 1998-2041 (% of households)

Figure C.2: Real median mix-adjusted house prices by broad region, England 1997-2041 (£ @ 2006 values)

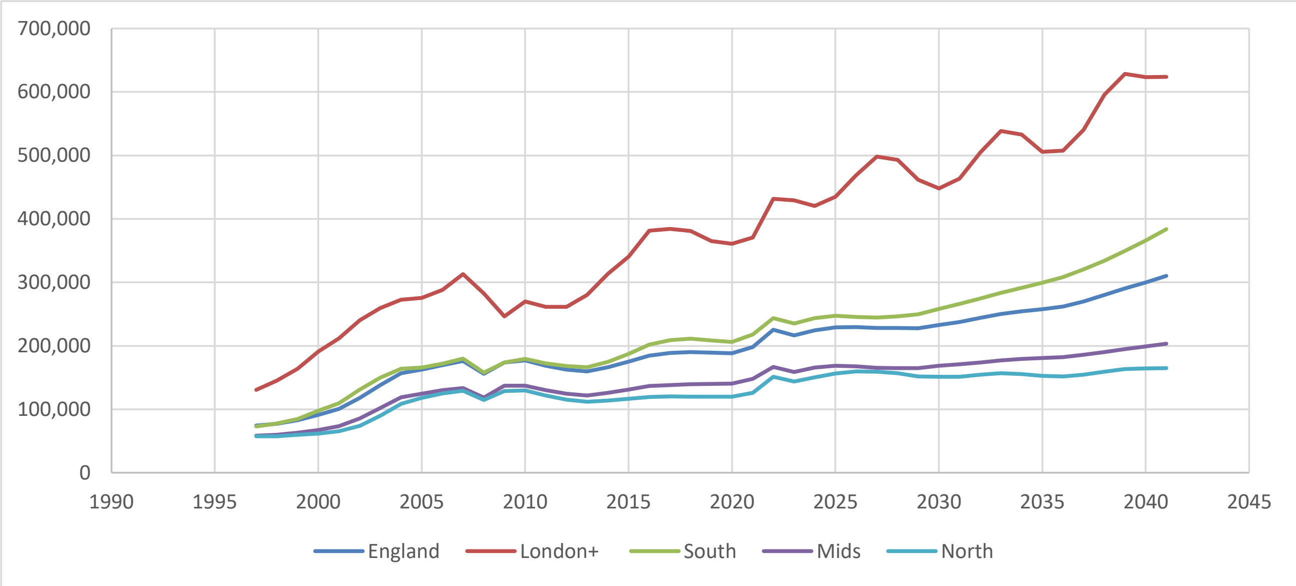


Figure C.3: Real private market rent for 2 bedroom home by region of England 2001-41 (£ pw @2006 prices)

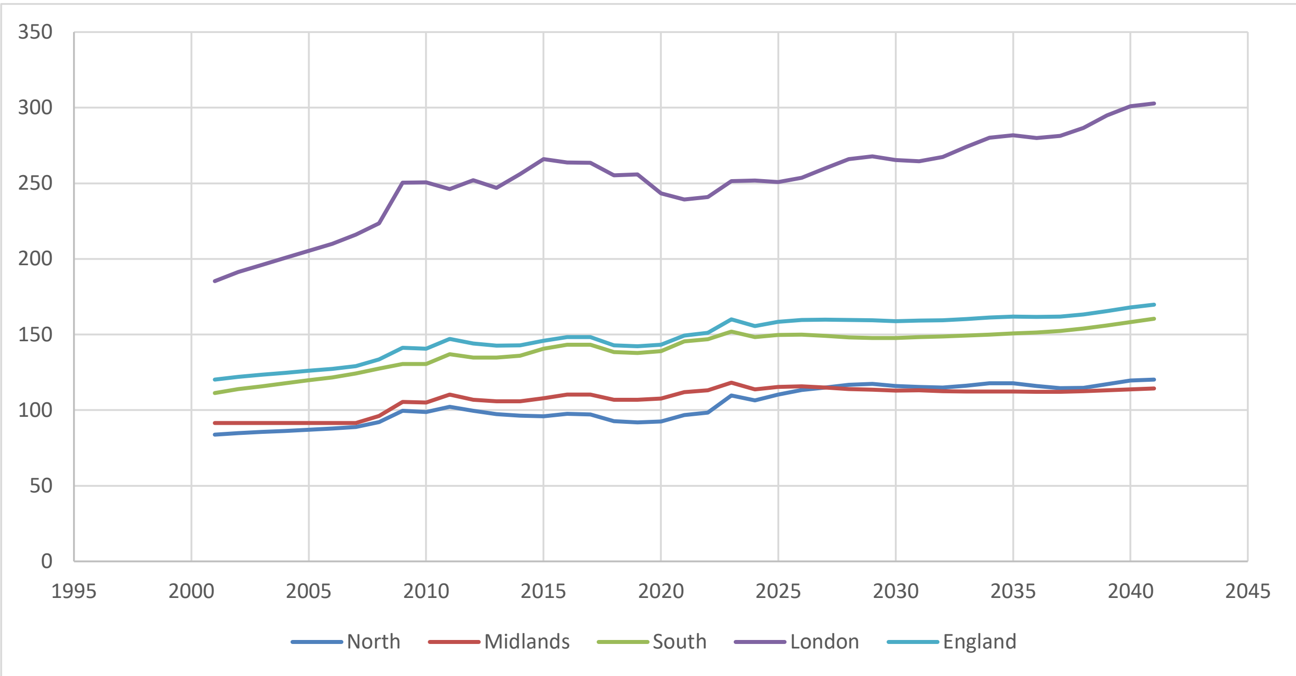


Figure C.4: Private renting share of all households by broad region of England 1997-2041 (percent of households)

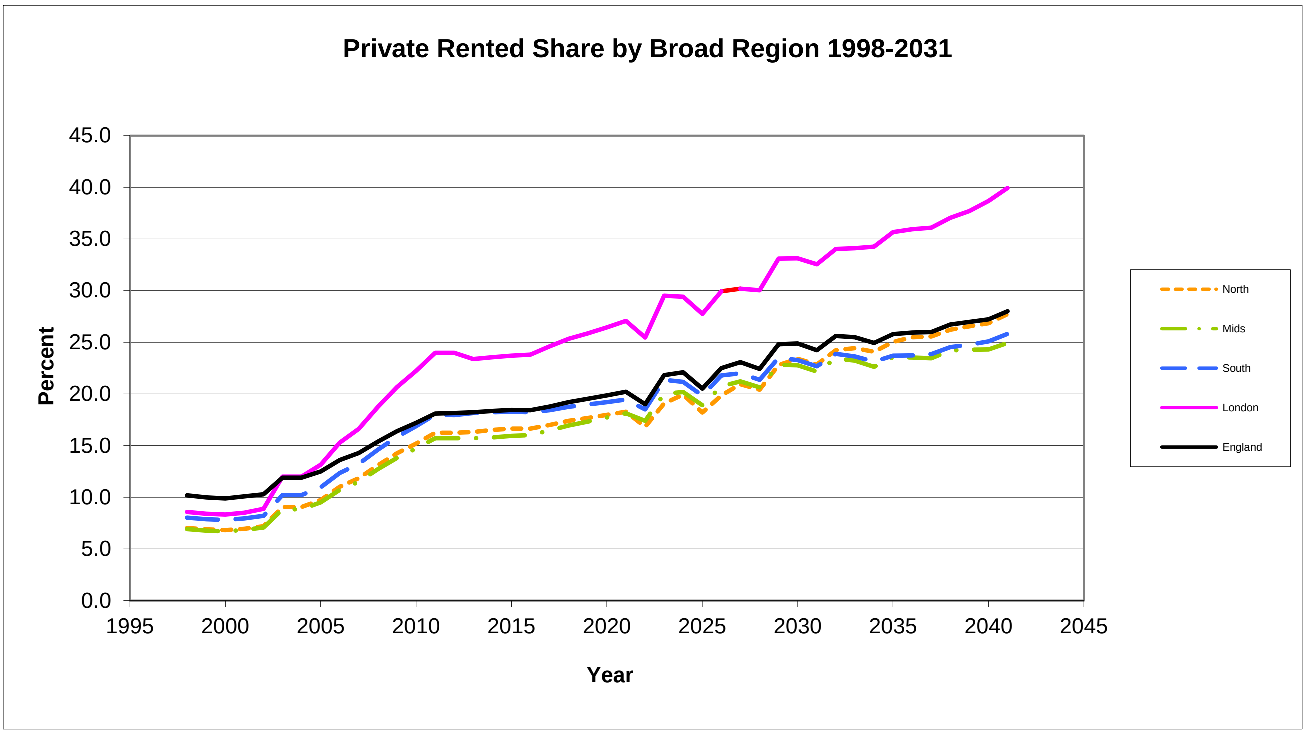


Figure C.5: Social lettings rate to new tenants by region for England, 1997-2041 (percent of households)

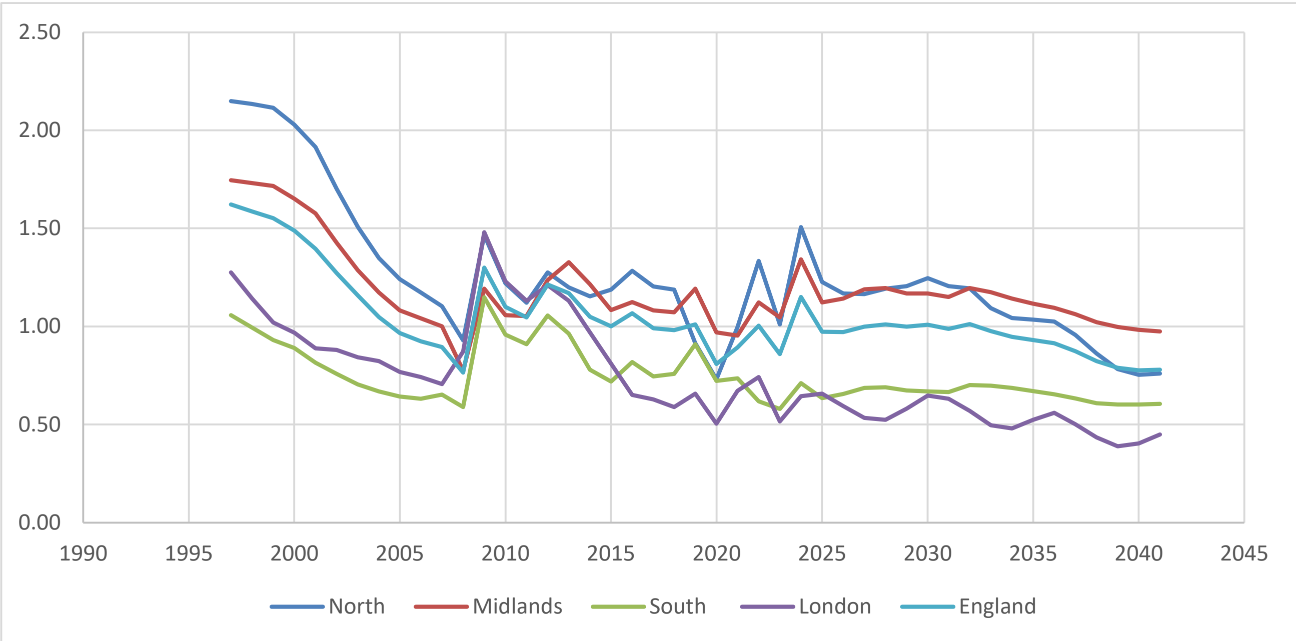


Figure C.6: Median House Price: Earnings ratio by broad region of England, 1997-2041

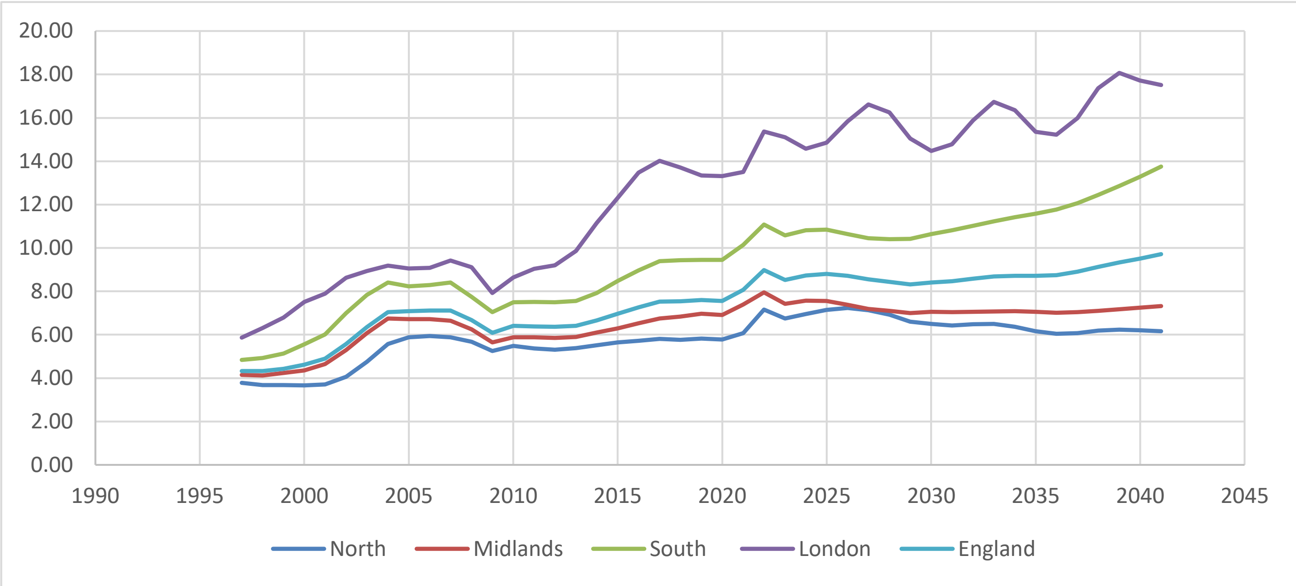


Figure C.7: Poverty after housing costs by broad region of England, 2011-41 (proportion of households)

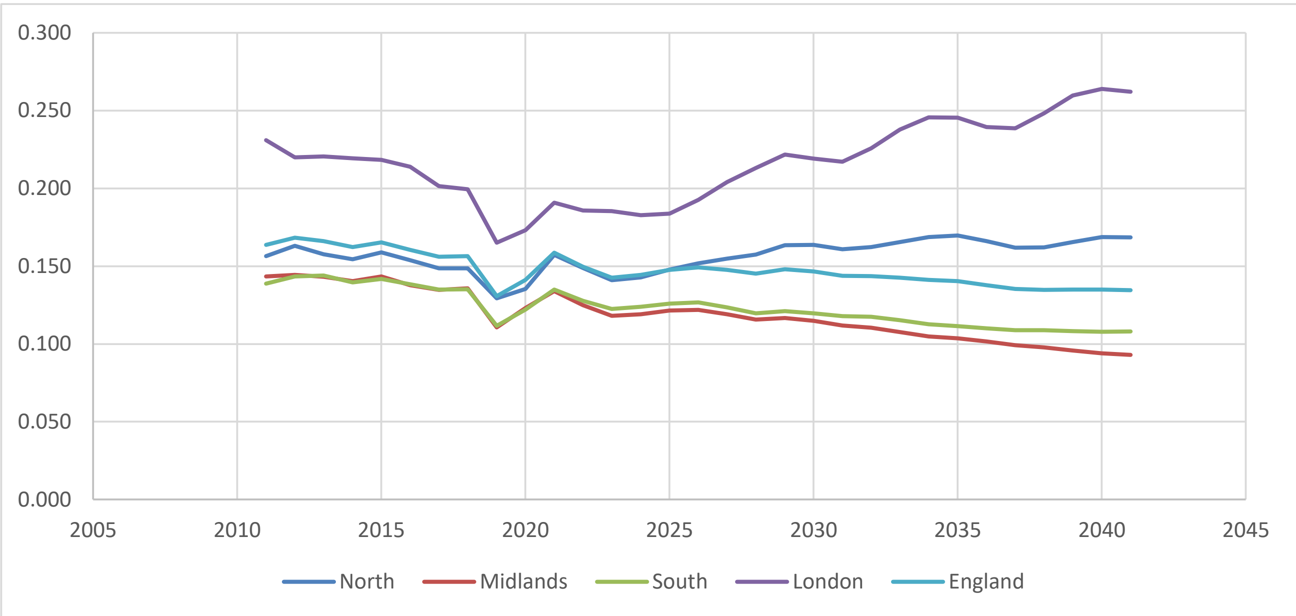
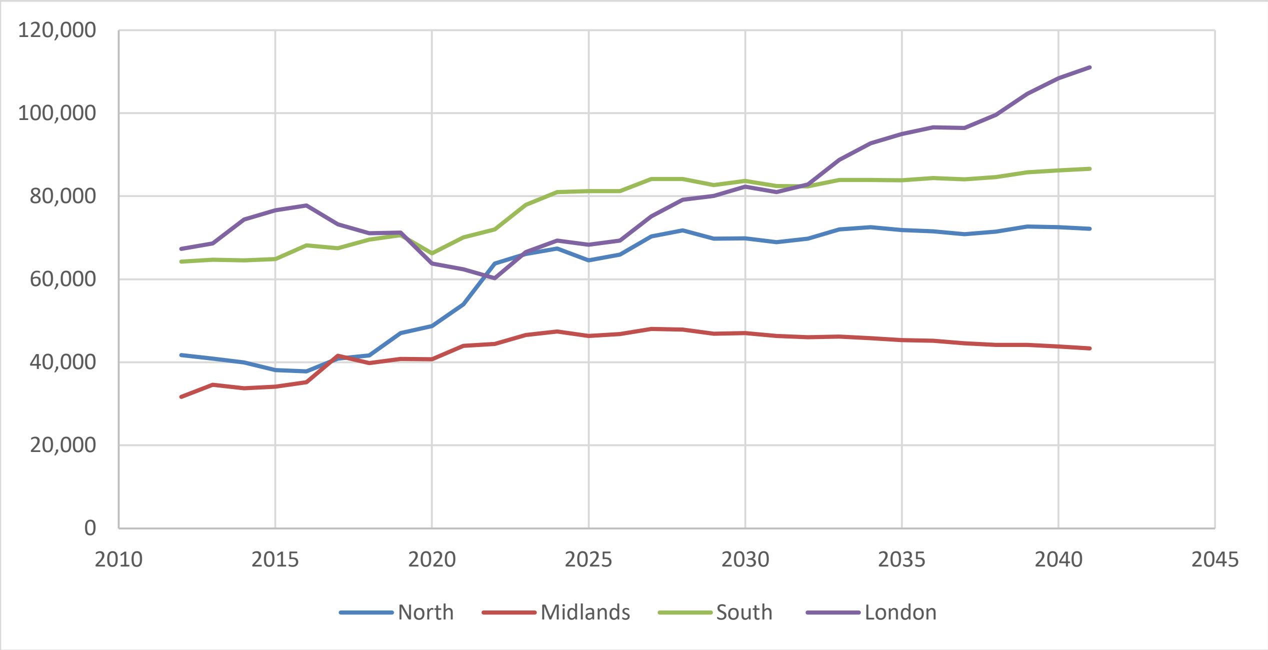


Figure C.8: Core homeless numbers of households by broad region of England, 2012-41 (number)



APPENDIX D

PREDICTIVE MODELS UPDATED IN THIS ROUND

Table D.1: New private build supply model fitted at local authority district level, 2010-21 (completions as % of households)

Model Variable description	Varname	Coeff B	Std Coeff Beta	t stat	signif p	Collinearity VIF
Constant	(Constant)	0.451		3.326	0.001	
Lagged private completions rate (time-varying component) % hhd	tvppcmp_1	0.119	0.175	15.372	0.000	1.064
New planning permissions flow rate % hhd	pppflow_1	0.017	0.036	2.566	0.010	1.609
Log stock of permissions % hhd	lpdopp2_1	0.041	0.107	8.458	0.000	1.323
Social completions % hhd	pscmp	0.892	0.508	38.729	0.000	1.416
Lagged real median mix -adj house price (time-varying component)	tvrlmapric_1	0.587	0.207	16.257	0.000	1.339
Lagged dwelling vacany rate %	pvac_1	-0.026	-0.080	-6.891	0.000	1.103
Mortgage intereste rate	mir	-0.131	-0.185	-4.779	0.000	12.328
Previously developed (brownfield) land %	pdl	-0.004	-0.287	-23.561	0.000	1.223
Small sites share of permissions %	psmstprivpp	-0.168	-0.062	-5.449	0.000	1.081
Dummy year 2010	yr10	0.083	0.075	5.451	0.000	1.572
Dummy Covid year 2020	covid	-0.069	-0.065	-2.827	0.005	4.341
Dummy post-Covid year 2021	postcovid	-0.078	-0.073	-2.077	0.038	10.072

a. Dependent Variable: ppcmp

b. Weighted Least Squares Regression - Weighted by hhdwgt

Model Summary

Model	R	R Square	Adj R-sq	S E E
1	0.738	0.545	0.543	0.20300

ANOVA

Model		Sum of Squares	df	Mean Square	F
	Regression	185.764	12	15.480	374.202
	Residual	155.257	3753	0.041	Sig F
	Total	341.022	3765		0.000

This model is very similar to that previously used as reported in 2020-21, and has a reasonably good fit for such a supply model. The main variables are the same, apart from additional year dummies. Variables with a stronger influence include the stock of planning permissions, social completions, house price level, and mortgage interest rate (-ve), while variables with a weaker influence this time included lagged completions, the flow of new permissions, and small sites. The only variable with a high degree of collinearity was the mortgage interest rate.

Figure D.2: House price model re-estimated at HMA level for years 2009-21 (log of median mix-adjusted real house price @ 2006 price level)

Variable description	Varname	Coeff B	Std Coeff Beta	t stat	signif p	Collinear VIF
1	(Constant)	2.374		16.177	0.000	
Log median mix-adjusted real price lag 1yr	lmaprc_1	0.397	0.390	32.057	0.000	7.986
Lagged log difference real spatial price (adjacent in HMA)	ldspatrlprc_1	0.056	0.007	1.563	0.118	1.177
Log vacancy rate %	lpvac	-0.065	-0.043	-5.851	0.000	2.852
Log total completions rate % hhd	lptcmp	-0.009	-0.009	-1.711	0.087	1.333
Log *difference in* household-dwelling ratio	ldhhddwg	0.575	0.021	4.304	0.000	1.244
Log household disp income £ /wk /hhd	lrhdiph	0.762	0.421	30.687	0.000	10.148
User cost of capital for home owner	lucc1	-0.076	-0.070	-11.145	0.000	2.124
FTSE Index '000 x London dummy	londftsek	0.021	0.103	10.229	0.000	5.434
FTSE Index '000 x South regions dummy	southftsek	0.016	0.119	18.137	0.000	2.308
Year 2010	yr10	0.038	0.026	5.376	0.000	1.215
Year 2020	covid	0.035	0.025	5.362	0.000	1.129
Year 2021	postcovid	0.056	0.039	8.214	0.000	1.234

Dependent variable: log median mix-adjusted real price

Weighted by ntrlwgthma

Model Summary

Model	R	R Square	Adj R-sq	S E E
1	.988[a]	0.976	0.976	0.06064

Model		Sum of Squares	df	Mean Square	F
1	Regression	193.543	12	16.129	4386.784
	Residual	4.732	1287	0.004	Sig F
	Total	198.275	1299		0.000

This house price model follows on similar lines to previous versions but with one or two changes in predictor variables. The model is a partial adjustment model , generally in log-log form, and includes a spatially lagged price term as well. Supply side influences are represented by three variables, vacancy rate, total completions, and the household-dwelling balance, while as in much of the literature income plays a strong role, this time represented by household disposable income. Also as in much literature we have a ‘user cost of capital term which incorporates the interest rate, and two regional FTSE variables representing wealth effects. This model has a very high fit, explaining 97.6% of the variance.

Figure D.3: Private market rent model at local authority level, 2010-21 (real median asking rent, £pw)

Variable description	Varname	Coeff B	Std Coeff Beta	t stat	signif p	Collinear VIF
Constant	(Constant)	-5.626		-2.628	0.009	
Lagged real median rent £pw	rlmdrentz_1	0.902	0.910	118.643	0.000	16.121
Real median house price £000	rlmdpricek	0.024	0.040	5.263	0.000	15.605
Log difference house price	ldprice	54.817	0.033	15.600	0.000	1.261
Predicted private lets % hshlds	pr(prletsshh)	-0.007	-0.001	-0.120	0.904	9.482
Median earnings £'000 per year	mdearnkpa	0.425	0.024	7.418	0.000	2.826
Predicted housing vacancy rate	Pr(pvac)	-3.394	-0.014	-5.581	0.000	1.834
Private completions % hshlds	ppcmp	-1.010	-0.004	-2.119	0.034	1.147
Unemployment rate % ec act	punem	0.175	0.005	1.972	0.049	1.974
Young adult (15-24) % popn	pcyngad	0.162	0.006	2.361	0.018	1.800
Aged 25-39 % of popn	pc2539	0.400	0.025	5.422	0.000	5.868
Lone parent households % hhd	phh1k	-0.334	-0.007	-2.775	0.006	1.876

a. Dependent Variable: rlmdrentwkz

b. Weighted Least Squares Regression - Weighted by hhdwgt

Model Summary

Model	R	R Square	Adj R-sq	S E E
1	0.994	0.988	0.988	7.99722

ANOVA[a,b]

Model		Sum Sq	deg frdm	Mn Sq	F ratio
1	Regression	17335195	11	1575926.791	24640.995
	Residual	201844	3156	63.955	Signif F
	Total	17537038	3167		0.000

This model for private rents has been updated from the 2020 version, using a longer dataset which for the last 6 years is based upon Zoopla asking rents data, and prior to that VOA. This is a partial adjustment model and it is clear that rents are slow to change. Key drivers include house prices (level and change), earnings and younger adult populations, with some negative supply feedback from vacancies and private completions (although private lettings are not significant). The positive sign on unemployment is against expectations but the effect is weak.

Table D.4: Model for private rental share of stock, local authority level 2011-21

Variable description	Varname	Coeff B	Std Coeff Beta	t stat	signif P	VIF
Constant	(Constant)	-5.909		-8.844	0.000	
Lagged 3yr private rented share %	ppr_3	0.815	0.801	96.301	0.000	1.921
Rental rate of return %	prror3	1.487	0.183	18.406	0.000	2.760
House price:earning ratio	hper	0.337	0.176	14.815	0.000	3.904
Post 2016 dummy	Post2016	1.030	0.083	11.530	0.000	1.434
Mortgage interest rate	mir	-0.754	-0.055	-7.392	0.000	1.556
Real ftse index	rlftse	3.834	0.041	5.921	0.000	1.333
London dummy	london	0.414	0.024	2.704	0.007	2.190

Dep Var: ppr, private rental share of households %

Weighted by hhdwgt

Model Summary

Model	R	R Square	Adj R-sq	S E E
1	0.934	0.873	0.873	2.21631

Model		Sum Sq	deg frdm	Mn Sq	F ratio
1	Regression	119159	7	17022.7	3465.521
	Residual	17334	3529	4.912	Signif F
	Total	136493	3536		0.000

This model is another partial adjustment formulation, albeit with a three year lag, and the high value of the coefficient on the lagged share is no surprise. The positive relationship with rental rate of return is expected, reflecting landlord supply behaviour, while the positive effect of the house price:earnings ratio is likely to reflect a key demand determinant. The negative effect of interest rates is expected, but the positive sign on FTSE is not as expected (as this represents the return on the main alternative investment outlet), and neither is the post -2016 dummy, given that this represents the period of less favourable fiscal treatment.

Table D.5: OLS Model to predict gross household income, £k pa - UKHLS data aggregated to HMA level, annual panel 2011-19.

Model		Coeff B	Std Coeff Beta	t stat	Sig.	Collinear VIF
1	(Constant)	10.298		3.026	0.003	
Real GVA /capita (£k)	rgvapck	0.171	0.175	7.718	0.000	2.106
Median f t earnings £k/yr	mdeftkpa	0.089	0.094	4.753	0.000	1.602
Hi Occupations 1&2	soc12	21.626	0.182	7.203	0.000	2.610
Lo Occupations 9	soc9	-38.286	-0.148	-8.503	0.000	1.246
Number employed/hhd	nemp	14.415	0.274	11.209	0.000	2.457
Part-time workers	parttime	-4.992	-0.028	-1.661	0.097	1.188
Unemployment (LA)	punemla	-0.317	-0.105	-4.843	0.000	1.921
L T sick/disabled	ltsickdis	-19.072	-0.069	-4.042	0.000	1.191
Single adult hhd	Sing	-7.175	-0.059	-2.892	0.004	1.702
Lone parent hhd	Lpar	-8.562	-0.032	-1.807	0.071	1.313
Number of children/hhd	numchild	3.317	0.053	2.694	0.007	1.596
N Rooms /dwg	rooms	1.809	0.081	3.596	0.000	2.082
Flat	Flat	22.071	0.318	13.001	0.000	2.451
CT Band A&B	ctbab	-24.161	-0.078	-4.477	0.000	1.253
CT Band G&H	ctbgh	110.678	0.088	5.366	0.000	1.103

a. Dependent Variable: ginchhyrk

b. Weighted Least Squares Regression - Weighted by ntrlhmawgt

Model Summary

Model	R	R Square	Adj R Sq	S E Est
1	0.906	0.821	0.817	2.25519

	SoS	df	Mn Sq	F
Regression	17113.757	15	1140.917	224.330
Residual	3733.040	734	5.086	Signif F
Total	20846.797	749		0.000

This is an updated version of a standard proxy-based prediction of household income levels for use at sub-regional level. Data from UKHLS were aggregated to HMA level by year and OLS regression was run to calibrate the model. The variables used are commonly found to be associated with different levels of household income and all had effects in line with expectations.

Table D.6: Updated model for net relet rate of social housing, local authority level panel 2016-21 (log of percent of social housing stock)

Variable description	Varname	Coeff B	Std Coeff Beta	t stat	Sig. p	Collinear VIF
1	(Constant)	6.534		12.067	0.000	
Log Real median house price	lrlmdpricen	-0.395	-0.409	-9.668	0.000	5.141
Log difference house price	ldprice	-1.758	-0.163	-8.154	0.000	1.148
Affordability ratio rent/ hhd income	affrat2	-1.046	-0.096	-3.095	0.002	2.774
Low income poverty (benefit based)	plwincid	-0.937	-0.105	-2.641	0.008	4.531
Social renting %	psr	-0.009	-0.139	-3.855	0.000	3.741
Social completions rate (% hhd)	pscmp	-0.129	-0.040	-1.805	0.071	1.440
Private completions rate (% hhd)	ppcmp	0.111	0.083	3.704	0.000	1.439
Log vacancy rate %	lpvac	0.156	0.114	4.843	0.000	1.583
Net density dwelling/ha	netdens2	0.001	0.078	2.604	0.009	2.563
Social renters aged 16-29 in 2011	psrage1629	1.762	0.074	3.221	0.001	1.527
Black ethnicity, % of popn	pblacka	-0.007	-0.088	-2.516	0.012	3.478
Covid year	covid	-0.099	-0.084	-4.362	0.000	1.069

a. Dependent Variable: lnreletrt4

b. Weighted Least Squares Regression - Weighted by hhdwgt

Model Summary

Model	R	R Square	Adj R Sq	S E Est
1	0.608	0.370	0.366	0.36310

Model		Sum Sq	deg frdm	Mn Sq	F
1	Regression	140.162	12	11.680	88.592
	Residual	238.635	1810	0.132	Signif F
	Total	378.797	1822		0.000

This model is in a long tradition of relet models developed by the author over the preceding 35 years. Data problems and inconsistencies associated with changes in the way local authorities made and social landlords made statistical returns to DCLG/DLUHC have plagued this model for some time and account for the shorter time period used for estimation and the poorer fit of this model. Nevertheless, nearly all of the variables included have effects in line with expectations from theory and previous research.

Table D.7: Regression model for new homeless applications rate at local authority level, annual for two periods (log of applications as % of households, 2014-21 & 2018-21)

Variable description	Varname	Coeffic 1 B	Std Coeff Beta	t stat	Signif p	Collinear VIF	Coeffic 2 (2018-21)	Average Coeffic
Constant	(Constant)	-2.351		-42.064	0.000		-0.738	-1.545
HRA dummy	hradum	0.209	0.152	7.091	0.000	3.494		0.104
Lone parent household %	phh1k	0.091	0.211	9.848	0.000	3.490	0.063	0.077
Unemployment rate %	punem	0.026	0.065	3.360	0.001	2.879		0.013
Sick/disabled econ status	pcsick	-0.080	-0.168	-7.427	0.000	3.915	-0.055	-0.068
Private renting share hshlds %	ppr	0.007	0.065	3.620	0.000	2.454	0.011	0.009
Excess rent over LHA £pw	exrent2	0.0012	0.054	3.717	0.000	1.589		0.0006
Affordability ratio (rent/hhd income)	affrat2	0.478	0.029	1.686	0.092	2.334	0.600	0.539
Homeless applicants lost PR tenancy % hshlds	phlendrent	1.191	0.355	20.358	0.000	2.321	1.097	1.144
Welfare reform cuts £ pa /wkg age	wrcut	0.001	0.032	1.869	0.062	2.298	0.003	0.002
SMD destitution rate %	pdestsmd	1.040	0.167	7.579	0.000	3.712	1.390	1.215
Poor children %	ppoorchld	0.010	0.097	4.524	0.000	3.507	0.002	0.006
Business & education centres	BECent	0.088	0.047	3.442	0.001	1.423	-0.090	-0.001
Prevention/all homeless apps	lprevrat3	0.183	0.492	41.334	0.000	1.082	-0.118	0.032
Covid year (2020) dummy	covid	0.092	0.045	3.240	0.001	1.451		0.046
Prevention into soc or priv rental	pprevsrpr						-0.144	-0.072

a. Dependent Variable: lpnewhlapp
b. Weighted Least Squares Regression - Weighted by hhdwgt

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.819[a]	0.671	0.669	0.40129

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	824.620	14	58.901	365.770	.000[c]
	Residual	404.679	2513	0.161		
	Total	1229.299	2527			

This model follows in a long tradition of similar models going back to the DCLG study 'Estimating Housing Need' in 2009. The model explains two-thirds of the variance, with effects largely in line with expectations, and includes a number of directly relevant 'policy lever' variables. One of the variables with a strong effect in this model (phlendrent) is actually predicted in another model within the suite (see below). In projecting core homelessness, the key role of this model is driving the level of total and unsuitable temporary accommodation. On the right are shown the coefficients estimated from the shorter period post-HRA.

Table D.8: Regression model for homeless applications leaving private renting due to eviction of other loss of tenancy at local authority level, annual (log of ex PRS applications as % of households, 2014-21)

Variable description	Varname	Coeffic. B	Std Coeff Beta	t stat	signif. p	Collinear VIF
Constant	(Constant)	2.201		4.672	0.000	
HRA dummy	hra	1.189	0.500	25.412	0.000	3.315
Children % popn	Aged 0 - 15	0.093	0.146	10.629	0.000	1.621
Black ethnicity	pblacka	0.021	0.097	5.082	0.000	3.117
Log real hhd disp income	lrhdiph	-1.456	-0.315	-10.867	0.000	7.182
Welfare Reform benefit cuts £ph	wrcut	0.002	0.029	1.724	0.085	2.415
Real median rent £pw	rlmdrentwkz	0.004	0.228	6.384	0.000	10.900
Private renting % hhd	ppr	0.017	0.087	5.165	0.000	2.433
Change in private renting (3yr)	chgppr3yr	-0.079	-0.060	-4.588	0.000	1.485
No qualifications	pnoqual	-0.050	-0.211	-10.804	0.000	3.278
Log prevention ratio to all hless applicn	lprevrat3	-0.332	-0.295	-20.883	0.000	1.711
Prevntion cases rehoused in soc renting	pprevsr	-0.417	-0.066	-5.525	0.000	1.206
Covid year dummy	covid	-0.517	-0.148	-12.176	0.000	1.257

a. Dependent Variable: lphlendrent

b. Weighted Least Squares Regression - Weighted by hhdwgt

Model Summary

Model	R	R Square	Adj R Sq	S E Est
1	0.847	0.718	0.717	0.64331

Model		Sum Sq	degr frdm	Mn Sq	F ratio
1	Regression	2542.966	12	211.914	512.052
	Residual	999.039	2414	0.414	Signif F
	Total	3542.005	2426		0.000

This model has a good fit, explaining 72% of the variance, and captures important affordability factors as well as expected tenure factors (the larger the PRS locally, the greater the likely numbers, but an increase in the size of the sector could provide more alternative renting opportunities). Children and black households appear more vulnerable to eviction. Two prevention policy indicators are significant, as is the Covid dummy which reflections the eviction moratorium applied during the emergency.

Table D.9: Regression model for total temporary accommodation at local authority level, annual (log of hhd in all TA as % of households, 2014-21)

Variable description	Varname	Coeff 1 B	Std Coeff Beta	t stat	signif p	Collinear VIF	Coeff 2 (2018-21)	Ave Coeffic
1	(Constant)	-0.411		-7.687	0.000		-0.167	-0.289
HRA dummy	hra	0.083	0.029	4.718	0.000	1.196		0.041
Log of lagged TA % hhd	lptatot_1	0.876	0.878	86.299	0.000	3.290	0.839	0.857
Log of new h'less applics % hhd	lpnewhlapp	0.064	0.026	3.906	0.000	1.440	0.138	0.101
Real median rent level £pw 2br	rlmdrentwkz	0.001	0.055	5.277	0.000	3.513	0.001	0.001
Net social lettings rate % hhd	pslets	-0.031	-0.011	-1.830	0.067	1.214	-0.020	-0.026
Prevention into social renting	pprevsr	-0.064	-0.009	-1.301	0.067	1.230		-0.032
London dummy	london	0.082	0.021	2.080	0.038	3.102	0.124	0.103
Hostel resid on HB % hhd	phostelnew	0.118	0.030	4.794	0.000	1.226	0.100	0.109
Covid emergency accom % hhd	pcovemerg	0.290	0.006	0.965	0.335	1.160	0.479	0.384
Log ratio prevention to total	lprevrat3						-0.043	-0.021
Propn prevention accom into Soc or Priv rent	pprevsrpr						-0.169	-0.085

Dependent Variable: lptatot

Weighted by hhdwgt

Model Summary

Model	R	R Square	Adj R sq	S E E
1	.961[a]	0.924	0.924	0.40074

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4719.510	9	524.390	3265.396	.000[c]
	Residual	386.540	2407	0.161		
	Total	5106.050	2416			

This model is primarily needed as an intermediate step in predicting unsuitable TA, but it is an important measure of statutory homeless activity by LAs and the associated costs. It is a partial adjustment model with a very good fit to the data (92-93%). Changes are driven partly by key inflows and outflows but also influenced by other rmarket factors, independent provision, a London effect, and important prevention influences. The latter become apparent when we run the model for the shorter post-HRA period and as in other cases we take average coefficients from the two period of estimation.

Table D.10: Regression model for unsuitable temporary accommodation at local authority level, annual (log of hhd in unsuitable TA as % of households, 2014-21)

Variable description	Varname	Coeff 1 B	Std Coeff Beta	t stat	signif p	Collinear VIF	Coeff 2 (2018-21)	Avera coeff
Constant	(Constant)	-1.427		-9.756	0.000		-1.393	-1
HRA dummy	hra	0.041	0.016	1.283	0.199	2.166		0
Log difference (change) in total TA	ldta	0.616	0.198	22.918	0.000	1.048	0.636	0
Lagged log of rate of unsuitable TA	lpbadta_1	0.648	0.631	41.838	0.000	3.209	0.588	0
Log new homeless applications % hhd	lpnewhlapp	0.124	0.057	4.974	0.000	1.864	0.092	0
Real median market rent (Zoopla)	rlmdrentwkz	0.001	0.066	3.76	0.000	4.363	0.001	0
Affordability ratio, rent/hhd income	affrat2	2.053	0.068	4.716	0.000	2.963	2.549	2
Net social lettings rate % hhd	pslets	-0.106	-0.043	-4.637	0.000	1.216	-0.117	-0
Private renting % hhd	ppr	0.009	0.044	3.164	0.002	2.764	0.010	0
Hostel resid on HB % hhd	phostelnew	0.156	0.044	4.332	0.000	1.476	0.070	0
London dummy	london	0.286	0.081	5.188	0.000	3.42	0.394	0
Business & educ centresdummy	BECent	-0.181	-0.053	-4.335	0.000	2.069	-0.143	-0
log ratio prevention to all apps	lprevrat3	-0.103	-0.086	-7.024	0.000	2.094	-0.099	-0
Prevention into SR propn '18/19	pprevsr	-0.078	-0.011	-1.21	0.226	1.265		-0
Covid emergency accom % hhds 2020	pcovemerg	1.544	0.035	3.771	0.000	1.21	1.546	1
All Prevention & Relief cases accommodated by closure propn							-0.528	-0

Dependent Variable: lpbadta

Weighted by hhdwgt

Model Summary

Model	R	R Square	Adj R sq	S E E
1	0.911	0.830	0.829	0.53500

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3348.600	14	239.200	835.300	0.000
	Residual	686.900	2399	0.289		
	Total	4035.560	2413			

This model again follows previous practice, with a partial adjustment model reflecting pressures from changes in total TA as well as new homeless applications, counterbalanced by supply of social lettings, but also influenced by affordability conditions, tenure and other homeless provision, and some area type effects. Again prevention factors as well as special provision under Everyone In are reflected. Again we use the technique of averaging coefficients from the 8 year and 4 year models. Again, this is a model with a reasonably good fit (83% & 77%), and this directly drives one of the more sensitive elements of core homelessness.

Table D.11: Regression model for homeless applications previously rough sleeping or no fixed abode[14] at local authority level, annual 2018-21 (log of relevant applicants as % of households)

Variable description	Varname	Coeff B	Std Coeff beta	t stat	signif p	Collinear VIF
Constant	(Constant)	-4.506		-16.108	0.000	
Single person % hhd	sing	0.030	0.147	3.214	0.001	3.984
Crime rate per 1000	crimratept	0.003	0.102	2.428	0.015	3.370
Complex need destitution rate % hhd	pdestsmd	3.477	0.406	6.918	0.000	6.591
Destitution general rate %	pdestgen	-0.821	-0.157	-3.690	0.000	3.462
Excess rent over LHA £pw	exrent2	0.003	0.101	3.264	0.001	1.844
Adults no qualifications %	pnoqual	-0.017	-0.064	-2.342	0.019	1.440
Hostel resid on HB % hhd	phostelnew	-0.530	-0.248	-9.032	0.000	1.445
London dummy	london	-0.478	-0.202	-6.343	0.000	1.946
LA sparsity level (ha/pers)	laspars	0.115	0.174	4.734	0.000	2.582
Homeless ex-PRS % hhd	phlendrent	1.195	0.276	10.657	0.000	1.287
Covid year	covid	0.147	0.076	2.750	0.006	1.449
Log ratio prevention /all apps	lprevrat3	-0.101	-0.050	-1.854	0.064	1.382
Accommodated % of all completed episodes	ppracc	-0.989	-0.168	-6.376	0.000	1.322

Dependent Variable: lphclicrsprox

Weighted by hhdwgt

Model Summary

Model	R	R Square	Adj R Sq	S E Est
1	0.598	0.357	0.351	0.69796

Model		Sum Sq	Degr Frdm	Mn Sq	F ratio
1	Regression	333.228	13	25.633	52.618
	Residual	599.197	1230	0.487	Signif F
	Total	932.425	1243		0.000

This model is a significant advance on its predecessor, as it is now able to utilise four years of post-HRA data. As noted in the main text, this model shows a stronger link with complex needs factors than mainstream homelessness. It is also noteworthy for containing a

[14] The measure used is half of the number of applicants whose immediately preceding place stayed was 'rough sleeping' or 'No Fixed Abode'; on average this is equivalent to all of the rough sleepers plus 35% of the no fixed abode group.

number of factors which provide strong links to policy measures, including the 'homeless ex-PRS' factor, the 'excess rent over LHA' factor and two prevention measures.

Table D.12: Logistic regression models for core homelessness and rough sleeping fitted to composite dataset from UKHLS 2018-19 and DUKS 2019 combined (using common set of variables)

Variable Description	Varname	**Core Homeless** Coeffic	Signif p	Odds Ratio	**Rough Sleep** Coeffic	Signif p	Odds Ratio
Female gender	female	-0.199	0.014	0.819	-1.025	0.000	0.359
Aged 60 & over	age60ov	-1.385	0.000	0.250	-1.224	0.000	0.294
Born overseas	bornos	0.241	0.046	1.273	0.741	0.000	2.098
Black/B British ethnicity	black	0.295	0.073	1.343	-0.276	0.204	0.759
English language used	englishlangd	-1.172	0.000	0.310	0.510	0.004	1.665
Couple household	cpl	-2.395	0.000	0.091	-1.984	0.000	0.138
Lone parent family	lpf	-2.207	0.000	0.110	-2.459	0.000	0.086
Couple family	cpfam	-1.264	0.000	0.282	-1.440	0.000	0.237
Number of children	nkids	-0.142	0.005	0.868	-0.299	0.004	0.741
Multi-adult household	mult	-0.154	0.114	0.857	-0.664	0.000	0.515
Mental health problem	mhprob	0.121	0.202	1.128	0.218	0.071	1.243
Poor health reported	poorhlth	0.226	0.059	1.254	0.674	0.000	1.963
Universal credit*	ucd	1.057	0.000	2.878	0.667	0.000	1.948
Home owner	own	-1.149	0.000	0.317	-1.598	0.000	0.202
Social rent tenure	socr	-0.796	0.000	0.451	-1.212	0.000	0.298
Evicted from priv rent	evictpr	1.014	0.000	2.757	1.143	0.000	3.137
Relationship breakdown	relbd	0.339	0.010	1.403	-0.080	0.656	0.923
Log equiv hh income AHC (£pw)	leqincahc18	-0.200	0.000	0.819	-0.340	0.000	0.712
Log estimated savings (£)	lestsavgb2	-0.274	0.000	0.760	-0.358	0.000	0.699
Other relatives living	othrelalive	-0.366	0.000	0.693	-0.837	0.000	0.433
Rent-Local Allowance gap (propn)	lhagap18	1.140	0.000	3.126	0.107	0.811	1.113
Social rent lettings % hhd	pslets18gb	-0.324	0.000	0.723	-0.230	0.041	0.795
Average dwelling size rooms	avrooms	-0.357	0.000	0.700	-0.152	0.223	0.859
Complex need band	psmdband	0.157	0.001	1.170	0.069	0.296	1.071
Rural area	rural	-0.276	0.032	0.759	-0.444	0.048	0.641
Constant	1	3.311	0.000	44.295	-0.609	0.006	9.882

		Chi-square	df	Sig.	Chi-square	df	Sig.
		4085.583	25	0.000	2632.32	25	0.000

-2 Log likelihood	Cox & Snell R Sq	Nagelkerke R Square	-2 Log likelihood	Cox & Snell R Sq	Nagelkerke R Square
4921.679	0.176	0.506	2676.42	0.117	0.527

	Predicted	corehless	% Correct	Predicted	roughsleep	% Correct
Observed	0	1		0	1	
0	19755	239	98.8	20472	106	99.5
1	742	420	36.2	426	153	26.5
			95.4			97.5

The next model considered, summarised in Table D.12, represents a new and distinct approach, utilising micro household survey data and binary logistic regression analysis, but in the unique context of being able to combine two complementary but overlapping surveys: 'Understanding Society' (UKHLS), which is a multi-purpose household panel survey, and the Destitution in the UK (DUKS) survey of users of crisis services, for the same time period (2019) and a common set of variables. To facilitate comparison of coefficients, a common set of predictor variables are used in both models, the first for core homelessness and the second for rough sleeping (the latter nesting within the former). Variables included were significant in one, other or both models. The rough sleeping model is one of three used to predict rough sleeping variations over time and space, each of which was controlled to equal the base year estimate of rough sleeping for 2022. The core homelessness model is used by taking 57.5% of its predicted rates, to represent the average share of sofa surfing in core homeless, and again controlled to the base year estimate for total sofa surfing in England. Again, this model was one of three used for sofa surfing, given equal weight.

Variables down to 'othrelalive', above the line, are individual/household-based measures; variables below the line are local authority area-based measures, and it may be noted that only two of these were significant in the rough sleeping model. While the models are similar overall, there are different signs in two cases (Black ethnicity and English language), and rough sleeping coefficients are not significant in four cases where they were for core homelessness overall (relationship breakdown, LHA gap, average dwelling size, complex need band). For the two health variables the effects on rough sleeping were stronger and more significant than their effects on core homelessness.

Table D.13: Logistic regression model for sofa surfing fitted to English Housing Survey data 2014-19, including supplementary coefficients for not usually resident sub-group

Variable description	varname	Coeff 1 B	Wald	Sig.	Odds ratio Exp(B)	Coeff 2 B (NUR grp)	Wtd Combin Coeff
Aged under 30	ageu30	-0.293	2.490	0.115	0.746	0.696	-0.026
Aged 65 & over	age65ov	-0.835	16.303	0.000	0.434	-0.887	-0.849
Lone parent household	lpfam	1.031	11.980	0.001	2.805	0.399	0.861
Multi-adult household	mult	3.753	520.706	0.000	42.666	1.542	3.156
Full time employed HRP	hrpftemp	0.331	5.875	0.015	1.392		0.241
Long term sick/disabled	ltsick	0.679	26.960	0.000	1.971	1.021	0.771
High occupational class	hisec	-0.653	6.338	0.012	0.520	-0.488	-0.608
Social renter	tensr	0.692	20.232	0.000	1.997	1.290	0.853
Private renter	tenpr	0.370	5.069	0.024	1.448	0.901	0.514
HRP born overseas	migrant	0.653	19.953	0.000	1.921	0.258	0.546
Black ethnicity	black	0.325	2.370	0.124	1.384		0.237
Asian ethnicity	asian	0.827	22.151	0.000	2.287	-0.949	0.348
Social letting rate	pslets	-0.222	3.832	0.050	0.801		-0.162
International in migration	intinmr	0.144	7.377	0.007	1.154		0.105
Lone parent hhds (LA)	phh1k	0.067	3.072	0.080	1.069		0.049
Lower decile earnings FT&Pt	ldearnfpt	-0.010	8.568	0.003	0.990		-0.007
Rural dummy	rural	-0.739	2.372	0.124	0.477	-0.561	-0.691
Excess of market rent over LHA	exrent2					0.011	0.0030
	Constant	-6.816	171.099	0.000	0.001	-6.182	-6.644

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	1190.503	17	0.000
	Block	1190.503	17	0.000
	Model	1190.503	17	0.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2771.010[a]	0.019	0.307

Classification Table[a]

Observed	Predicted		
	sofasurf2		Percentage Correct

			.00	1.00	
Step 1	sofasurf2	.00	60376	0	100.0
		1.00	317	0	0.0
	Overall Percentage				99.5

DLUHC enabled the attachment of local authority codes to this EHS dataset so enabling the inclusion of demographic and market variables at this level to be attached and used as regressors. Six variables at the bottom of the table (pslets to exrent2) are in this category. We believe this is a reasonable model given the relatively rare incidence of sofa surfing in the general household population. It has also been enhanced in this round by the inclusion of a supplementary model for the incidence of sofa surfing involving persons who were not usually resident in the household but stayed with it temporarily in the preceding year to avoid having otherwise been homeless. A weighted combination of the two elements feeds into the overall predictive model[15].

[15] For a point in time estimate, it was calculated that a weight of 0.73 on the main part of the model and 0.27 on the supplementary model coefficients for not usually resident adults staying temporarily would be appropriate.