

Estimating relative needs formulae for new forms of social care support

Final report

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Personal Social Services Research Unit
PSSRU Discussion paper 2877/2
March 2018

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Acknowledgements

This is an independent report commissioned and funded by the Department of Health Policy Research Programme (Study to Review and Update RNF Allocation Formulae for Adult Social Care, 056/0018). The views expressed in this publication are those of the author(s) and not necessarily those of the Department of Health.

We would like to thank Karen Jones for leading on the ethics and research governance applications, as well as for her involvement with the LA-funded social care service users’ survey and the care home survey data collection. We would like to thank Olena Nizalova, Jose-Luis Fernandez and Jane Dennett for their support with this report, and are very grateful for the comments and suggestions from Sarah Horne, Jonathan White and other colleagues in DH, DCLG and DWP.

We also like to thank anonymous reviewers for very helpful comments on this report.

Furthermore, we also like to thank the local authorities that took part in the research and provided data, and members of the advisory panel for their invaluable advice on research design and data collection.

Data from the English Longitudinal Study of Ageing (ELSA) were made available through the UK Data Archive (UKDA). ELSA was developed by a team of researchers based at the National Centre for Social Research, University College London and the Institute for Fiscal Studies. The data were collected by the National Centre for Social Research. The funding is provided by the National Institute of Aging in the United States, and a consortium of UK government departments co-ordinated by the Office for National Statistics. The developers and funders of ELSA and the Archive do not bear any responsibility for the analyses or interpretations presented in this report.

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Executive Summary

Introduction

1. Local authorities in England have responsibility for securing adult social care for their local populations. Historically, social care support has included: services such as home care and residential care; personal budgets and direct payments; equipment; and also some professional support, such as social work.
2. Following the Layfield enquiry in 1976 (Cmnd 6453 1976), social care funding has been allocated to local authorities using a formula to help account for differences in local funding requirements (Bebbington and Davies 1980). The latest incarnation – in operation since 2006/7 – is the relative needs formula (RNF) (Darton, Forder et al. 2010).
3. The fundamental principle underpinning the use of allocation formulae is to ensure equal opportunity of access to ‘support’ for equal need. The conventional way to interpret this principle is that each council should have, after their allocation, sufficient net funding so that they can provide an equivalent level of support (services or otherwise) to all people in their local population who would satisfy national standard eligibility conditions (Gravelle, Sutton et al. 2003; Smith 2007).
4. Broadly, social care eligibility is dependent on recipients meeting all three of: (i) a sufficient level of impairment according to national eligibility criteria; (ii) insufficient informal care support; and (iii) limited income/wealth so that they meet the means test. Social care need therefore reflects all of these factors. Differences in this social care need between local authorities are incorporated into the Local Government Finance Settlement by using formulae. Some additional grants are also distributed between local authorities via the same formulae.
5. The number of people satisfying eligibility tests for public support for social care, and the amount of that support, will vary between local authorities according to a range of impairments, living conditions, and wealth/income factors. These factors can be largely regarded as being ‘exogenous’, beyond the (reasonable) control of the local council, and therefore funding allocations should be adjusted to compensate local authorities accordingly.
6. The Care Act 2014 laid out the requirement for local authorities to meet the costs of care for people whose cumulative cost of care has exceeded a certain threshold amount – the ‘cap’ limit. In order to determine people’s progression towards the cap, authorities would need to regularly assess the needs of all people with possible care needs. The Care Act 2014 will also introduce a new deferred payment scheme. This policy allows people to defer paying assessed charges for their care from local authorities until a later date, up to their time of death.
7. We consider the new forms of support to be provided by local authorities as arising from the Care Act 2014: the additional responsibility for the assessment of need and the provision of deferred payment agreements (DPAs). The main aim is to develop two relative needs formulae that will determine funding allocations to local authorities for these new responsibilities.

Key concepts

8. The principle of formula allocations is that local authorities are compensated for externally driven cost variation. In applying this principle, we need to determine what factors are considered external, and so beyond the control of the local authority, and which are not. The main drivers of cost for social care are the needs characteristics of the local population. Needs factors are the core variables in relative needs formulae and can be regarded as external.

9. Some other factors, such as council preferences about setting local eligibility thresholds, are clearly within council control and should not be 'controlled for' in the formula. But other factors are between these two cases. At least three merit further discussion in the context of this analysis.
 - a. First, the supply of care services. Most LAs commission services from independent sector providers, and so do not have direct control over that form of supply. Nonetheless, LAs do have powers to directly provide services and are able to manage local markets to some extent. For this reason, supply conditions were not treated as exogenous in developing relative needs formulae.
 - b. The second factor concerns the demand for services. Differences in demand can lead to variation in the use of services beyond that expected on the basis of (eligible) need alone. In this study we did not include these factors in the formula because they are at least in part affected by LA policies. In particular, LAs operate with need-assessment criteria with regard to publicly-funded care, including for the new responsibilities. Also, more pragmatically, behavioural effects are very hard to anticipate and model. For example, there are no sound data or theoretical models on which to predict demand for assessments or DPA.
 - c. The third is population sparsity. The main argument is that the costs of providing services could be higher in rural areas than in urban areas. Formula funding directly accounts for differences in unit cost by applying the area cost adjustment and the sparsity adjustment (in the older people's RNF component). There may also be supply effects, but these are treated as above: i.e. excluded from the formula. There could be an argument that rurality implies some direct need effect. Nonetheless, in theory, the other direct-need proxies used in the analysis should account for this effect.
10. The general approach was not to include factors in the formulae unless they were clearly considered to be external. The concern otherwise is that by including factors which could be affected by LA policies, LAs would partly be able to control the allocation share that they receive.

Methods

11. There are broadly two alternative approaches to determining resource allocation formulae: the *utilisation-based* approach, and the *normative (or epidemiological)* approach. An essential difference in the approaches concerns how the concept of 'need' is defined and determined. In social care, people are supported by the public (local authority) system because they have issues with personal (physical or mental) impairment, suffer risks to safety (which include environmental factors) and lack sufficient informal care. There are also financial means-testing rules that determine a person's eligibility. Together these factors affect the overall need for care services and support to be met by LAs. In principle, where we know the level of need for a given population, this figure can be translated into a required amount of services and, in turn, an amount of public funding needed to pay for this care.
12. The central premise of the *utilisation-based* approach is that the effect of need is reflected in observed patterns of service use in a local population. This approach does not require the definition of some absolute level of need, but rather the *relative* patterns between individuals. In practice, need in a population is not the only factor that determines what services are actually used. First, local authorities can interpret need factors differently. Second, service supply in a local area will also affect what is actually used. Finally, publicly-funded care services are also financially means-tested as well as needs-tested, as noted. Statistical techniques (generally

regression analysis) are used to isolate the different need effects and provide estimates of their scale for particular local populations. Since need has a number of components in social care (e.g. impairment, safety, informal care availability), a statistical approach allows us to estimate the relative importance of these factors from actual practice (in so far as this is reflected in the patterns of services that are provided). Because 'need' is being estimated from service utilisation data, this approach can use indicator variables for which we have data to approximate the components of need (e.g. we do not need to measure impairment directly as long as we have variables that are closely correlated with impairment rates). Differences in the scale of need effects between local authorities are the basis for a relative needs formula.

13. In the *normative* approach a measure of need in a local population is inferred directly from the criteria (ideally best-practice) that local authorities use to define need. For example, we could measure the number of people with impairment. The relative scale of this indicator of need between local authority populations is then used to generate a relative needs formula.
14. These different approaches have their theoretical strengths and weaknesses. However, there are practical limitations in using the normative approach in social care. First, no national set of criteria exists to define need (at least with sufficient specificity). Second, there is no basis for how the different elements of need (impairment, safety, informal care availability) can be combined into a single indicator of relative need. A particular problem is to specify rules for how much need can be met by informal care. This issue has proved to be extremely difficult and controversial and, therefore, care systems in some countries simply disregard informal care (with the range of policy consequences this brings). Third, eligibility for care also depends on people's financial situation, and these eligibility rules would also have to be taken into account.
15. The practical limitations of the (full) normative approach are therefore significant in social care, and this approach was not used in this study. However, given that the aim of this work was to estimate formulae for the new responsibilities, a pure utilisation approach was also not applicable either (as there are not specific utilisation data). Rather, we adopted a *hybrid* analysis, using utilisation data and methods, combined with (normative) prevalence-based simulation for predicting financial eligibility for either LA care support or DPA.
16. The problem with using social care utilisation data is that current utilisation rates will be determined by the financial means-test, LA preferences/efficiencies and current supply patterns, as well as by the need test. These non-need influences had to be removed or 'cleaned'.
17. With respect to supply, allocation formulae can either incorporate these effects or not, depending on whether supply is considered to be externally determined or influenced by the care system. As LAs do have powers to directly provide services and are able to manage local markets to some extent, we have not considered supply to be externally determined. Therefore, supply effects were cleaned by including various indicators of supply in the regression analyses, and then removed by setting the corresponding supply variable(s) to a constant for all LAs. Similarly, the effect of LA practices on utilisation were estimated and removed by using LA fixed effects (i.e. LA dummy variables).
18. The financial means-test is more difficult to clean because it is determined by variables that also explain need: e.g. living alone and income/income benefits. If we set all relevant financial indicator variables to a constant for each LA, we risk under-measuring some important aspects of need differences. We tackled this problem by estimating the effect of relevant financial indicator variables on a *simulated* version of the current financial eligibility test.

19. Once these non-need influences were removed, the result was an equation predicting differences in relative needs between LAs, and this was used to calculate a relative needs equation for additional assessments.
20. The simulation approach could also be used to model the new DPA financial eligibility test. In the same way as above, the results could be used in combination with the needs test to determine likely up-take patterns for DPAs in each LA. By estimating the relationship between these expected up-take patterns and relevant exogenous factors, we had a basis for estimating a relative needs formula in the DPA case.
21. One of the important benefits of using data on existing local authority-funded services is that this approach avoids problems of out-of-area placement. We use data on what LAs spend, not on what services are used within the local authorities.

Empirical analysis

22. Two datasets were used. First, we constructed a (small) area dataset comprising data on the numbers of LA-supported clients and routinely-available need and wealth variables such as rates of benefit uptake and Census variables. These data were collected for each *lower super-output area* (LSOA) – a standard geographical unit – in a final sample of 53 LAs, giving a total of around 14,000 LSOAs. Data for LA-supported clients were provided at LSOA level by LAs that agreed to participate in the study.
23. The second dataset was the English Longitudinal Survey of Ageing (ELSA). This dataset has a wide range of data about individuals in the survey, including information about their needs-related characteristics and their wealth and income, including benefit uptake.

Simulation of financial eligibility

24. Five waves of ELSA were combined (with financial variables inflated to be in line with the last wave). The sample of people aged 65 and over (or 65+ in shorthand) was selected. This provided 25,420 observations for people aged 65+. These data were then reweighted so that rates of home ownership, living alone and pension credit uptake were in line with rates in the LSOA data.
25. The small area data were used to model the combined effect of local authority need and financial eligibility. The ELSA data were used to directly simulate (a) the financial means-test for current social care support and (b) the new test for DPA eligibility. The results could be used to remove the effect of the current financial means-test, as outlined above.

Assessment and DPA estimations

26. A relative needs formula for assessments was estimated both for people with a residential care need and with a non-residential care need. The following steps were repeated for each case:
 - a. We used a regression model to estimate the probability that a person satisfies the current financial means-test (E) using ELSA data with wealth and need variables (ones that are also available at small area level).
 - b. We used another regression model to estimate the numbers of people in an LSOA that have LA-supported services – i.e. that satisfy both need and financial means-test ($R + E$) – with need, wealth and supply variables.
 - i. We remove LA fixed effects and supply effects using their national average values from the estimation at this step.
 - c. The predicted values from these two estimations (steps a. and b.) were used to calculate the number of people in an LSOA that would pass the needs test (only) (R).

- d. A regression model was used to estimate an equation for the number of people in an LSOA that would pass the needs test only (R) (as determined at step c.) in terms of need, wealth, supply and (population) scaling variables.
 - i. We calibrated between the two estimations (steps a. and b.) by scaling all the coefficients in this equation using a common factor so that the net effect of home ownership on the numbers of people satisfying the need test was zero.
 - e. Statistical error for the process in steps b. to d. was estimated (using bootstrapping).
 - f. A linear approximation was calculated for the coefficients from the equation in step d. This involved calculating the change in the predicted numbers with need for small changes in each need-related and wealth variable from their sample mean values.
27. An additional assessments formula was found by subtracting the LA-supported clients (linear equation ($R + E$)) from the linear equation for numbers of people passing the need test (R).
28. The DPA formula was produced in a similar way with the predicted value of DPA eligibility (D) also applied at step c. to produce a value for the expected count of DPA-eligible people in each LSOA, and in total for the LA.

Results

29. The estimations used the following variables:

Need:	Supply:
Attendance Allowance claimants 65+ per capita 65+	Total care home beds per MSOA per MSOA pop 65+
Limiting (significantly) condition 85+ per capita 65+	Population/scale:
Living arrangements: couples per households 65+	Population 65+ (log)
Wealth/income:	Sparsity:
Home owner household 65+ per households 65+	Population density (total pop. per hectare)
Pension Credit Claimants 80+ per capita 65+	

30. Both age and gender variables were initially included but proved not to be significant. Sparsity was not significant in the residential care estimation but was for non-residential care. Relative needs formulae (RNFs) were derived holding supply, scale and sparsity constant.
31. Table 1 gives RNFs for residential care. For non-residential care, we used two different specifications: the first with the number of clients using either LA-funded home care or direct payments (Table 2); and the second with the number of clients using any LA-funded non-residential care service (Table 3). The former variable had fewer missing values.

Table 1. Relative needs formulae, residential care

	Need + Elig (LA-supp clients)	Need (All clients)	Additional assessments (Need and not eligible)	DPA
Attendance Allowance claimants 65+ per person 65+	0.01213	0.02072	0.00858	0.00436
Limiting (significantly) condition 85+ per person 65+	0.00736	0.01022	0.00286	0.00098
Home owner households 65+ per households 65+	-0.00244	0.00000	0.00244	0.00317
Pension Credit Claimants 80+ per person 65+	0.01166	0.01552	0.00387	0.00331
Living arrangements: couple households per HHs 65+	-0.00377	-0.00735	-0.00358	-0.00598
Constant	0.00743	0.01012	0.00269	0.00169

Table 2. Relative needs formulae, non-residential care (Home care + DP)

	Need + Elig (LA-supported clients)	Need (All clients)	Additional assessments (Need and not eligible)
Attendance Allowance claimants 65+ per person 65+	0.07983	0.09998	0.02014
Limiting (significantly) condition 85+ per person 65+	0.20773	0.33162	0.12389
Home owner households 65+ per households 65+	-0.02195	0.00000	0.02194
Pension Credit Claimants 80+ per person 65+	0.10760	0.07773	-0.02986
Living arrangements: couple households per HHs 65+	-0.03785	-0.04246	-0.00461
Constant	0.05288	0.05523	0.00235

Table 3. Relative needs formulae, non-residential care (All NR services)

	Need + Elig (LA-supported clients)	Need (All clients)	Additional assessments (Need and not eligible)
Attendance Allowance claimants 65+ per person 65+	0.08339	0.11082	0.02744
Limiting (significantly) condition 85+ per person 65+	0.13912	0.22154	0.08242
Home owner households 65+ per households 65+	-0.01681	0.00000	0.01681
Pension Credit Claimants 80+ per person 65+	0.10011	0.08257	-0.01754
Living arrangements: couple households per HHs 65+	-0.03101	-0.03596	-0.00495
Constant	0.05025	0.05650	0.00625

32. The condition whereby a person satisfies the need test but is not financially eligible (*Need and not eligible*) is calculated by subtracting the first column from the second column. It gives an RNF for *additional assessments*. The DPA formula only applies in the residential care case.

33. To provide combined formulae (residential plus non-residential clients), we weighted the individual formulae together by the respective number of total supported clients in England for residential and non-residential services – see Table 4 and Table 5.

Table 4. Relative needs formulae, combined res and NR (HC + DP) 65+

	Need + Elig (LA-supported clients)	Need (All clients)	Additional assessments (Need and not eligible)	DPA
Attendance Allowance claimants 65+ per person 65+	0.06051	0.07736	0.01684	0.00436
Limiting (significantly) condition 85+ per person 65+	0.15055	0.23991	0.08935	0.00098
Home owner households 65+ per households 65+	-0.01638	0.00000	0.01638	0.00317
Pension Credit Claimants 80+ per person 65+	0.08022	0.05998	-0.02023	0.00331
Living arrangements: couple households per HHs 65+	-0.02812	-0.03244	-0.00432	-0.00598
Constant	0.03991	0.04236	0.00245	0.00169

Table 5. Relative needs formulae, combined res and NR (all non-res) 65+

	Need + Elig (LA- supported clients)	Need (All clients)	Additional assessments (Need and not eligible)	DPA
Attendance Allowance claimants 65+ per person 65+	0.06306	0.08511	0.02206	0.00436
Limiting (significantly) condition 85+ per person 65+	0.10152	0.16124	0.05972	0.00098
Home owner households 65+ per households 65+	-0.01271	0.00000	0.01271	0.00317
Pension Credit Claimants 80+ per person 65+	0.07487	0.06344	-0.01143	0.00331
Living arrangements: couple households per HHS 65+	-0.02324	-0.02780	-0.00456	-0.00598
Constant	0.03803	0.04327	0.00523	0.00169

Discussion

34. Formula-based allocations differ substantially from allocations that are worked out solely on LA population 65+ shares. Assuming the same total budget was allocated in each case, the most-affected LAs would receive nearly 40 per cent less or over 12 per cent more money respectively than a population shares allocation as regards additional assessments. The corresponding comparison for DPAs is that some LAs would receive over 40 per cent less funding while others would receive over 30 per cent more money than a population shares allocation.
35. A range of robustness checks were carried out. We also compared the results regarding additional assessments as derived using the methods in this study (i.e. the *hybrid* approach) with those using an entirely different method based on re-weighting person-level data in ELSA to reflect LA-level characteristics (i.e. the microsimulation-based approach). Full details of this method are outlined in Fernandez and Snell (2018). Overall, we found a correlation of 0.80, which gives us confidence that each method is properly reflecting differences in need, even though the methods differed slightly in their assumptions.
36. There are different methods available to determine relative needs formulae, each with their strengths and weaknesses. The main strength of this approach is that it estimates 'need' according to current local authority need-eligibility criteria. These need-criteria should be a good indicator of the need for the new forms of support, although this argument depends on how far new eligibility criteria change. We also remove the effects of supply to give a better indicator of actual need. The main weakness is that its analytical methods embody certain statistical assumptions which, although reasonable, must be taken as read. Also, as noted, if the new eligibility criteria are quite different then it might be better to use an alternative approach.

1 Introduction

Local authorities in England have responsibility for securing adult social care for their local populations. Historically, social care support has included: services such as home care and residential care; personal budgets and direct payments; equipment; and also some professional support such as social work.

Following the Layfield enquiry in 1976 (Cmnd 6453 1976), social care funding has been allocated to local authorities using a formula to help account for differences in local funding requirements (Bebbington and Davies 1980). The latest incarnation – in operation since 2006/7 – is the relative needs formula (RNF) (Darton, Forder et al. 2010).

The fundamental principle underpinning the use of allocation formulas is to ensure equal opportunity of access to ‘support’ for equal need. The conventional way to interpret this principle is that each council should have, after their allocation, sufficient net funding so that they can provide an equivalent level of support (services or otherwise) to all people in their local population who would satisfy national standard eligibility conditions (Gravelle, Sutton et al. 2003; Smith 2007).

In other words, the objective of the system of Relative Needs Formulae is to provide a way of assessing the relative need for a particular set of services or support by different local authorities. The formulae need to be based on factors that are measured and updated routinely, which have a demonstrable and quantifiable link with needs and costs, and are outside the influence of local authorities (particularly through past decisions about services). The formulae have to be designed to measure variations in needs between local authorities. They are not concerned with the absolute level of expenditure needed, or with the short-run implications of actual funding arrangements. The current formula contains four components (i.e. a need component, a low income adjustment, a sparsity adjustment, and an area cost adjustment), which are applied to local population levels.

Two sets of eligibility conditions/tests are relevant for public social care support in general (Wanless, Forder et al. 2006; Forder and Fernandez 2009; Fernandez and Forder 2010; Fernandez, Forder et al. 2011). First, the *access and support test* that determines whether a person should receive support and if so how much, given their condition (e.g. the level of impairment) and circumstances (e.g. the availability of informal care). Second, any *financial means test* which determines whether a person is eligible for any public support on the basis of relevant non-need criteria, particularly the person’s financial circumstances.

Together these tests determine how much needs-related funding is required to meet the national standard. The number of people satisfying these tests and the public cost of their support as dictated by the tests will vary between local authorities according to the size and nature of both ‘need’ and wealth within the local population. These factors can be largely regarded as being ‘exogenous’, that is beyond the (reasonable) control of the local council, and therefore the funding allocations going to local authorities should be adjusted to reflect differences in these exogenous factors. Relevant factors will include indicators of need, such as rates of disability in the local population. These will largely affect expenditure requirements through the first test. Furthermore, factors will include markers of asset-holding and income, which mainly work through the second test – see Box 1. Conventionally, a formula is deployed to account for these exogenous factors and adjust each local authority’s funding allocation accordingly.

This analysis concerns the development of allocation formulae for the new forms of support as specified in the Care Act 2014, namely: the additional responsibility on local authorities for the

assessment of need, including for people that are currently not eligible for support on the basis of their financial means (i.e. self-payers); and the provision of **deferred payment agreements (DPAs)**.

The provisions of the Care Act 2014 are for local authorities to meet the costs of care for people whose cumulative cost of care has exceeded a certain threshold amount – the *cap on lifetime care costs*. In order to determine people’s progression towards the cap, authorities will be required to regularly assess the needs of all people with potential care needs. The 2013 DH consultation document suggests that, as a result of the reforms, up to 500,000 more people with eligible care needs – mostly people that currently fund their own care (i.e. self-funders) – could make contact with their local authority to request a needs assessment (Department of Health 2013). This activity will create a new cost burden for councils which will require funding that is allocated by a relative needs formula.

The deferred payment scheme allows people to defer paying assessed charges for their care from local authorities until a later date, up to their time of death. A deferred payment agreement will involve the local authority meeting an agreed proportion of the cost of a care home until the agreed time, with the debt secured against the equity in the person’s housing assets. Since the local authority will have to fund the loan, particularly during the initial period of this policy, additional public funding is likely to be required for LAs to meet this obligation. Again, the relevant funding will be allocated from the centre using a relative needs formula.

The study described in this report was commissioned to examine the needs component for associated RNFs. The main aim of this work is to develop two relative needs formulae that will determine funding allocations to local authorities for these new responsibilities. Ethical approval for this study was gained from the National Institute of Social Care and Health Research Ethics Committee on 29 April 2013.

Box 1 Exogenous factors

Relative needs formulae should therefore include exogenous need factors. They also need to allow for the effects of preferences and supply when establishing the relationship between expenditure requirements and need factors.

The **needs factors** are likely to include:

- Age and sex
- Marital status
- Impairment, disability, chronic conditions
- Environment, e.g. housing
- Informal care
- Health care provision (endogenous)
- Affluence
- Education/socio-economic status
- Ethnicity

2 Methods

There are broadly two alternative approaches to determining resource allocation formulae as debated in the literature (although almost exclusively referring to the distribution of healthcare

funding). An essential difference in the approaches concerns how the concept of 'need' is defined and determined.

The first is the *utilisation-based* approach (Gravelle, Sutton et al. 2003; Smith 2007; Darton, Forder et al. 2010). The central premise is that the effect of need – and differences in patterns of need between individuals – is reflected in observed patterns of utilisation: people with high levels of need will use more services/support than people with low levels of need. Importantly, this approach does not require definition of some absolute level of need, but rather the *relative* patterns between individuals. Statistical techniques (generally regression analysis) can then be used to estimate the causal effects of need and other factors on utilisation. After deciding which of the factors in the estimation are legitimately beyond the control of the public care system, the size of the effect of these factors is used as the basis for a relative needs formula.

There are three key concepts/assumptions involved with this approach. The first is that when we think about 'need' – with respect to the underlying principle of resource allocation (equal access for equal need) – we are assuming that the actual needs-related criteria that care commissioners use in their decisions about how much care to provide to people (of given assessed need) are in some sense 'appropriate'. In other words, the criteria and professional judgements that commissioners employ must be accepted as defining the concept of need. This assumption might be challenged if some externally-determined normative standard was available and current practice was found not to conform to this standard. In that case, the utilisation approach would be perpetuating existing practice, not the 'best' practice.

The second assumption is that the other, non-need, influences on final patterns of utilisation can be sufficiently accounted for in the analysis. The main other influence is the supply of care services. In particular, if current supply has been affected by factors other than need, then observed patterns of utilisation will also embody these non-need influences. We would want to identify these non-need influences in the analysis and be content that the methods employed for this purpose are robust. To complicate that issue with regard to supply, there is an important question – especially regarding social care – about whether supply should be 'removed', especially if supply factors are beyond the control of the public care system. In any case, if supply effects can be separately identified in the analysis, then any allocation formula can either incorporate these effects or not, depending on whether supply is considered to be externally determined or influenced by the care system. We revisit this issue below.

The third assumption is that we can find appropriate empirical measures of need in practice that are good indicators or proxies for the theoretical concepts of need. For example, in making decisions about meeting people's need, care staff will assess the person's level of functional impairment. We would therefore need datasets that contain variables that are good indicators of functional impairment. In practice, we can never capture *every* aspect of need. Rather, the assumption of the utilisation approach is that *unbiased* estimates of need effects can be obtained.

The second method might be called the *epidemiological* or *normative* approach. In this case, need is determined on the basis of specific normative criteria, and the measures of need populating these criteria are used directly to allocate resources (Asthana, Gibson et al. 2004; Vallejo-Torres, Morris et al. 2009; Asthana and Gibson 2011; Galbraith and Stone 2011). This approach has been described in health care and would involve using morbidity data to allocate health care resources. In particular, one option is for resources to be allocated geographically, within disease groups, on the basis of relative prevalence of the disease.

There are three key assumptions in this case too. The first is that a normative definition of need exists and is agreed nationally. In particular, this standard must be specified in a way that so that it can be implemented in an allocation formula, including the determination of the relative weight given to key elements.

The second assumption is that the need factors used in the normative criteria are measurable and are free from non-need influences. For example, if we use prevalence data, can we be sure that diagnosis thresholds are not influenced by non-need factors, such as supply?

Third, as with the utilisation approach, we need good-quality empirical datasets with the required need indicators. This can often be a particular challenge for the normative approach since it requires specific indicators, and these are not normally part of routine, administrative datasets, e.g. information on disability rates.

As regards the healthcare case, to date the vast majority of allocation formulae have used the utilisation approach. Social care formulae have thus far also been determined on this basis. In theory, if social care decision-makers were using the 'best-practice' normative criteria to determine service levels, the two approaches would produce essentially the same allocation formula. In practice, the assumptions are not all likely to hold and therefore the preferred approach becomes a second-best choice. The main judgement is whether the needs-criteria that can be inferred from a utilisation analysis are more or less robust than a practical interpretation of need and support criteria from the normative principles underpinning social care.

In the social care case, we argue that sufficiently specific normative principles are not available – there are no agreed national definitions. There is a needs-based eligibility framework that is used by local authorities, although this does allow significant room for interpretation by care managers and social workers on the ground, and for each local authority (Department of Health 2010; Department of Health 2014). This framework encompasses multiple aspects of 'need', including not only personal impairment but also concepts such as risks to safety (which includes environmental factors) and, importantly, the availability of informal care. There are also financial means-testing rules (which are highly specific for residential care) which apply to determine access to the publicly-funded care system (Department of Health 2010; Department of Health 2014).¹

However, these criteria are not in a form that allows a direct synthesis of a normative allocation rule for the purposes of developing a resource allocation formula. A normative approach would need to determine weights for each of the main elements – personal impairment, safety, informal care and financial situation – to reflect their significance in the local population when assessing 'overall need' for an allocation formula. Particular challenges in this regard for social care are as follows. First, as social care is a *local* system, with 152 local authorities able to interpret needs-based eligibility criteria to some extent, any normative approach would need to synthesise and average-out a national set of criteria. Second, setting out specific rules for how much need can be met by informal care has proved to be extremely difficult and controversial in other countries. Those countries that have adopted an entitlement-based care system – usually a long-term care (social) insurance system – which requires explicit criteria, have had to make the system 'carer-blind', so avoiding this problem (Fernandez and Forder 2012).

The practical limitations of the (full) normative approach are therefore significant in social care, and this approach was not used in this study. However, given that the aim of this work was to estimate formulae for the new responsibilities, a pure utilisation approach was also not applicable (as there

¹ See section 6.119.

are not specific utilisation data). Rather, we adopted a *hybrid* analysis, using utilisation data and methods, combined with (normative) prevalence-based simulation for predicting financial eligibility for either LA care support or DPA.

In the case of the assessment formula, we compare the results of the *hybrid* approach with results generated by an entirely different method, more akin to a normative approach (i.e. the *microsimulation-based* approach).² This comparison indirectly informs us about the degree to which the assumptions of the two approaches were met. We could not directly test assumptions of the hybrid approach – for example, that utilisation data can reveal needs – because we lack a (full) set of normative criteria by which to make this judgement. Nonetheless, we did conduct a range of sensitivity analyses to assess the significance of making different assumptions.

By using utilisation data, it was important to identify supply effects. We used indicators of social care provider capacity in the analysis of utilisation. Since supply might also be affected by the level of demand for services in any locality, other things being equal, we also used an estimation method (instrumental variables) that can account for this potential circularity. We tested a range of different ways to account for supply effects.

Previous studies to develop relative needs formulae in social care have generally adopted a utilisation approach, using data on the support that local authorities currently provide, and establishing (using statistical models) the relationship between exogenous need variables and the amount of that support (Darton, Forder et al. 2010).

In this case we are concerned with new forms of support, and therefore lack data on actual level of support. Nonetheless, we can assume that the relative needs for these new forms of support is directly proportionate to the number of people that would satisfy the need test. This ‘information’ is embodied in current patterns of service utilisation.

The specific aim is to determine the relative proportion of the national cost of assessments and DPAs that each LA will need to fund. Eligibility for both these forms of support will be determined by a needs test. Neither will be subject to the current financial means-test for social care, although DPAs will be subject to new financial eligibility conditions.

As regards needs-based eligibility, current datasets provide a range of indicators of need (and different aspects of need), such as benefit claimants’ rates, physical impairment rates in population, age, sex and so on. These need factors will determine whether a person satisfies the need test. The problem is that the need test embodies a combination of needs-related conditions. We might in principle use just a single need factor, e.g. the size of the local older population, but this approach would almost certainly not capture all relevant factors. What we require is a way of combining these indicators into a single *index of need* for each LA. One way of doing this is to model the current social care needs test. We can see how far these factors explain current social care utilisation (service user numbers) by LAs, using regression analysis. A formula for a relative needs index can be estimated on this basis. If we assume that the need for assessments and DPAs is proportionate to this index, then the index can directly serve as a basis for determining funding shares that should go to each LA.

² The *microsimulation-based* approach uses (individual) survey data to directly model the inter-play of need (measured by ADLs) and wealth, making assumptions about eligibility. To determine the amount of support and the impact of informal care, it uses an analysis of (the utilisation of) social care packages. See Fernandez and Snell (2018).

The limitation with using social care provision is that utilisation of support reflects both the current financial means-test and current supply patterns, as well as needs factors.

These influences need to be ‘cleaned’ from the social care utilisation data because they have no basis to inform a *relative needs* formula about assessments and/or DPAs. Leaving these factors in such a formula (e.g. using the current relative needs formula) will bias the results.

As mentioned, allocation formulae can either incorporate supply factors or not, depending on whether supply is considered to be externally determined or influenced by the care system. Because LAs are able to manage local markets to some extent, we do not consider supply to be exogenous. Therefore, supply effects are ‘cleaned’ by including a supply variable directly in the regression analysis. The relative effect of supply is then removed by setting this variable to a constant for all LAs.

The financial means-test is more difficult to clean because it is determined by variables that also explain need, i.e. living alone and income/income benefits. If we set all relevant financial indicator variables to a constant for each LA, we risk under-measuring some important aspects of need differences. One way to tackle this problem is to estimate the effect of relevant financial indicator variables on a *simulated* version of the current financial eligibility test. In theory, the relative contributions of financial indicator variables can then be removed from the estimated need test. One of the steps needed in this process is to calibrate this adjustment. For this purpose, we select one of the financial indicator variables that is least likely to also reflect need and then set this value to zero in the need formula. In this analysis we selected home ownership rates as the calibration variable.

Simulation can also be used to model the new DPA financial eligibility test. In the same way as above, the results can be used in combination with the needs test to determine likely up-take patterns for DPAs in each LA. By estimating the relationship between these expected up-take patterns and relevant exogenous factors, we have a basis for estimating a relative needs formula in the DPA case.

One of the important benefits of using existing local authority-funded services for estimating relative need is that this avoids problems of out-of-area placement. Many LAs, but particularly those in London, have some residents placed in care homes outside the LA boundaries. The public costs of care for these people generally remains the responsibility of the referring LA. We use data on what LAs spend, not on what services are used within the local authorities, so precluding this issue.

In what follows we outline the analytical framework, discuss data and methods and then provide results. Finally, relative needs formulae are presented.

3 Key concepts

The principle of formula allocations is that local authorities are compensated for externally driven cost variation. In applying this principle, we need to be able to determine what factors are considered external, and so beyond the control of the local authority, and which are not. The *needs-related characteristics* of the local population can generally be regarded as external. These characteristics would include indicators of population disability, health, age and age and gender mix, income and wealth characteristics and so on. Needs factors are the core variables in relative needs formulae and would be expected to account for most of the difference in care utilisation patterns between councils.

Some other factors, such as council preferences about setting local eligibility thresholds, are clearly within council control and should not be ‘controlled for’ in the formula. But other factors are between these two cases. At least three merit further discussion in the context of this analysis.

The first is the supply of care services. Most LAs commission services from independent sector providers, and so do not have direct control over that form of supply. Nonetheless, LAs do have powers to directly provide services and are able to manage local markets to some extent. For this reason, we did not treat supply conditions as exogenous in developing relative needs formulae. Relevant factors were included in the underlying analysis to account for supply effects, and so identify need, but these were factors set to their national average and treated as a constant in the RNFs.

The second consideration relates to factors that drive demand or individual preferences for services, where differences in demand can lead to variation in use of service beyond that expected on the basis of (eligible) need alone. In other words, while a certain number of people in an area might be eligible for support, the actual number of people taking up support could differ. Local characteristics such as information, wealth etc. can explain differences in demand. Again, in this paper we did not include these factors in the formula because they are at least in part affected by LA policies. In particular, LAs operate with need-assessment criteria with regard to publicly-funded care, including the new responsibilities. As a consequence, for example, any people/families with preferences such that they enter residential care earlier than indicated by LA assessment criteria (by self-funding), would not be eligible for DPAs (or for metering towards the cap).

Preferences for care might lead to under-utilisation of care relative to eligible levels in some cases. But again, LAs may be able to influence these factors. Moreover, it would not seem appropriate to have a formula that rewards under-utilisation of care relative to eligible levels. Also, more pragmatically, behavioural effects are very hard to anticipate and model. For example, there are no sound data or theoretical models on which to predict demand for assessments or DPA, as opposed to the numbers who might meet eligibility criteria for these forms of support.

A third factor relates to rurality or population sparsity. The main argument is that the costs of providing could be higher in rural areas than in urban areas. Formula funding directly accounts for differences in wage-driven unit cost by applying the area cost adjustment on top of the relative needs formula. However, differences in the costs of delivering services can also affect the amount of supply, not just the unit cost. For example, in areas with low labour costs and/or low transport costs, the supply of non-residential care would be higher than in high-cost areas, other things being equal. As outlined above, we need to isolate supply from need differences and therefore should include supply indicators. For residential care, we did have a direct measure in the form of the total number of available places in care homes in the area. We did not have a similar variable for non-residential care. Rather, we included population density (population per hectare). In treating this variable as a supply indicator, it was used in the underlying analysis but was not incorporated into the relative needs formulae. There could be an argument that rurality implies some direct need effect. Nonetheless, in theory, the other direct need proxies used in the analysis should account for this effect.

The general approach was not to include factors in the formulae unless they were clearly considered to be external. The concern otherwise is that by including factors that could be affected by LA policies, the amount of 'compensatory' funding an LA receives would become partly under its control. As such, formula approaches have tended to take the most parsimonious route and only include factors if they are unambiguously exogenous. But ultimately this is a design philosophy.

The methods used in this study and the related assumptions are summarised in Box 2.

Box 2. Methods and key assumptions

Methods:

- **Hybrid** approach using a combination of *utilisation* data and methods, but (normative) *prevalence-based* simulation for predicting financial eligibility.

Key assumptions:

- The assessment criteria used by care commissioners are appropriate for determining social care needs.
- Other (non-need) influences on final patterns of utilisation (e.g. supply of social care services) can be sufficiently accounted for in the analysis.
- Available data include appropriate measures of need (e.g. rates of Attendance Allowance uptake, rates of limiting long-standing illness in population, etc.) that are good indicators for the theoretical concepts of need and allow the estimation of *unbiased* need effects.
- Individual level characteristics of people in each small-area population (i.e. LSOA) are similar.

Additional assumptions:

- Older people aged 75 and over and needing help with at least one activity of daily living (ADL) have eligible needs according to LA assessment
- Individuals with assets just above the capital limit have the same behaviour and are assessed consistently across all LAs

4 Analytical framework

The two tests that determine access to LA-supported social care for each person are: the needs test and the (financial) eligibility test. For shorthand, we can abbreviate the former as R and the latter as E . Our aim was to determine the nature of the LA needs test R and, in particular, to estimate the probability that a person satisfies this test. Again as a shorthand, we can denote this probability as $p(R)$. With a suitable measure of this probability, we could use a statistical model to determine how it is affected by relevant exogenous factors that are available in routine data sets. In other words, this would give an equation for need comprising variables as given in Box 1, as we require.

We did not, however, have a *direct* measure of this probability. The number of people that are LA-supported is directly available and this number will depend on this probability, but it also depends on the probability that those people also meet the means-test (E). Also, we could not simulate the needs test even if we had a suitable dataset, because the needs test guidance is insufficiently precise and subject to local interpretation (Fernandez and Snell 2012). Any decision we would make on the criteria and threshold(s) to use for simulating a needs test would be rather subjective, and ultimately affect the geographic distribution of simulated 'need' (i.e. the estimated number of individuals in each LA who passed the subjectively chosen needs threshold). We could, however, estimate this probability indirectly.

Any person that actually receives LA-funded support will have satisfied both tests. For an individual, the probability of doing this is $p(R + E)$. With data on the proportion of people that are LA-supported, we had an estimate of this joint probability and we know that this joint probability encompasses the two probabilities of satisfying each individual test. The problem was that the probability of meeting these tests is not independent across a population. A person who has high needs is also more likely to have lower financial means, for example. As such, the joint probability of a person passing both tests is their probability of being in need times their 'conditional' probability of satisfying the financial means test *given that they have eligible needs*. This equation can be rearranged as:

$$p(R) = p(R + E)/p(E|R) \quad (1)$$

i.e. the probability of people with care needs is equal to the probability of people both in need and eligible divided by the probability of those people in need being eligible.

With suitable measures for $p(R + E)$ and $p(E|R)$ the above ratio could be used to calculate a measure of $p(R)$. In turn, a need equation could be estimated using routinely available needs data (as in Box 1).

As noted, the joint probability of satisfying need and eligibility tests could be measured using data on the numbers of people using LA-supported care. We also needed an estimate of the (conditional) probability of passing the financial eligibility test, given the person having assessable need $p(E|R)$, when using this method. As with the need test, we could not directly observe the numbers of people that satisfied this test from utilisation data because that is the result of both tests. But instead the financial eligibility test could be simulated by approximating the eligibility rules in a sample dataset. Because the eligibility rules are formulaic and explicit (especially for residential care), the eligibility of a person with given characteristics can be calculated, as least to a reasonable degree of approximation.

For this purpose, we needed a dataset with relevant variables enabling us to most closely simulate the eligibility test. Furthermore, the dataset should have need variables. The English Longitudinal Survey of Ageing (ELSA) data were considered to be most suitable.

A range of variables captured in ELSA – such as people’s housing and non-housing wealth, whether they owned a home, whether they lived alone, their income and level of disability – were used. The relevant variables are not available in routine datasets at the local authority level and so eligibility cannot be directly established with routine data. Rather, we used variables that are available in both ELSA and routinely as predictors of financial eligibility so as to have predicted numbers of people that are eligible at the area level.

The result of these calculations was a (linear) equation predicting need:

$$\hat{p}(R) \cong \alpha_0 + \alpha_1x + \alpha_2y + \alpha_3s \quad (2)$$

where the terms in the equation are: need proxies, x , wealth proxies, y , and supply, s , and the coefficients are the α s. It remained to set the supply variable to its national average value to give a relative needs equation that can be applied at local authority level. Traditionally RNFs are provided as linear formulae that apply at the LA level. Adding up the individual probabilities for all people in an LA, this formula becomes:

$$C_l^R = \alpha_0^R + \alpha_{11}^R X_{1l} + \alpha_{12}^R X_{2l} + \dots + \alpha_{21}^R Y_{1l} + \alpha_{22}^R Y_{2l} \dots \quad (3)$$

where C_l^R is the predicted number of people in each local authority (as denoted by the subscript l) with an assessable level of need i.e. $C_l^R = \sum_i \hat{p}_i(R)$ when expressed mathematically. This equation has various need and wealth proxies: the X s and Y s being the numbers with need or with given wealth at the local authority level, added up from their individual person values, x and y . The derivation of these equations is given in annex A1.

4.1 Assessment formula

A relative needs formula (RNF) for total assessments would be based on (3) where R is the (LA-assessed) need for social care. It would be used to determine the proportion of the total England number of assessments arising in each LA. We can assume that the number of assessments is a fixed

multiple of the number of people with any need (e.g. σC_l^R). For a relative needs formula which determines the shares of total assessments arise in each LA, the multiplier drops out.

A similar approach can be used for additional assessments, i.e. above those already carried out by LAs. The number of LA-supported clients is subtracted from the total number with need C_l^R , and the difference is used to calculate relative needs shares.

4.2 Deferred payment agreements

A person's overall eligibility for a DPA is determined by the LA need test (for residential care) and also a new financial test. An important condition is that a person must have non-housing assets (savings) below a certain level. We have assumed this threshold to be £23,250 in line with the main support eligibility test. Anyone with more than £23,250 in assessable non-housing capital is not eligible. Also, the amount of a DPA will depend on the person's income.

Another important criterion is that the person has assessable property: i.e. is a home owner in circumstances where the value of the home can be taken into account. In the main, the latter requires that no (eligible) dependants live at the home.

As with the means-test E above, our approach was to simulate this DPA financial test. In lieu of actual regulations we approximated the eligibility conditions, applying these criteria according to the characteristics of people in the ELSA dataset. The main variables for this purpose were measures of people's non-housing wealth, whether they owned a home and whether they lived alone. Income will also have a bearing. For example, people with high levels of income and modest non-housing wealth may not be eligible for a DPA. Nonetheless, relevant groups of people so affected will be small and ignorable for the purposes of establishing relative needs.³

The relevant variables determining DPA eligibility are not available in routine area-level data and so this eligibility cannot be directly established at area level. Rather, routine need and wealth variables were used in ELSA to predict the numbers of people calculated to be eligible and those not eligible at area level.

As above, we can define the eligibility condition D for a DPA. This includes a requirement that the potential recipient also owns a home. The probability of a person being financially eligible for a DPA (conditional on need) is $p(D|R)$. The probability of a person satisfying both the need test and being financially eligible was calculated as:

$$p(R + D) = p(R) \times p(D|R) \quad (4)$$

This calculation used the estimate of $p(R)$ as outlined above.

With analogy to the assessment formula, we used statistical models to estimate a formula predicting the number of people in each LA, using routine need and wealth variables:

$$C_l^{R+D} = \alpha_0^{R+D} + \alpha_{11}^{R+D} X_{1l} + \alpha_{12}^{R+D} X_{2l} + \dots + \alpha_{21}^{R+D} Y_{1l} + \alpha_{22}^{R+D} Y_{2l} \dots \quad (5)$$

5 Empirical analysis

Two datasets were used. First, we constructed a (small) area dataset comprising data on the numbers of LA-supported clients, as well as routinely-available need and wealth variables such as

³ The proportion of these people is strongly correlated with housing wealth, and the relative differences in this proportion between LAs, after accounting for the effect of different levels of housing wealth in the population, will be very modest.

rates of benefit uptake and Census variables. These data were collected initially at the lower super-output area (LSOA) corresponding to a final sample of 53 LAs, with around 14,000 LSOAs – see annex A2 for details. As LSOAs are coterminous with local authority boundaries, these data could also be aggregated to form a LA-level dataset with the same variables.

The second dataset was the English Longitudinal Survey of Ageing (ELSA). This dataset has a wide range of data about individuals in the survey, including information about their needs-related characteristics and their wealth and income, including benefit uptake.

5.1 Estimating financial eligibility

Financial eligibility for LA support was modelled using the ELSA data. Specifically we set condition E as follows:

$$\begin{cases} E = 1 \text{ if } NHW + HW \times alone < \pounds 23,250 \\ E = 0 \text{ if } NHW + HW \times alone \geq \pounds 23,250 \end{cases} \quad (6)$$

where NHW is non-housing wealth and HW is housing wealth, where the latter only applies if people live alone (*alone*).

Five waves of ELSA were combined (with financial variables inflated to be in line with the last wave). The sample of people aged 65 and over (or 65+ in shorthand) was selected. This provided 25,420 observations for people aged 65+. These data were then reweighted so that rates of home ownership, living alone and pension credit uptake were in line with those rates in the LSOA data.

We estimated a linear regression model⁴ over a sub-sample of people with at least one ADL and aged 75 or over – chosen pragmatically after experimentation to include a sufficiently large sample size. Both need and wealth factors were used in the estimation:

$$p(E|R) = \beta_0^E + \beta_1^E x^E + \beta_2^E y^E + \epsilon^E \quad (7)$$

The following variables were included, based mainly on the criteria that they are routinely collected at small area level, have a proved relation to social care needs, and are exogenous:

Need x^E :

- Attendance Allowance claimant
- Age 75 to 84 (as opposed to Age 85+)
- Living arrangements: lives alone
- Female

Wealth/income y^E :

- Home owner
- Pension Credit claimant

The resulting estimation could be applied to (small area) populations by treating individual level variables as rates per capita 65+.

Financial eligibility for a DPA was also simulated in ELSA using the rules outlined above:

$$\begin{cases} D = 1 \text{ if } HW \times alone > 0 \text{ and } NHW < 23,250 \\ D = 0 \text{ if } HW \times alone = 0 \text{ or } NHW \geq 23,250 \end{cases} \quad (8)$$

Since being a home owner and living alone are dominant factors in this DPA means test, we estimated this condition in two parts in the ELSA data:

⁴ Specifically, a linear probability model using OLS.

$$p(D|R) = p(\text{own, alone, need}) \times p(\text{NHW} < 23,250) \quad (9)$$

Administrative data (Census) give both home ownership rates per 65+ and living alone rates 65+ in any population, but do not give the combined chance of being a home owner, living alone and with some care need. Instead, we first used a model in ELSA to predict how the joint probability of being alone and a home owner varied with a number of need and wealth proxies. The estimation results were then used to adjust the area-level home ownership and living alone rates in the population, using need and wealth proxies. This approach is based on the expectation that the number of people in an area who are jointly a home owner, live alone and have care needs is correlated with the independent rates of these variables in the population.

The second step was to estimate the probability of having sufficiently low non-housing wealth (NHW) to qualify, conditional on being a home owner, living alone, and having a care need, i.e.

$p(\text{own, alone, need}) = 1$. In this case the living alone (*alone*) and home owner (*own*) variables were directly available. Having a care need was indicated if the person reported at least one problem with activities of daily living in ELSA.

Two regression (OLS linear probability) models were used for these two steps, with analogy to (7), and used similar need and wealth variables.

5.2 Estimating need eligibility

Small area data were used to approximate the experience of individuals while offering a means to link datasets, specifically local authority records, Census data, DWP Benefits data, CQC data and a number of ONS variables.

The individual person-level probabilities discussed above in the analytical framework can be approximated by the proportion of people in the LSOA population aged 65 and over that meet the relevant test(s) – e.g. the proportion of people 65+ in receipt of LA-supported social care for $p(R + E)$. Or for relevant exogenous factors, e.g. the proportion 65+ who live alone, are in receipt of pension credit and so forth. Equivalently, the count of people satisfying the condition could be used in the analysis after we multiplied by the LSOA population 65+. Annex A1 provides further details.

In generalising in this way, we needed to assume that the respective probabilities of individual people meeting eligibility tests was about the same as others in same population within the small area. This assumption seems reasonable if the relevant characteristics of people in that population are also similar. For this reason, we used as small a population level as possible for the analysis: namely LSOA populations; LSOA are designed to be homogeneous by dwelling type and tenure. We also selected only the LSOA population aged 65 and over.

The general method used involves calculating the expected counts of people in each LSOA who satisfy the relevant ‘test’ condition – i.e. either need and financial means tests $R + E$, need-only, R , and need plus DPA eligibility, $R + D$ – and then using a regression model to determine the relationship between these counts and LSOA population rates of relevant (routinely-available) need, wealth and supply factors.

A standard set of variables was included in each estimation. They can be grouped by primary variable type: need, wealth and supply. The variables included passed several rather restrictive inclusion criteria: they are measured and updated routinely at small area level, have a demonstrable link with social care needs, and are outside the influence of local authorities. After experimentation, a range of explanatory variables, such as age groups and gender, did not prove to be statistically significant in any specification and so were not used. We also scaled the estimation by population 65+ and

accounted for LA fixed effects in order to control for any non-need effects at LA level (e.g. differences in commissioning practices, local area characteristics, data collection methods and quality, etc.).

Need x:

Attendance Allowance claimants 65+ per capita 65+

Limiting (significantly) condition 85+ per capita 65+

Living arrangements: couples per households 65+

Population (all) density (LSOA) [Sparsity]

Wealth/income y:

Home owner 65+ per Households 65+

Pension Credit Claimants 80+ per capita 65+

Supply, s:

Total care home beds per MSOA per MSOA pop 65+

Population/scale:

Population 65+ (log)

Annex A2 describes the data sources and basic data manipulation used for the small area analysis.

A range of age group and gender variables was tested but did not prove to be statistically significant in any specification and so were not used.

Population density (total population per hectare) was used to measure any effects of sparsity (low population density). Total care home beds per capita was used as a supply measure. It was used for both residential and non-residential estimations, where we expect a positive effect on the former and a negative effect on the latter. Because supply could also be affected by need levels, it was important to isolate supply effects. For this reason, rather than use number of beds at the LSOA level, we used for each LSOA observation the total number of beds in the corresponding middle-layer super-output area (MSOA); there are 6,791 MSOAs in England compared with 32,844 LSOAs.⁵ There is still a possibility that this supply variable could affect estimated coefficients for relative need, but the standard diagnostic test for this problem was negative at the 5 per cent significant level.

In the models we included the supply variable directly. We also tested for endogeneity of supply variables, but the results – which are reported in annex A3 – did not suggest that our supply variable was simultaneously affected by demand for services. This result is likely to have arisen because we are using an aggregated supply variable.

LA fixed effects were modelled to account for (a) differences in policy and efficiency between LAs and (b) differences in data collection methods and quality. As to the latter, in the residential care data there were a number of LAs that had some problems in identifying pre-care addresses (LSOAs), giving us data with missing values. We dropped LAs where this problem was significant. Another issue was that some LAs appeared to select clients for the downloaded data in a way that was inconsistent with their RAP/ASC-CAR returns. In other words, the LA-level total clients differed from the number reported in RAP/ASC-CAR. The inclusion of LA fixed effects in the models should deal with this latter problem, although we also ran models with some excluded LAs where differences were substantial. In the main, this made relatively little difference to the results.

Regarding the non-residential care data specifically, there appeared to be a higher degree of inconsistency in the data supplied by LAs on total counts of service users for all non-residential service types. For this reason, we also estimated models where we simply added home care and

⁵ MSOAs and LSOAs are coterminous.

direct payment service users together. As shown in the results below, there was relatively little difference in terms of the formulae produced.

The particular econometric models used in the analysis are described below. In general, we opted to use an (exponential) count (of service users) models, given the nature of the data. We can hypothesise about the underlying interplay of demand and supply which leads to an (integer) number of clients in any given area. We observe the latter number in the data rather than the underlying (continuous) probabilities, making non-linear count models the more appropriate statistical estimation method.

Although a third of LSOAs had zero residential care (supported) service users, this is likely to be a characteristic of the small size of some LSOAs (where the count data are integers) rather than there being a different underlying process for whether an LSOA has any service users and the subsequent number of service users in that LSOA. As such, a count model (as opposed to a two-part model) is likely to be most appropriate. For non-residential care, only 3.7 per cent of sample LSOAs had zero clients.

5.3 Assessment and DPA estimations

A relative needs function for assessments was estimated for both people with a residential care need and with a non-residential care need. The following steps were repeated for each case:

1. We estimated the probability that a person satisfies the financial means-test (E) using ELSA with variables that are also available at (small) area level.
2. We estimated the number of people in an LSOA that have LA-supported services – i.e. that satisfy both need and financial means-test ($R + E$) – with need, wealth and supply variables. Data for the dependent variable were provided directly by participating LAs at LSOA level.
3. The predicted values from these two estimations (steps 1 and 2) were used to calculate the number of people in an LSOA that would pass the needs test (only) (R).
 - a. We removed LA fixed effects and supply effects using their national average values from the estimation at step 2.
 - b. The predicted probability for each person with care needs in the LSOA of satisfying the financial means-test was calculated using the equation estimated at step 1. As outlined in the introduction, we needed to calibrate between the two sets of estimation results. We did this by scaling all the coefficients in this equation using a common factor so that the net effect of home ownership on the numbers of people satisfying the need test was zero.
4. A regression model was used to estimate an equation for the number of people in an LSOA that would pass the needs test (only) (R) (as determined at step 3) in terms of need, wealth, supply and (population) scaling variables.
5. Statistical error for the process in steps 2 to 4 was estimated (using bootstrapping methods).
6. A linear approximation was calculated for the coefficients from the equation in step 4. This involved calculating the change in the dependent variable (numbers with need R) for small changes in each need and wealth variable from their sample mean values.

An additional assessment formula can be created by subtracting the (linearised) equation for LA-supported clients ($R + E$) (step 2) from the linear equation for numbers of people passing the need test (R).

The DPA formula was produced in a similar way using steps 1 to 6. In this case, the predicted value of DPA eligibility (D) was also applied at step 3 to produce a value for the expected count of DPA-eligible people in each LSOA.

6 Estimation results

6.1 Descriptive statistics

Descriptive data and sample sizes for the models are given in Table 6 (residential care) and Table 7 (non-residential care). The respective variable mean values are compared to the national values. In the main, both estimation samples appeared to be very similar to the England values, suggesting high representativeness.

Table 6. Representativeness of sample viz. National England averages: LSOA level means for various samples

	National		Res care sample		
	Obs	Mean	Obs	Mean	% national
Attendance Allowance claimants 65+ per capita 65+	32697	0.16	13805	0.15	97%
Limiting (significantly) condition 85+ per capita 65+	32843	0.06	13805	0.06	98%
Home owner households 65+ per households 65+	32843	0.64	13805	0.66	102%
Pension Credit Claimants 80+ per capita 65+	32697	0.09	13805	0.08	93%
Living arrangements: couple households per HH 65+	32843	0.44	13805	0.45	102%
Population (all) density (LSOA)	32844	43.09	13805	40.56	94%
Population 65+ (log)	32843	5.51	13805	5.54	100%
Total MSOA care home beds per MSOA pop 65+	32844	0.04	13805	0.04	99%
Population 65+	32844	275.74	13805	282.73	103%
Females 65+	32844	152.34	13805	155.69	102%
Population (all)	32844	1628.72	13805	1626.05	100%
Households 65+	32844	174.21	13805	177.32	102%

Table 7. Representativeness of sample viz. National England averages: LSOA level means for various samples

	HC + DP sample			All non-res care sample		
	Obs	Mean	% national	Obs	Mean	% national
Attendance Allowance claimants 65+ per capita 65+	13373	0.16	99%	13251	0.16	99%
Limiting (significantly) condition 85+ per capita 65+	13373	0.06	99%	13251	0.06	99%
Home owner households 65+ per households 65+	13373	0.66	102%	13251	0.65	101%
Pension Credit Claimants 80+ per capita 65+	13373	0.08	96%	13251	0.09	97%
Living arrangements: couple households per HH 65+	13373	0.44	101%	13251	0.44	101%
Population (all) density (LSOA)	13373	40.65	94%	13251	41.50	96%
Population 65+ (log)	13373	5.53	100%	13251	5.53	100%
Total MSOA care home beds per MSOA pop 65+	13373	0.04	100%	13251	0.04	99%
Population 65+	13373	280.94	102%	13251	280.93	102%
Females 65+	13373	155.11	102%	13251	155.05	102%
Population (all)	13373	1629.17	100%	13251	1630.95	100%
Households 65+	13373	176.30	101%	13251	176.39	101%

6.2 Count models

The following three tables give the results of the main models: that is, the predicted number of clients in an average LSOA with the specified combination of needs characteristics. The results are

provided for each condition to be satisfied and respectively for residential care, home care plus direct payment clients, and all non-residential care. In each case, the table lists the relevant condition:

- Those people satisfying the LA need and eligibility tests, i.e. those clients who are LA-supported
- Those people satisfying the LA need test, regardless of eligibility (the basis for calculating total assessments)
- Those people satisfying the LA need test and qualifying for a DPA.

Table 8. Residential care client numbers (per LSOA), various conditions, bootstrapped

	Need + Elig (LA-supported clients)		Need (All clients)		DPA	
	Coeff	Z-stat	Coeff	Z-stat	Coeff	Z-stat
Attendance Allowance claimants 65+ per capita 65+	2.106***	5.70	2.256***	5.71	2.463***	6.17
Limiting (significantly) condition 85+ per capita 65+	1.278**	2.27	1.113*	1.87	0.553	0.89
Home owner households 65+ per households 65+	-0.424***	-2.98	0.000	0.00	1.795***	13.25
Pension Credit Claimants 80+ per capita 65+	2.023***	4.87	1.691***	4.09	1.871***	4.26
Living arrangements: couple households per HH 65+	-0.654***	-4.57	-0.801***	-5.68	-3.381***	-24.57
Population 65+ (log)	0.845***	30.72	0.850***	29.57	0.811***	26.19
Total MSOA care home beds per MSOA pop 65+	0.856***	3.92				
Constant	-4.612***	-20.61	-4.337***	-19.27	-6.027***	-21.64
Log-likelihood	212833.75		20877.63		22309.27	
Number of observations (LSOAs)	13806.00		13805.00		13805.00	

Table 9. Non-residential care, home care + direct payments: service user numbers, various conditions, bootstrapped

	Need + Elig (LA-supported clients)		Need (All clients)	
	Coeff	Z-stat	Coeff	Z-stat
Attendance Allowance claimants 65+ per capita 65+	1.610***	9.04	1.392***	8.31
Limiting (significantly) condition 85+ per capita 65+	4.189***	11.74	4.618***	12.77
Home owner households 65+ per households 65+	-0.443***	-6.85	0.000	0.00
Pension Credit Claimants 80+ per capita 65+	2.170***	7.61	1.082***	3.64
Living arrangements: couple households per households 65+	-0.763***	-6.17	-0.591***	-4.75
Population (all) density (LSOA)	0.001***	5.87	0.001***	6.47
Population 65+ (log)	0.933***	29.23	0.931***	26.70
Total MSOA care home beds per MSOA pop 65+	-1.243***	-7.52		
Constant	-3.337***	-20.57	-3.276***	-17.47
Log-likelihood	182033.59		-9115.24	
Number of observations (LSOAs)	13374		13373	

All variables had the expected signs and scales of effect. Note that these are the coefficients for non-linear models. They tell us the direction and significant of effect, including supply and population scaling effects, but predict the log of the number of people satisfying the listed factor. We provide

the linear coefficients for RNFs below, which predict the number of service users per capita given the need variables in these equations.

The asterisks denote significance levels: * 10%, ** 5%, and *** 1%.

In general, the model coefficient on (log) population was close to 1 in value. This suggests that scale effects were relatively small (justifying our assumption of treating population size as a constant).

Table 10. Non-residential care, all services: service user numbers, various conditions, bootstrapped

	Need + Elig (LA-supported clients)		Need (All clients)	
	Coeff	Z-stat	Coeff	Z-stat
Attendance Allowance claimants 65+ per capita 65+	1.761***	11.05	1.629***	10.07
Limiting (significantly) condition 85+ per capita 65+	2.939***	12.71	3.257***	14.93
Home owner households 65+ per households 65+	-0.355***	-9.55	0.000	0.00
Pension Credit Claimants 80+ per capita 65+	2.114***	12.36	1.214***	6.04
Living arrangements: couple households per households 65+	-0.655***	-8.01	-0.529***	-6.16
Population (all) density (LSOA)	0.001***	7.22	0.001***	5.86
Population 65+ (log)	0.889***	34.29	0.890***	29.61
Total MSOA care home beds per MSOA pop 65+	-0.803***	-6.16		
Constant	-2.434***	-14.55	-2.320***	-10.03
Log-likelihood	171093.51		-14015.02	
Number of observations (LSOAs)	13252		13251	

6.2.1 Model performance: prediction correlations

The regression models used in the above estimations are non-linear to account for the nature of the data and do not produce the 'r-squared' goodness-of-fit statistics of standard (OLS) estimation. Nonetheless, we can assess the correlation between the data on LA-supported clients and the number of such clients predicted by the statistical model. Table 11 has these results. In general, the two non-residential care models were more closely able to predict the actual number of LA-supported clients.

Table 11. Correlations between actual and predicted LA-supported clients

	Model		Correlation, r	r-squared	n
Residential	Table 8, need + elig	With area dummies	0.55	0.30	13806
		Without area dummies	0.45	0.20	
HC + DP	Table 9, need + elig	With area dummies	0.69	0.48	13374
		Without area dummies	0.62	0.39	
All NR	Table 10, need + elig	With area dummies	0.81	0.66	13252
		Without area dummies	0.62	0.38	

6.3 Eligibility models

Table 12 reports the estimation models for whether a person satisfies (simulated) financial eligibility, using the ELSA data. With a linear probability, the coefficients can be interpreted as the change in the probability of being eligible of having the listed condition. For example, being female was associated with a 6.4 per cent increase in the likelihood of being eligible, other things being equal. As expected

given the nature of the means-test, being a home owner was found to mean a person being significantly less likely to be eligible for LA supported care, especially for residential care. Being in receipt of pension credit was associated with a significantly increased chance of being eligible in both cases. Living alone reduced the probability of being financially eligible for residential care because in that case the home can normally be counted as an assessable asset.

In these estimations we included both 9-category region dummies and ELSA wave dummies.⁶

Variants with additional interaction terms – e.g. Lives alone and home owner – produced very similar results.

The results of these models were applied at small area to predict the share of financially eligible people with social care need in the population aged 65 and over. Predicted values for all models were in the range [0, 1].

Table 12. Financial eligibility estimation, OLS models

	Non-residential care		Residential care	
	Coefficient	Z-stat	Coefficient	Z-stat
Female	0.064	3.37	0.002	0.13
Aged 75 to 84	0.002	0.12	0.020	1.46
Home owner	-0.268	-10.87	-0.602	-28.98
In receipt of pension credit	0.274	11.44	0.421	11.33
Lives alone	-0.022	-0.94	-0.206	-10.84
Home owner x pension credit	0.275	10.98	-0.163	-5.9
Lives alone x pension credit	0.013	0.57	-0.178	-5.07
Constant	0.691	16.96	0.909	24.74
Wave dummies	Yes		Yes	
Area dummies	Yes		Yes	
Weighted	Yes		Yes	
n	3693		3684	
F	104.62		407.99	
R ²	0.293		0.527	
Condition				
Age	>=75		>=75	
ADLs	>0		>0	
Live alone	Any		Any	
Home owner	Any		Any	

Table 13 gives the equivalent eligibility results as regards DPAs. As outlined above, we used a model in ELSA to predict how the joint probability of being alone and a home owner varied with a number of need and wealth proxies (column 3). Conditional on being a home owner, living alone and in need,

⁶ Approximately 0.12 per cent of the sample had missing region codes. The missing values were included in the dummy variable reference category. Excluding these cases made no material difference to the results (e.g. only small changes at the 3rd decimal place).

the risk factors for a person being financially eligible for a DPA were also modelled (column 2). As anticipated, people in this sub-group who were also pension credit recipients (compared to those not in receipt) were significantly more likely to qualify for a DPA in principle.

As above, these results were applied in the small areas models. Predicted values were once more in the range [0, 1].

Table 13. Eligibility conditions for DPAs, OLS models

	Home owner, lives alone		DPA financially eligible	
	Coefficient	Z-stat	Coefficient	Z-stat
female	0.015	0.48	0.157	6.63
Aged 75 to 84	-0.046	-1.47	-0.083	-3.6
Aged 85+	-0.032	-0.91		
In receipt of pension credit	0.254	8.92	-0.082	-3.93
In receipt of AA	0.061	1.91	-0.039	-1.76
Constant	0.479	8.84	0.353	7.89
Wave dummies	Yes		Yes	
Area dummies	Yes		Yes	
Weighted	Yes		Yes	
n	1560		3850	
F	5.64		6.32	
R ²	0.058		0.048	
Condition				
Age	>=65		>=75	
ADLs	>0		>0	
Live alone	Yes		Any	
Home owner	Yes		Any	

7 Relative needs formulae

As described above, we derived RNFs by holding supply, scale and sparsity constant. As such, each relative needs formula has the following variables:

- Attendance Allowance claimants 65+ per person 65+
- Limiting (significantly) condition 85+ per person 65+
- Home owner households 65+ per households 65+
- Pension Credit Claimants 80+ per person 65+
- Living arrangements: couple households per HHs 65+
- Constant

Both age and gender variables were initially included but proved not to be significant. Sparsity was not significant in the residential care estimation (but was for non-residential care).

Table 14 give RNFs for residential care. For non-residential care, RNFs are given in Table 15 and Table 16. The former is based on the analysis using home care plus direct payments-supported clients as

the indicator variable, and the latter used supported clients for all non-residential services as the indicator variable.

The condition whereby a person satisfies the need test but is not financially eligible (*Need and not eligible*) is calculated by subtracting the first column from the second column. It gives an RNF for *additional assessments*.

The DPA formula only applies in the residential care case.

Table 14. Relative needs formulae, residential care

	Need + Elig (LA-supported clients)	Need (All clients)	Need and not eligible	DPA
Attendance Allowance claimants 65+ per person 65+	0.01213	0.02072	0.00858	0.00436
Limiting (significantly) condition 85+ per person 65+	0.00736	0.01022	0.00286	0.00098
Home owner households 65+ per households 65+	-0.00244	0.00000	0.00244	0.00317
Pension Credit Claimants 80+ per person 65+	0.01166	0.01552	0.00387	0.00331
Living arrangements: couple households per HHs 65+	-0.00377	-0.00735	-0.00358	-0.00598
Constant	0.00743	0.01012	0.00269	0.00169

Table 15. Relative needs formulae, non-residential care (Home care + DP)

	Need + Elig (LA-supported clients)	Need (All clients)	Need and not eligible
Attendance Allowance claimants 65+ per person 65+	0.07983	0.09998	0.02014
Limiting (significantly) condition 85+ per person 65+	0.20773	0.33162	0.12389
Home owner households 65+ per households 65+	-0.02195	0.00000	0.02194
Pension Credit Claimants 80+ per person 65+	0.10760	0.07773	-0.02986
Living arrangements: couple households per HHs 65+	-0.03785	-0.04246	-0.00461
Constant	0.05288	0.05523	0.00235

Table 16. Relative needs formulae, non-residential care (All NR services)

	Need + Elig (LA-supported clients)	Need (All clients)	Need and not eligible
Attendance Allowance claimants 65+ per person 65+	0.08339	0.11082	0.02744
Limiting (significantly) condition 85+ per person 65+	0.13912	0.22154	0.08242
Home owner households 65+ per households 65+	-0.01681	0.00000	0.01681
Pension Credit Claimants 80+ per person 65+	0.10011	0.08257	-0.01754
Living arrangements: couple households per HHs 65+	-0.03101	-0.03596	-0.00495
Constant	0.05025	0.05650	0.00625

To provide combined formulae (residential plus non-residential clients), we weighted the individual formulae together by the respective number of total supported clients in England for residential and

non-residential services – see Table 17 based on the home care plus DP results, and Table 18 based on the results using all non-residential services. Note these are not cost-weighted and so favour the NR contribution, which has 418,000 clients versus 167,000 supported in residential care (2012/3).

Table 17. Relative needs formulae, combined res and NR (HC + DP) 65+

	Need + Elig (LA-supported clients)	Need (All clients)	New Assessments (i.e. Need and <i>not</i> eligible)	DPA
Attendance Allowance claimants 65+ per person 65+	0.06051	0.07736	0.01684	0.00436
Limiting (significantly) condition 85+ per person 65+	0.15055	0.23991	0.08935	0.00098
Home owner households 65+ per households 65+	-0.01638	0.00000	0.01638	0.00317
Pension Credit Claimants 80+ per person 65+	0.08022	0.05998	-0.02023	0.00331
Living arrangements: couple households per HHs 65+	-0.02812	-0.03244	-0.00432	-0.00598
Constant	0.03991	0.04236	0.00245	0.00169

Table 18. Relative needs formulae, combined res and NR (all non-res) 65+

	Need + Elig (LA-supported clients)	Need (All clients)	New Assessments (i.e. Need and <i>not</i> eligible)	DPA
Attendance Allowance claimants 65+ per person 65+	0.06306	0.08511	0.02206	0.00436
Limiting (significantly) condition 85+ per person 65+	0.10152	0.16124	0.05972	0.00098
Home owner households 65+ per households 65+	-0.01271	0.00000	0.01271	0.00317
Pension Credit Claimants 80+ per person 65+	0.07487	0.06344	-0.01143	0.00331
Living arrangements: couple households per HHs 65+	-0.02324	-0.02780	-0.00456	-0.00598
Constant	0.03803	0.04327	0.00523	0.00169

The calculation to determine final (Area Cost adjusted) relative need in an area is as follows:

Step 1. Calculate relative need (RN) per capita (the number of people aged 65 and over meeting the condition in the local area population 65 and over). For example, for DPAs:

RN per capita =

Attendance Allowance claimants 65+ per person 65+	×	0.00436
Limiting (significantly) condition 85+ per person 65+	×	0.00098
Home owner households 65+ per households 65+	×	0.00317
Pension Credit Claimants 80+ per person 65+	×	0.00331
Living arrangements: couple households per HHs 65+	×	-0.00598
	+	0.00169

Step 2. Calculate RN (total number for the local area in question)⁷:

$$RN = RN \text{ per capita} \times \text{population 65 and over}$$

Step 3. Apply Area Cost Adjustment (ACA):

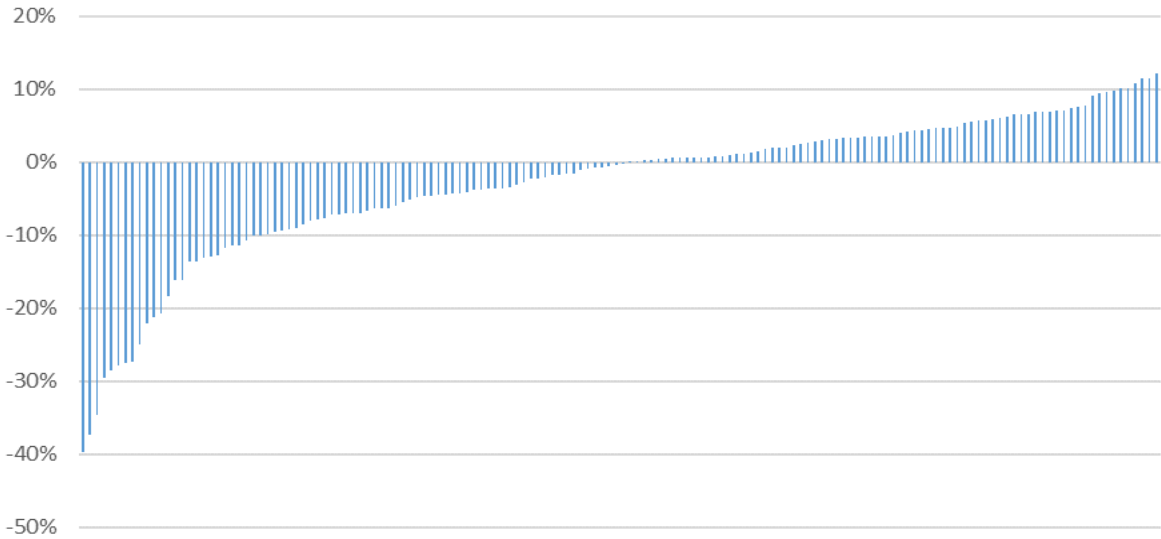
$$\text{Final RN} = RN \times ACA$$

8 Discussion

Figure 1 shows the how a formula-based allocation of resources for additional assessments would differ from an allocation that worked solely on LA population 65+ shares. Assuming the same total budget was allocated in each case, the most affected LAs at either end of the distribution would receive nearly 40 per cent less or over 12 per cent more money respectively than a population shares allocation. Figure 2 shows the corresponding comparison in allocation for the funding of DPAs. In this case, some LAs would receive over 40 per cent less whilst others would receive over 30 per cent more money than a population shares allocation.

These figures show that using relative needs formulae can make a substantial difference to an LA's actual monetary allocation, reflecting the differences in need beyond that implied by differences in older population alone between LAs.

Figure 1. Percentage difference in total monetary allocations compared to a pop 65+ allocation – additional assessments



⁷ Noting that we can dismiss scale effects.

Figure 2. Percentage difference in total monetary allocations compared to a pop 65+ allocation – deferred payment agreements

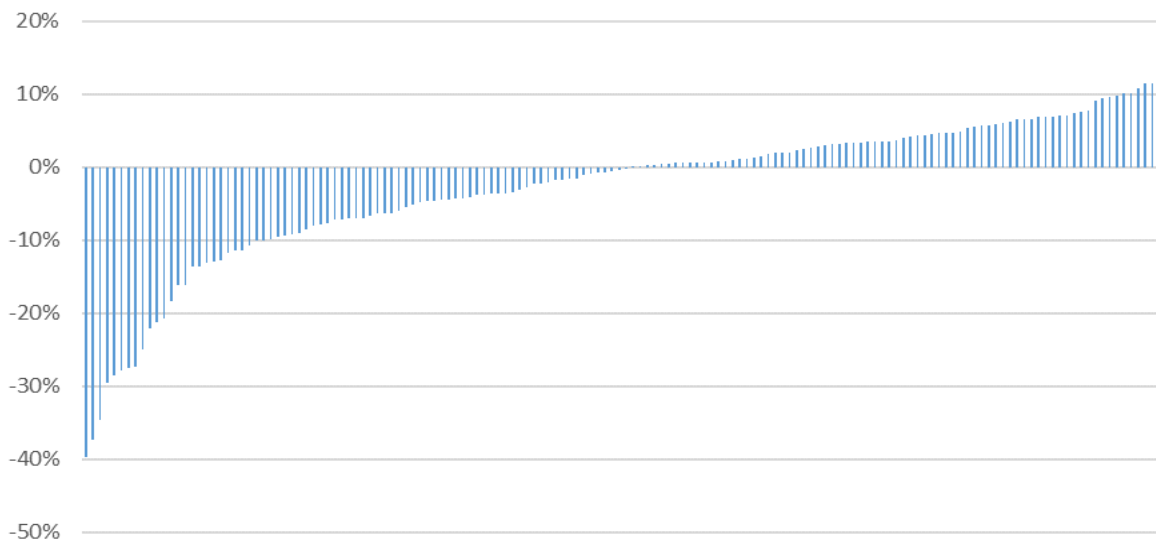
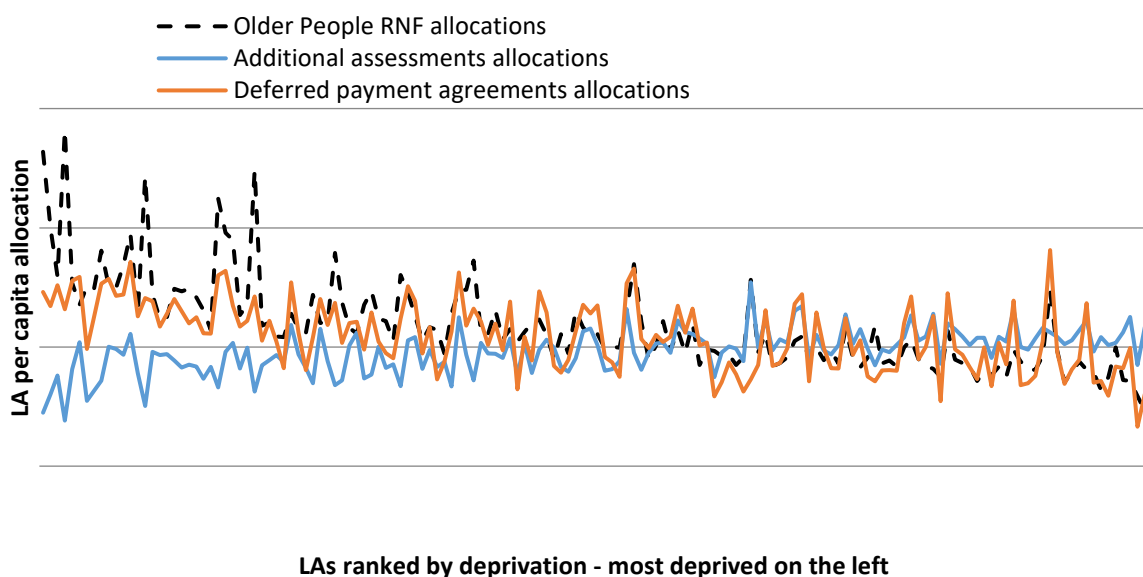


Figure 3 illustrates that the development of separate formulae for the new forms of social care support was warranted. In particular, the per capita allocations for additional assessment were quite different from allocations based on the older peoples RNF (correlation coefficient of -0.52). This was mainly due to the fact that the allocations based on the older people RNF are addressed to people with care needs who cannot afford to pay for their care (i.e. more likely to reside in more deprived areas), while the additional assessments allocations are for people with care needs, but (currently) having sufficient income and/or assets to cover their care needs (i.e. self-funders; more likely to reside in less deprived areas).

Figure 3. Comparison of per capita allocations by local authority between early assessment formula, DPA formula, and older people RNF



Note: Per capita allocations are based on a hypothetical budget.

8.1 Sensitivity and robustness

Given the nature of the problem, a number of assumptions have been made in the analysis. Throughout the analysis, these assumptions have been flexed and the implications considered. Two particular robustness checks were undertaken.

First, as outlined above, as well as data on total clients using any non-residential care services, formulae were estimated using just the utilisation of home care and direct payments. Figure 4 (below) shows the correlation between an additional assessment allocation per capita 65+ based on the home care plus direct payments model and the all non-residential services model. The correlation in this case is 97.27 per cent. If we compare total allocations (after multiplying the rates variables by population 65+), the correlation increases to 99.97 per cent.

The second major robustness check involved comparing the results regarding additional assessments as derived using the methods in this paper (i.e. the hybrid approach) with those using an entirely different method based on re-weighting person-level data in ELSA to reflect LA-level characteristics (i.e. the microsimulation-based approach). Full details of this method are outlined in Fernandez and Snell (2018). Figure 5 gives a comparison of the relative needs shares per capita 65+ for each LA as derived using the two methods – as based on Table 5 in Fernandez and Snell (2018). Overall, we found a correlation of 0.80, which gives us confidence that each method is properly reflecting differences in need, even though the methods differed slightly in their assumptions.

Figure 4. Correlation between an additional assessments RNF per capita 65+ based on the home care plus direct payments model and the all-non-residential services model.

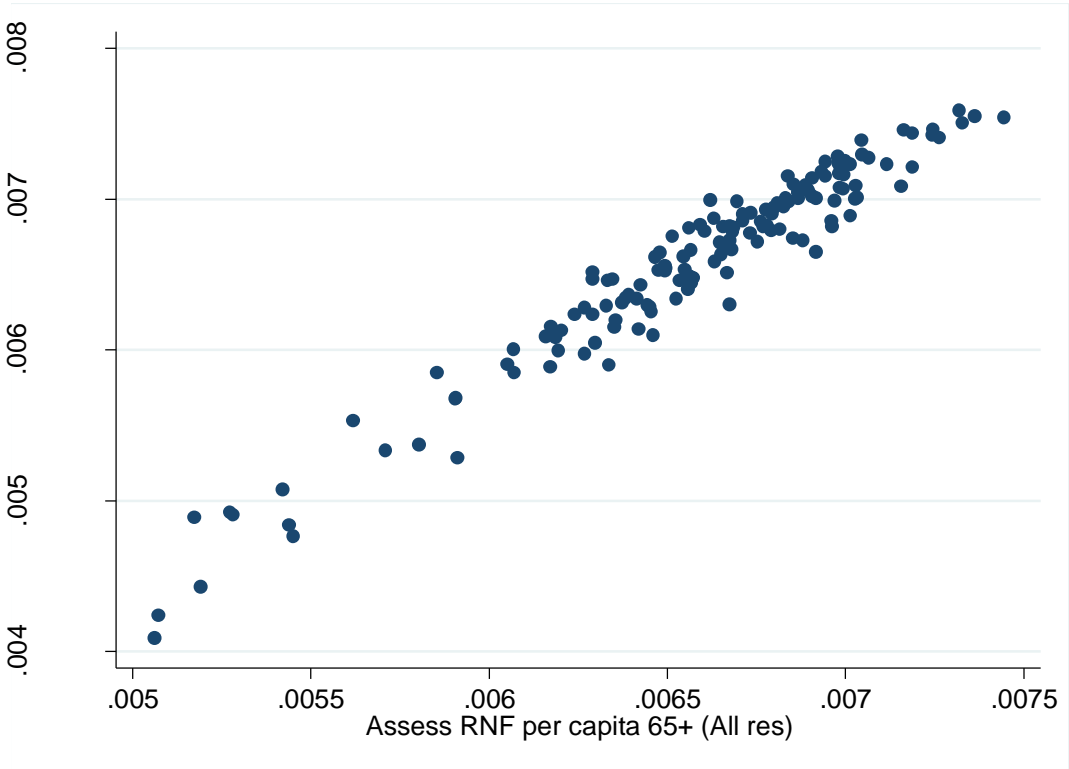
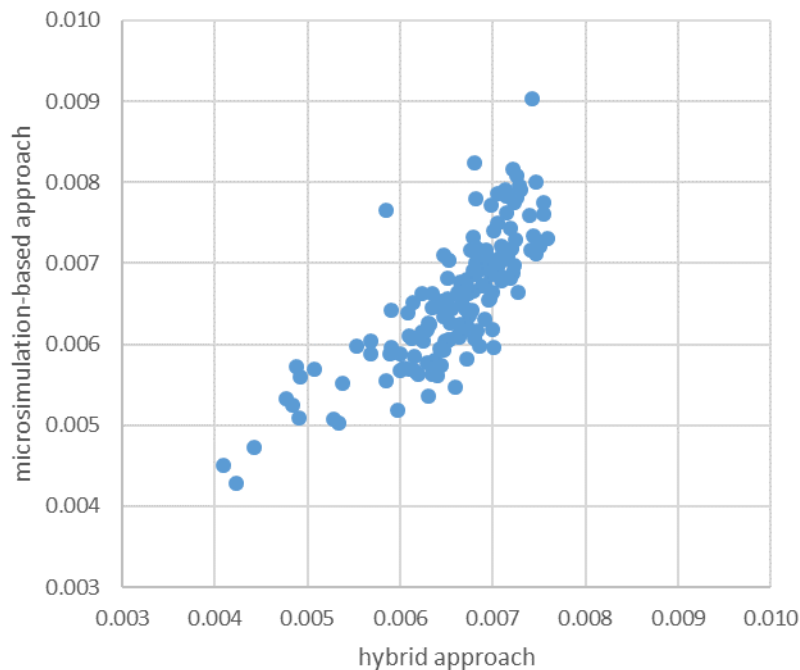


Figure 5. Comparing the additional assessments per capita relative needs: hybrid approach and microsimulation-based approach



8.2 Policy implications

There are a number of alternative methodologies for estimating relative needs formulae, with strengths and weaknesses. Their suitability often depends on which assumptions and principles are chosen to be embodied in relative needs formulae. The utilisation-based method produces a relative needs formula where need is principally defined by local authority eligibility assessment. This concept of 'need' differs from the actual utilisation of services, where the latter is also determined by demand and supply factors. The choice as to whether demand and supply factors should be in the final needs formula depends on assumptions as to whether they are within or beyond the control of local authorities.

Although actual patterns of LA-supported care will depend on local supply conditions, the relative needs formula ought to provide sufficient funding to LAs to meet the support needs of the expected number of people with such need in their locality. LAs can make choices about how to best meet that need locally and have the power to provide services directly if independent sector supply is insufficient. Also, local unit cost differences are accounted for by the ACA. So this argument suggests that current supply indicators should not be used in the formula. The current approach uses data on supply to remove short-term supply effects from the formula.

Given that the aim of this work was to estimate formulae for the new responsibilities, a pure utilisation approach was also not possible (as there are not specific utilisation data). Rather, we adopted a *hybrid* analysis, using utilisation data and methods, combined with (normative) prevalence-based simulation for predicting financial eligibility for either LA care support or DPA.

The weaknesses with this approach are twofold. First, modelling assumptions need to be made in extrapolating from current LA practice. Regression analysis imposes certain statistical assumptions, for example. The second point is that LA eligibility criteria will change to some extent, so that needs-

based eligibility for the new forms of support could differ from current practice. The suitability of this approach therefore depends on any judgement as to whether current practice is still the best indicator for future eligibility.

The results in this paper do support the principles of need adjustment (however that is made). Need levels differ between areas and do impact on the amount for care support each local authority will need to provide to meet its obligations.

Annexes

A1 Analytical framework

A1.1 Predicting need

The probability that a person in the population satisfies these two tests is $p(R + E)$ where R is the needs test and E is the eligibility test.

Our aim is to determine the nature of the LA needs test R , and in particular to estimate the probability $p(R)$ for the average person in each LA as a function of the available need and wealth proxies.

Given the interdependence of conditions R and E , we can write:

$$p(R) = \frac{p(R + E)}{p(E|R)} \quad (10)$$

i.e. the probability of people with care needs is the probability of people both in need and eligible divided by the probability of those people in need who are eligible.

We therefore need an estimate of $p(R + E)$ and $p(E|R)$, as a function of relevant risk factors: need proxies, x , wealth proxies, y , and supply, s .

The former, $p(R + E)$ corresponds to the actual activity of LAs in providing services for eligible people. We can therefore use data on this activity directly to model:

$$p(R + E) = f^{R+E}(x, y, s) \quad (11)$$

We also need an estimate of $p(E|R)$. As outlined in the main text, we cannot directly observe the number of people that satisfied this test because actual utilisation is the result of both tests. Instead, we can simulate the eligibility test by approximating the eligibility rules in a sample dataset. For this purpose, we need a dataset with relevant variables enabling us to most closely simulate the eligibility test. Furthermore, the dataset should have need variables. In general, $p(E|R) \neq p(E)$ because people in need generally have a different wealth situation compared to those with no need. The ELSA data are suitable. We use this dataset to capture the conditional nature of the probability of being eligible on the probability of being in need.

In general, we have:

$$p(E) = f^E(y; R) \quad (12)$$

and so, restricting to just those people with care needs:

$$p(E|R = 1) = f^{E|R}(y) \quad (13)$$

We cannot directly observe R but we can use need proxies x to identify populations that could yield appropriate relationships:

$$p(E|R = 1) = f^{E|R}(y) \cong f^E(y; x > \underline{x}) \quad (14)$$

Here \underline{x} is some minimum threshold of needs-related characteristics that should correspond to the person having the equivalent of a care level need.

Having made these two estimations, the two functions (11) and (14) can then be combined using (1):

$$p(R) = \frac{f^{R+E}(x, y, s)}{f^E(y; x > \underline{x})} \quad (15)$$

We used predicted values $f^{R+E}(x, y, s)$ in (15) to better accommodate censored distributions of LA-supported utilisation data.

Finally, the predicted value of $\hat{p}(R)_i$ from (15) can be estimated in terms of the need, wealth and supply factors:

$$\hat{p}_i(R) = f^R(x, y, s) \quad (16)$$

A1.2 New forms of support

A1.2.1 Assessment formula

A relative needs formula (RNF) for total assessments would be based on (16) where R is the (LA-assessed) need for social care. It would be used to determine the proportion of the total England number of assessments arising in each LA. We need to assume that the proportion of full assessments, σ , is a fixed multiple of the number of people with any need:

$$\sigma \hat{p}_i(R) = \sigma f^R(x, y, s) \quad (17)$$

The proportion of total assessments in England that go to each LA is:

$$\frac{\sigma \hat{p}_i(R)}{\sum_i \sigma \hat{p}_i(R)} = \frac{\sigma \hat{p}_i(R)}{\sigma \sum_i \hat{p}_i(R)} = \frac{\hat{p}_i(R)}{\sum_i \hat{p}_i(R)} \quad (18)$$

As σ drops out, this means we do not need to actually put a value on this factor to estimate each LA's share. A similar approach can be used for additional assessments, i.e. above those already carried out by LAs.

A1.2.2 Deferred payment agreement

In this case, we need to determine those people in the population with (i) an LA-assessed care home level of need and (ii) who might be in a position to need a DPA and be eligible on the basis of the DPA rules. Essentially the latter (ii) will be self-payers. Anyone with a home that is assessable under the current means-test will be a self-payer (unless the home is of very low value). People with high levels of income and non-housing wealth may not be eligible for a DPA, but this will be a small group and probably ignorable for the purposes of establishing relative needs.⁸

As above, we can define the eligibility condition D for a DPA. This includes the requirement that the potential recipient also owns a home:

$$p(D|R = 1) = f^{D|R}(y) \cong f^D(y; x > \underline{x}) \quad (19)$$

and so

$$p(R + D) = p(R)(p(D|R)) = \frac{f^{R+E}(x, y, s)}{f^E(y; x > \underline{x})} f^D(y; x > \underline{x}) = f^{R+D}(x, y, s) \quad (20)$$

⁸ The proportion of these people is strongly correlated with housing wealth, and the relative differences in this proportion between LAs, after accounting for the effect of different levels of housing wealth in the population will be very modest.

A1.3 Estimating financial eligibility

Financial eligibility for LA support (14) was modelled using the ELSA data. Specifically, we set condition E as described in (6). We estimated (14) with ELSA data using a linear probability model (OLS) over a sub-sample of people with at least one ADL, a proxy for the $R = 1$ condition in (14). Both need and wealth factors were used in the estimation:

$$E(R = x_A) = \beta_0^E + \beta_1^E x^E + \beta_2^E y^E + \epsilon^E \quad (21)$$

The independent variables are described in the main text.

Financial eligibility for a DPA was also simulated in ELSA using the rules outlined above (8). We estimated this model in two parts.

$$\begin{aligned} p(D|R = 1) &= p(\text{own, alone, need}) \times p(NHW < 23250) \\ &= f^{OA}(x^{OA}, y^{OA}) f^{D|OA}(x^{D|OA}, y^{D|OA}) \end{aligned} \quad (22)$$

The two functions f^{OA} and $f^{D|OA}$ were also estimated using linear (OLS) probability models.

A1.4 Estimating need eligibility

The discussion of the analytical framework above refers to individual person probabilities. But this analysis readily generalises to the population level (e.g. a LSOA). This generalisation is achieved by calculating the expected number of people in a population that would satisfy the relevant conditions.

Suppose there are j people in each LSOA i , then (1) can be written:

$$\sum_j p_{ij}(R + E) = \sum_j [p_{ij}(R)p_{ij}(E|R)] \quad (23)$$

We do not observe $p_{ij}(E|R)$ at LSOA level but rather use an individual level estimate from elsewhere (using ELSA data, see below) and assume that $p_j(E|R) = p_i(E|R)$, the mean value for the LSOA. As such, (23) becomes:

$$c_i^{R+E} = p_i(E|R) \sum_j [p_{ij}(R)] = p_i(E|R)c_i^R \quad (24)$$

where c_i^{R+E} is the count of people satisfying the needs and eligibility tests. Also, c_i^R is the count of people satisfying just the need test. A similar function can be written for the DPA test:

$$c_i^{R+D} = p_i(D|R)c_i^R \quad (25)$$

In generalising in this way, we need to assume that individual-level probabilities in a given small area population are about the same. This assumption seems reasonable if the relevant characteristics of people in that population are also similar. For this reason, we use as small a population level as possible for the analysis, namely LSOA populations.

We estimated a number of RNFs, for different conditions. As a shorthand, we use the variable g to summarise the relevant condition: $g = \{R + E, R, R + D\}$ for the three formulae.

The general method used involves calculating the expected counts of people in each LSOA who satisfy condition g and then using a regression model to estimate a prediction formula for these numbers based on LSOA population rates of relevant need, wealth and supply factors.

We fit count models to the small area data:

$$c_i^g = \exp\left(\beta_0 + \sum_k \beta^k \frac{z_i^k}{m_i} + \beta^m \ln(m_i)\right) \quad (26)$$

at the LSOA i level. Here c_i is the count of recipients per LSOA satisfying condition $g = \{R + E, R, R + D\}$. Also, z_i are both the need and wealth variables and m_i is the over 65s' population of the LSOA.

The inclusion of a population size variable in an LSOA-level analysis is mainly to account for scale effects. Other things being equal, the numbers of clients in any area should be proportional to the population in that area.

We could estimate a model in rates of service users per capita (65+), but count models should be better able to deal with integer effects in small areas by having population on the right-hand side. We only observe integer counts of service users by LSOA in the data, noting that the average number of clients in any LSOAs is *unlikely* to be an integer. Consequently, in small LSOAs we might observe zero clients even if the average is greater than zero (but less than one). Similarly, in larger LSOAs we are more likely to see positive integer numbers of clients, whereas the average is less than this amount. Consequently, the size of the LSOA can artificially affect the actual observed numbers of clients, and we need to control for this artefact in the analysis.

A standard set of variables, z^k , were included in each estimation (of the different g s), grouped by primary variable type: need, wealth and supply. These are described in the main text.

A1.5 Linear formulae

A linear approximation can be obtained using a first-order Taylor Series expansion of (26):

$$c_i^g \cong \pi_0^g + \sum_k \pi_i^{gk}(m_i) \frac{z_i^k}{m_i} + \pi_i^{gm}(m_i) m_i \quad (27)$$

where $\pi_i^k = \frac{\partial c_i^g}{\partial \left(\frac{z_i^k}{m_i}\right)}$ and $\pi_i^m = \frac{\partial c_i^g}{\partial m_i}$ are coefficients of a linear formula.

This formula can be summed to the LA level.

$$\sum_i^L c_i^g \cong N_l \pi_0^g + \sum_i^L \pi_i^{g1} \frac{z_i^1}{m_i} + \dots + \sum_i^L \pi_i^{gK} \frac{z_i^K}{m_i} + \sum_i^L \pi_i^{gm} m_i \quad (28)$$

This can be further simplified if we assume that the linear coefficients are not functions of population and therefore are constant for each LSOA i . We explore this assumption below. This means:

$$C_l^g \cong N_l \pi_0^g + \pi^{g1} \sum_i^L \frac{z_i^1}{m_i} + \dots + \pi^{gK} \sum_i^L \frac{z_i^K}{m_i} + \pi^{gm} \sum_i^L m_i \quad (29)$$

where $\sum_i^L c_i^g$ is written as C_l^g . The z terms are needs factors and these may be assumed to apply at the person level and not functions of the size of local populations, i.e.

$$z_i^k = \phi^k m_i \quad (30)$$

Consequently, $\sum_i^L \frac{z_i^k}{m_i} = \sum_i^L \phi^k = N_l \phi^k = N_l \frac{Z_l^k}{M_l}$, where $Z_l^k = \sum_i^L z_i^k$ is the LA sum of the need factor e.g. number of people claiming AA, and $M_l = \sum_i^L m_i$ the LA-level population 65+.

Using this result in (29) gives:

$$C_l^g \cong N_l \pi_0^g + \pi^{g1} N_l \frac{Z_l^1}{M_l} + \dots + \pi^{gK} N_l \frac{Z_l^K}{M_l} + \pi^{gm} M_l \quad (31)$$

Or

$$\frac{C_l^g}{M_l} \cong \frac{N_l}{M_l} \pi_0^g + \pi^{g1} \frac{N_l}{M_l} \frac{Z_l^1}{M_l} + \dots + \pi^{gK} \frac{N_l}{M_l} \frac{Z_l^K}{M_l} + \pi^{gm} \quad (32)$$

Finally, average LSOA population 65+ in LA l is $\bar{m}_l = M_l/N_l$ and therefore:

$$\frac{C_l^g}{M_l} \cong \frac{\pi_0^g}{\bar{m}_l} + \pi^{gm} + \frac{\pi^{g1}}{\bar{m}_l} \frac{Z_l^1}{M_l} + \dots + \frac{\pi^{gK}}{\bar{m}_l} \frac{Z_l^K}{M_l} \quad (33)$$

This method can be applied to any condition g and therefore we can write the general case as:

$$\frac{C_l^g}{M_l} \cong \alpha_0^g + \alpha_1^g \frac{Z_l^1}{M_l} + \dots + \alpha_K^g \frac{Z_l^K}{M_l} \quad (34)$$

where $\alpha_k^g = \frac{\pi^{gk}}{\bar{m}_l}$ and $\alpha_0^g = \frac{\pi_0^g}{\bar{m}_l} + \pi^{gm}$.

In theory, the α' are functions of population size, m_i , and therefore subject to scaling issues. Local authorities with different populations would have different coefficients. In practice, we might expect client counts to be directly proportional to LSOA population size, after accounting for any integer effects. In this case, we would expect that the coefficient β^m to have a value close to one. We have:

$$\begin{aligned} \alpha^k &= \frac{\pi^k}{\bar{m}_l} = \frac{1}{\bar{m}_l} \frac{\partial c_i^g}{\partial \left(\frac{z_i^k}{m_i} \right)} = \frac{\beta^k}{\bar{m}_l} \exp \left(\beta_0 + \sum_k \beta^k \frac{z_i^k}{m_i} \right) \exp(\beta^m \ln(m_i)) \\ &= \beta^k \exp \left(\beta_0 + \sum_k \beta^k \phi^k \right) m_i^{\beta^m - 1} \end{aligned} \quad (35)$$

Consequently if $\beta^m = 1$, then $\alpha^k = \beta^k \exp(\beta_0 + \sum_k \beta^k \phi^k)$, that is, not a function of m_i . We tested this assumption directly using the estimated value of β^m in the empirical analysis.

A2 Data sources and manipulation

A2.1 Population Estimates at July 2012

Source: We used mid-2012 population estimates for Lower Layer Super Output Areas 2011 by single year of age and sex, as they are the closest population estimates available to February 2013 (i.e. the month and year for the rest of statistics used in the analysis). The statistics are provided by the Office of National Statistics, Population Statistics Division.⁹

Manipulation: Using these statistics we computed through aggregation of single years of age and/or gender various population groups at LSOA 2011 level: total population, population aged 60 and over, population aged 65 and over, female population aged 65 and over, population aged 70 and over, and working age population (i.e. aged 16 to 64). Figure 6 presents the distribution of the population 65 and over at local authority level – this varied considerably, with the largest population 65 and over

⁹ <http://www.ons.gov.uk/ons/publications/re-reference-tables.html?edition=tcm%3A77-320861>

exceeding 250,000 (in Kent, Essex and Hampshire) and the smallest being 545 (Isles of Silly) and 1,106 (City of London).

A2.2 Benefits Claimants Data

Source: We used data on counts of benefits claimants at February 2013 (i.e. Attendance Allowance, Disability Living Allowance, Employment and Support Allowance, Income Support, Jobseekers Allowance and Pension Credit claimants) provided by the Department for Work and Pensions.¹⁰ The statistics are at 2001 Lower Layer Super Output Area (LSOA).

Manipulation: As the analysis is performed at 2011 LSOA level, we matched 2001 to 2011 LSOAs by using the “Lower Layer Super Output Area 2001 to Lower Layer Super Output Area 2011 E+W Lookup” provided by the UK Data Service Census Support.¹¹ For LSOAs 2011 that resulted from a merge of two or more LSOAs 2001 (i.e. 145 LSOAs 2011), the count of benefits claimants was computed as the sum of benefits claimants from the respective LSOAs 2001. For LSOAs 2011 that resulted from a split of a LSOA 2001 (i.e. 881 LSOAs 2011), the count of benefits claimants was estimated as a share of benefits claimants from the respective LSOA 2001. The shares are based on the population living in a LSOA 2011 that resulted from a split divided by the sum of populations living in all LSOAs 2011 that resulted from that particular split. We used different population groups to compute the population shares for the various types of benefit claimants:

1. for Attendance Allowance claimants we used the population aged 65 and over;
2. for Disability Living Allowance claimants - the total population;
3. for Employment and Support Allowance, Income Support, Jobseekers Allowance claimants - the working age population (i.e. aged 16 to 64);
4. for Pension Credit claimants - the population 60 and over; while
5. for Disability Living Allowance and Pension Credit claimants aged 70 and over - the population aged 70 and over.

We could not estimate the count of benefit claimants for 146 LSOAs 2011 that resulted from a mix of merges and splits of LSOAs 2001. For these LSOAs, the values for the count of benefit claimants are set as missing.

Figure 7 and Figure 8 illustrate the distribution by upper tier local authority of shares of Attendance Allowance claimants aged 65 and over and Pension Credit claimants aged 80 and over in the population 65 and over.¹² While the distribution of the count of Attendance Allowance claimants aged 65 and over and Pension Credit claimants aged 80 and over resembles that of the population 65 and over, the shares in the population 65 and over serve as a proxy for relative deprivation that is likely to be highly correlated with relative needs. The share of Attendance Allowance claimants aged 65 and over in the population 65 and over ranges from over 0.22 (in the case of Sandwell and Tower Hamlets) to about 0.10 (in the case of the City of London and Wokingham). Similarly, the share of Pension Credit claimants aged 80 and over in the population 65 and over ranges from 0.16 (Tower Hamlets) and 0.14 (Sandwell) to 0.04 (City of London and Wokingham).

¹⁰ <http://tabulation-tool.dwp.gov.uk/NESS/BEN/iben.htm>

¹¹ http://ukbsrv-at.edina.ac.uk/html/lut_download/lut_download.html?data=ls0a01_lsoa11_ew_lu

¹² The aggregation at upper tier LA has been made directly from the original statistics at LSOA 2001 level. Therefore, it includes also the benefit claimants we could not assign to the 146 LSOAs 2011.

A2.3 Number of Care Home Beds

Source: Data on the number of care home beds and type of clients at February 2013 were extracted from the Care Directory statistics provided by the Care Quality Commission.¹³ The statistics are at care home level.

Manipulation: Before estimating the number of care home beds at LSOA 2011 level, we cleaned the data by dropping duplicated care homes (24 care homes),¹⁴ correcting typos in identifiers (11 care homes) and replaced missing values for Service User Band (i.e. type of client) using information from carehome.co.uk (7 care homes).

The number of care home beds for “Old Age/Dementia” clients at LSOA 2011 level was estimated in two steps. In the first step, the number of care home beds of the care homes that registered to serve either “Old Age” or “Dementia” clients or both was aggregated at postal code level. Then, using the November 2013 Office for National Statistics Postcode Directory Open Edition,¹⁵ postcodes were matched to LSOAs 2011. In the second step, the care home bed numbers for “Old Age/Dementia” clients at postal code level were aggregated at LSOA 2011 level.

The “Number of care home beds for old age and dementia” is a measure of care supply. Not surprisingly, the highest number of care home beds are found in areas with the largest population 65 and over, as the demand for care is higher; the correlation between the “Number of care home beds for old age and dementia at LA level” and “Population 65 and over at LA level” is 0.983. However, due to cost reasons, the highest concentration of care home beds for old age and dementia in the population 65 and over is in areas with relatively lower house prices: the highest concentration is, for example, in Middleborough (0.073), Torbay (0.069) and Bournemouth (0.068), while the lowest concentration is in the City of London (nil) and London boroughs (e.g., Hackney [0.014], Westminster [0.015] and Camden [0.021]; see Figure 9).

A2.4 Residential Care Clients aged 65 and over

Source: Aggregated data at LSOA level on the Number of Local Authority (LA) Supported Permanent Admissions to Residential and Nursing Care during 1 April 2012 and 31 March 2013 were collected by LG Futures from 60 local authorities that agreed to participate in the study (see Table 19; for more details see LG Futures (2014) Report on Engagement and Data Collection Activities). Two datasets were created: first, the number of service users living in each LSOA prior to admission (the pre-care LSOA); and second, the number of service users living in each LSOA after admission.

This collection was of anonymous data. Only data on numbers of recipients per LSOA were collected. Although this is aggregated data, some LSOA counts were potentially small in number. Consequently, LAs provided masked data to the project with a “*” in place of actual count for LSOAs that had counts between 1 and 4.

From the 60 sampled LAs, three submitted incomplete data, while four were excluded as aggregated totals could not be validated when compared to national returns from the Community Care Statistics, Social Services Activity, England - 2012-13, Final release [NS], reported by the Health and Social Care Information Centre.¹⁶ The final sample included 53 Local Authorities, covering 14,003 LSOAs.

¹³ <http://www.cqc.org.uk/cqcdata>

¹⁴ Double entries in the Care Home register are sometimes due to a change in management.

¹⁵ http://ukbsrv-at.edina.ac.uk/html/pcluts_download/pcluts_download.html?data=pcluts_2013nov

¹⁶ <http://www.hscic.gov.uk/catalogue/PUB13148/comm-care-stat-act-eng-2012-13-fin-data.zip>

Manipulation: For each type of residence, we replaced missing values for Total Primary Clients with the sum of values for the respective primary client types. In total, 14 missing values were replaced for LA Staffed Residential Care, 60 missing values were replaced for Independent Residential Care, and 45 missing values were replaced for Nursing Care. Moreover, zero values of Total Primary Clients were replaced with the sum of values for the respective primary client types if at least one of the latter values was different from zero: 19 zero values were replaced for LA Staffed Residential Care, 88 zero values were replaced for Independent Residential Care, and 195 zero values were replaced for Nursing Care.

LSOAs with masked values were attached a synthetic value based on the average number of service users across all the LSOAs in the local authority that had five service users or more. Specifically, for Total Primary Clients in Residential Care (i.e. LA Staffed Residential Care + Independent Residential Care) and Total Primary Clients in Nursing Care, we gave “*” LSOAs a LA mean value calculated as follows:

$$\bar{*}_{RCi} = \frac{NRResCare_i - \sum_j ResCare_{ij}}{N_{RCi}^*}, \forall ResCare_{ij} \geq 5$$

where $NRResCare_i$ stands for National Return of Total Primary Client Types in Residential Care in the LA i , $ResCare_{ij}$ stands for Total Primary Client Types in Residential Care in LA i and LSOA j , and N_{RCi}^* represents the total number of “*” LSOAs for residential care clients in the LA i .

The “*” mean value for nursing care counts in LSOAs with masked values was computed as:

$$\bar{*}_{NCi} = \frac{NRNurCare_i - \sum_j NurCare_{ij}}{N_{NCi}^*}, \forall NurCare_{ij} \geq 5$$

where $NRNurCare_i$ stands for National Return of Total Primary Client Types in Nursing Care in the LA i , $NurCare_{ij}$ stands for Total Primary Client Types in Nursing Care in LA i and LSOA j , and N_{NCi}^* represents the total number of “*” LSOAs for nursing care clients in the LA i .

In order to remove outliers from both $\bar{*}_{RCi}$ and $\bar{*}_{NCi}$, values smaller than the 5th percentile weighted by the number of stars at LA level (i.e. N_{RCi}^* and N_{NCi}^* respectively) were replaced with the 5th weighted percentile value. Similarly, values higher than the 95th weighted percentile were replaced with the 95th weighted percentile value.

Total Primary Clients in Residential Care and Total Primary Clients in Nursing Care were used to compute **Gross** Weekly Residential Care Expenditures at LSOA level. As local unit cost can be influenced by differences in the commissioning practices of councils, national average unit costs were applied. The unit cost figures in Table 20 were taken from the Personal Social Services Expenditure and Unit Costs - England, 2012-13, Final release [NS] reported by the Health and Social Care Information Centre.¹⁷ The cost-weighted Gross Weekly Residential Care Expenditures for each LSOA k are:

$$GWResCareExp_k = 528.40 \times ResCare_k + 507.40 \times NurCare_k$$

A2.5 Non-residential Care Clients aged 65 and over

Source: Data on the Number of Clients Registered to Receive Community Based Services Provided or Commissioned by the CASSR on 31 March 2013 by primary client type and components of service were provided at LSOA level by local authorities that agreed to participate in the study. The data

¹⁷ <http://www.hscic.gov.uk/catalogue/PUB13085>

were collected by LG Futures from 60 local authorities (see Table 21; for more details see LG Futures (2014) Report on Engagement and Data Collection Activities). Four LAs could not submit all the data required and were not used in the analysis, while data from seven further LAs were excluded due to apparent inconsistencies between counts of clients at LA level and RAP returns. The dataset included counts by five primary client types (i.e. Physical Disability, Mental Health, Learning Disability, Substance Misuse, and Other Vulnerable People), eight components of service (i.e. Home Care, Day Care, Meals, Short-Term Residential Not Respite, Direct Payments, Professional Support, Equipment and Adaptions, and Other) and the Total of Clients.

As above, LAs provided masked data to the project with a “*” in place of actual count for LSOAs that had counts between 1 and 4.

Manipulation: Three components of service were used for the estimation of the Relative Needs Formulae: Total of Clients, Home Care, and Direct Payments. For each of these components, we first replaced missing values of total primary client types with the sum of values for the respective primary client types. In total, 83 missing values were replaced for Total of Clients, 82 missing values were replaced for Home Care, and 35 missing values were replaced for Direct Payments. Moreover, zero values of total primary client types were replaced with the sum of values for the respective primary client types if at least one of the latter values was different from zero. In total, 13 zero values were replaced for Total of Clients, 206 zero values were replaced for Home Care, and 200 zero values were replaced for Direct Payments.

LSOAs with a masked value were given a synthetic count value based on the average number of service users across all the LSOAs in the local authority that had five service users or more, computed as:

$$\bar{*}_{TCi} = \frac{Total_in_LA_i - \sum_j TotClient_{ij}}{N_{TCi}^*}, \forall TotClient_{ij} \geq 5$$

where $Total_in_LA_i$ is the total number of service users for the LA as reported in the RAP Returns. $TotClient_{ij}$ stands for Total of Clients in LA i and LSOA j , and N_{TCi}^* represents the total number of “*” LSOAs for the Total of Clients in the LA i . Synthetic values were used for total non-residential service users, total home care service users and total direct payments service users.

Values that were out of the [0,5] range were dropped, as in this case aggregated LA data were considered to differ significantly from RAP returns: values for 29 LAs had to be dropped from total non-residential as well as values for 8 LAs from the home care and direct payments totals. From the remaining, values smaller than the 5th percentile weighted by the number of stars at LA level were replaced with the 5th weighted percentile value. Similarly, values higher than the 95th weighted percentile were replaced with the 95th weighted percentile value.

The total counts of Home Care and Direct Payments service users were used to estimate the **Gross Weekly Non-Residential Care Expenditures** at LSOA level after applying the following unit cost weights. As local unit cost can be influenced by differences in the commissioning practices of councils, national average unit costs were applied. The unit cost figures were taken from the Personal Social Services Expenditure and Unit Costs - England, 2012-13, Final release [NS] reported by the Health and Social Care Information Centre.¹⁸ The cost-weighted Gross Weekly Non-Residential Care Expenditures for each LSOA k ($GWNonResCareExp_k$) are:

¹⁸ <http://www.hscic.gov.uk/catalogue/PUB13085>

$$GWNonResCareExp_k = 187.50 \times HomCare_k + 172.90 \times DirPay_k$$

The cost-weighted gross weekly residential and non-residential care expenditures for the sampled LAs are presented in Table 22.

A2.6 Census 2011 data

We used Census 2011 data at LSOA level for specific indicators of needs, wealth and sparsity:

- Count of people aged 85 and over with substantial activities of daily life limitations (i.e. day-to-day activities limited a lot) at LSOA level – Census 2011 Table ID LC3302EW;¹⁹
- Count of households with members living as a couple (i.e. married or cohabiting) aged 65 and over at LSOA level – Census 2011 Table ID LC1102EW;²⁰
- Count of homeowner households (i.e. home owned outright) aged 65 and over at LSOA level – Census 2011 Table ID LC4201EW;²¹
- Count of households with members aged 65 and over at LSOA level – Census 2011 Table ID LC4201EW;
- LSOA area (in hectares) – Census 2011 Table ID QS102EW;²²

We used the share of homeowner households aged 65 and over in the total number households 65 and over as a measure of housing wealth. As illustrated by Figure 10, housing wealth is quite unevenly distributed, ranging from over 0.75 in Wokingham, South Gloucestershire, Havering, and Solihull to about 0.20 in the London boroughs of Hackney and Tower Hamlets.

The share of couples aged 65 and over in the total number of households 65 and over offers an alternative indicator of needs, as people living as a couple may help each other in time need and access less LA care support. Again, we find quite a lot of variation (see Figure 11), with LAs such as Wokingham, Rutland, East Riding of Yorkshire, Isles of Scilly, Lincolnshire, South Gloucestershire and Dorset having more than 50 per cent of households 65 and over living as a couple, while only about 25 per cent of households over 65 live as a couple in the London boroughs of Hackney, Islington, Hammersmith and Fulham, and Lambeth.

A2.7 English Longitudinal Study of Ageing data

The English Longitudinal Study of Ageing (ELSA) began in 2002, drawing on the sample of individuals aged 50 and over from the Health Survey of England (1998, 1999, 2001). ELSA collects a large amount of data on the individual and family circumstances and quality of life among older people. It explores the dynamic relationships between health and functioning, social networks and participation, and economic position of people during the pre-retirement period and after retirement.

We used ELSA data to estimate the number of individuals financially eligible under the new Care Bill for local authority social care support and Deferred Payment Arrangements. This dataset provides a range of sound financial variables which are not routinely available at the regional level, but which determine eligibility. These data were used to model financial and DPA eligibility as outlined in the main text. The models included, variously, the respondent's sex, age group and number of activities of daily life (ADL) limitations; indicators for living alone, owning the accommodation (outright), receiving pension credit and receiving attendance allowance; and wave and regional controls. Summary statistics of these variables are presented in Table 23.

¹⁹ <https://www.nomisweb.co.uk/census/2011/lc3302ew>

²⁰ <https://www.nomisweb.co.uk/census/2011/lc1102ew>

²¹ <https://www.nomisweb.co.uk/census/2011/lc4201ew>

²² <https://www.nomisweb.co.uk/census/2011/qs102ew>

Table 19. Sampled Local Authorities – Residential Care

LA code	LA name	LA code	LA name
E06000055	Bedford	E08000034	Kirklees
E09000004	Bexley ^b	E10000017	Lancashire
E08000025	Birmingham ^a	E06000016	Leicester
E06000009	Blackpool	E10000019	Lincolnshire
E06000036	Bracknell Forest	E08000003	Manchester
E09000006	Bromley	E09000024	Merton
E10000002	Buckinghamshire	E06000042	Milton Keynes
E10000003	Cambridgeshire	E06000024	North Somerset
E09000007	Camden	E06000048	Northumberland
E06000049	Cheshire East	E10000024	Nottinghamshire
E06000052	Cornwall	E10000025	Oxfordshire
E06000047	County Durham	E06000031	Peterborough ^a
E08000026	Coventry	E06000038	Reading
E09000008	Croydon ^b	E08000005	Rochdale
E10000007	Derbyshire	E08000028	Sandwell
E09000009	Ealing	E08000014	Sefton
E10000011	East Sussex	E08000029	Solihull
E09000010	Enfield ^b	E08000013	St Helens
E10000012	Essex	E08000007	Stockport
E10000013	Gloucestershire	E10000029	Suffolk
E09000012	Hackney	E10000030	Surrey
E09000013	Hammersmith and Fulham	E09000029	Sutton ^a
E10000014	Hampshire	E06000030	Swindon
E09000014	Haringey	E06000027	Torbay
E06000001	Hartlepool	E09000030	Tower Hamlets
E09000017	Hillingdon	E09000031	Waltham Forest
E09000018	Hounslow ^b	E09000033	Westminster
E06000046	Isle of Wight	E06000054	Wiltshire
E09000020	Kensington and Chelsea	E08000031	Wolverhampton
E10000016	Kent	E06000014	York

Notes: ^a Excluded due to incomplete data submitted. ^b Excluded due to inconsistencies between aggregated totals and national returns.

Table 20. Unit costs

Service	Average gross weekly expenditure per older person at 31 March 2013 (£s)
Residential care (including full cost paying and preserved rights residents)	528.40
Nursing care	507.40
Home care	187.50
Direct payments	172.90

Table 21. Sampled Local Authorities – Non-Residential Care

LA code	LA name	LA code	LA name
E06000055	Bedford	E08000034	Kirklees
E09000004	Bexley ^b	E10000017	Lancashire
E08000025	Birmingham	E06000016	Leicester
E06000009	Blackpool	E10000019	Lincolnshire
E06000036	Bracknell Forest	E08000003	Manchester
E09000006	Bromley	E09000024	Merton
E10000002	Buckinghamshire	E06000042	Milton Keynes
E10000003	Cambridgeshire ^b	E06000024	North Somerset
E09000007	Camden	E06000048	Northumberland
E06000049	Cheshire East	E10000024	Nottinghamshire
E06000052	Cornwall	E10000025	Oxfordshire
E06000047	County Durham	E06000031	Peterborough ^a
E08000026	Coventry ^b	E06000038	Reading
E09000008	Croydon ^b	E08000005	Rochdale
E10000007	Derbyshire	E08000028	Sandwell
E09000009	Ealing	E08000014	Sefton
E10000011	East Sussex	E08000029	Solihull
E09000010	Enfield ^b	E08000013	St Helens ^a
E10000012	Essex	E08000007	Stockport
E10000013	Gloucestershire	E10000029	Suffolk ^a
E09000012	Hackney	E10000030	Surrey
E09000013	Hammersmith and Fulham ^a	E09000029	Sutton
E10000014	Hampshire	E06000030	Swindon
E09000014	Haringey	E06000027	Torbay
E06000001	Hartlepool	E09000030	Tower Hamlets
E09000017	Hillingdon	E09000031	Waltham Forest
E09000018	Hounslow ^b	E09000033	Westminster
E06000046	Isle of Wight	E06000054	Wiltshire
E09000020	Kensington and Chelsea ^b	E08000031	Wolverhampton
E10000016	Kent	E06000014	York

Notes: ^a Excluded due to incomplete data submitted. ^b Excluded due to inconsistencies between aggregated totals and national returns.

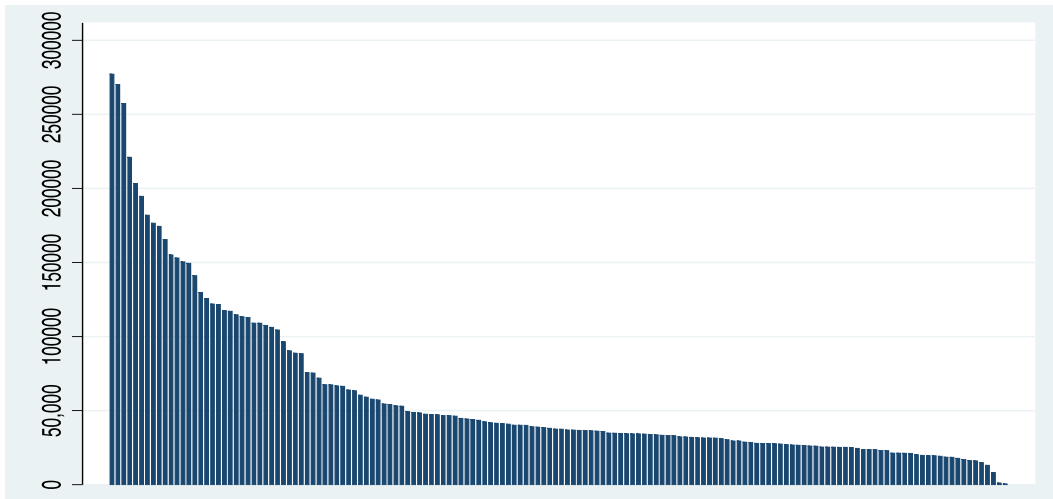
Table 22. Gross weekly residential and non-residential care expenditures by upper-tier local authority (cost-weighted)

Local Authority	Gross weekly residential care expenditures	Gross weekly non-residential care expenditures
Bedford	88,187	116,811
Birmingham	na	879,044
Blackpool	122,508	181,155
Bracknell Forest	59,219	81,551
Bromley	89,508	293,865
Buckinghamshire	137,971	326,481
Cambridgeshire	200,917	na
Camden	62,014	241,547
Cheshire East	89,257	183,830
Cornwall	364,134	475,695
County Durham	427,024	691,410
Coventry	130,758	na
Derbyshire	708,371	1,025,708
Ealing	58,647	306,365
East Sussex	372,907	526,793
Essex	824,602	997,850
Gloucestershire	302,051	333,120
Hackney	33,082	183,638
Hammersmith and Fulham	40,686	na
Hampshire	848,690	909,368
Haringey	54,135	184,403
Hartlepool	70,534	115,655
Hillingdon	74,532	385,217
Isle of Wight	187,350	145,351
Kensington and Chelsea	16,858	na
Kent	1,203,191	1,163,214
Kirklees	186,730	325,926
Lancashire	994,227	1,017,002
Leicester	173,978	388,243
Lincolnshire	635,576	642,157
Manchester	154,577	327,835
Merton	55,543	136,686
Milton Keynes	110,577	209,192
North Somerset	169,840	153,958
Northumberland	223,320	299,882
Nottinghamshire	396,366	425,396
Oxfordshire	299,227	418,473
Reading	109,415	129,806
Rochdale	124,304	197,093
Sandwell	167,043	274,254
Sefton	251,404	271,632
Solihull	149,127	193,675
St. Helens	111,222	na
Stockport	209,635	310,931
Suffolk	610,140	na
Surrey	583,580	818,061
Sutton	na	131,205
Swindon	78,930	141,504
Torbay	103,107	118,748
Tower Hamlets	54,642	214,038
Waltham Forest	57,484	119,926
Westminster	62,153	210,854
Wiltshire	247,549	316,171
Wolverhampton	144,704	197,007
York	92,375	142,619

Table 23. Summary statistics (mean values) ELSA data

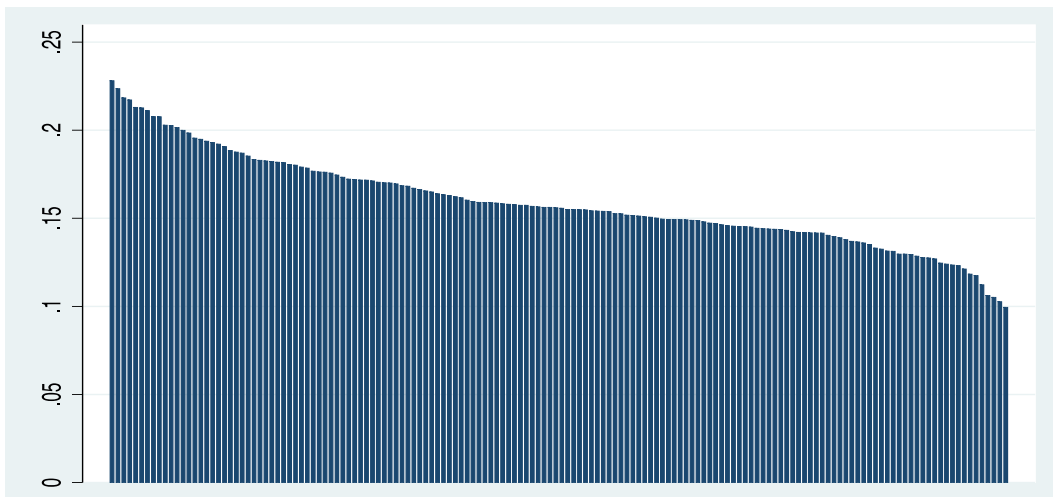
Variables	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
Female	0.555	0.556	0.560	0.545	0.545
Age group: 65 to 74	0.575	0.557	0.527	0.589	0.570
Age group: 75 to 84	0.343	0.354	0.349	0.311	0.327
Age group: 85 and over	0.082	0.089	0.124	0.100	0.104
Owns home (outright)	0.680	0.718	0.710	0.738	0.751
Attainment Allowance claimant	0.084	0.088	0.089	0.084	0.081
Pension Credit claimant	0.140	0.147	0.130	0.118	0.110
Lives alone	0.359	0.360	0.360	0.335	0.324
No. of activities of daily life limited (==0)	0.730	0.725	0.731	0.738	0.751
No. of activities of daily life limited (==1)	0.136	0.146	0.136	0.134	0.123
No. of activities of daily life limited (==2)	0.064	0.062	0.057	0.061	0.059
No. of activities of daily life limited (==3)	0.033	0.030	0.036	0.030	0.028
No. of activities of daily life limited (>=4)	0.036	0.036	0.040	0.037	0.039
Region: North East	0.068	0.066	0.068	0.066	0.066
Region: North West	0.131	0.131	0.119	0.121	0.114
Region: Yorkshire and the Humber	0.107	0.108	0.113	0.107	0.104
Region: East Midlands	0.091	0.096	0.095	0.099	0.101
Region: West Midlands	0.112	0.109	0.109	0.112	0.114
Region: East of England	0.115	0.118	0.124	0.123	0.128
Region: London	0.093	0.088	0.089	0.084	0.084
Region: South East	0.159	0.161	0.162	0.168	0.165
Region: South West	0.123	0.123	0.122	0.121	0.123
Observations	5,541	4,741	4,562	5,167	5,350

Figure 6. Population aged 65+ by Upper Tier LA



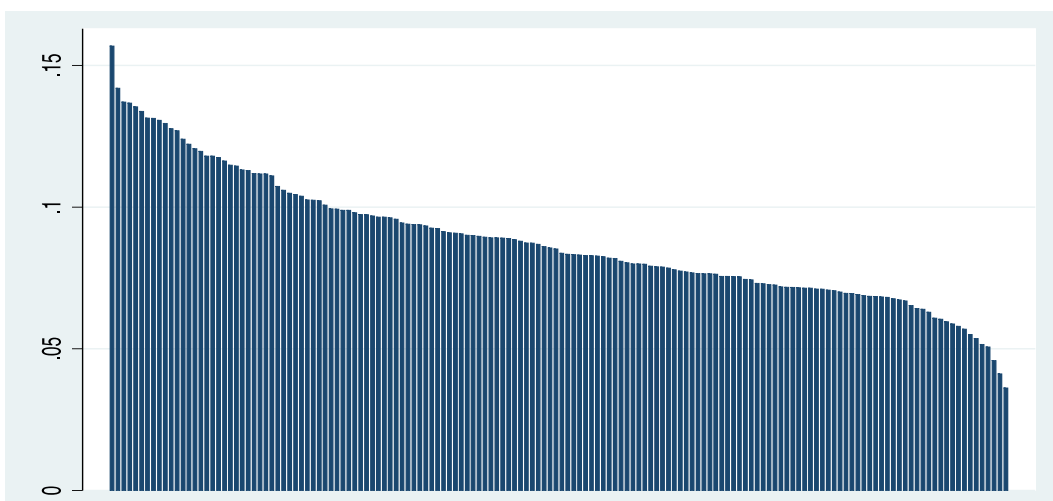
Data source: ONS, Mid-2012 Population Estimates.

Figure 7. Share of Attendance Allowance claimants aged 65+ in population aged 65+ by Upper Tier LA



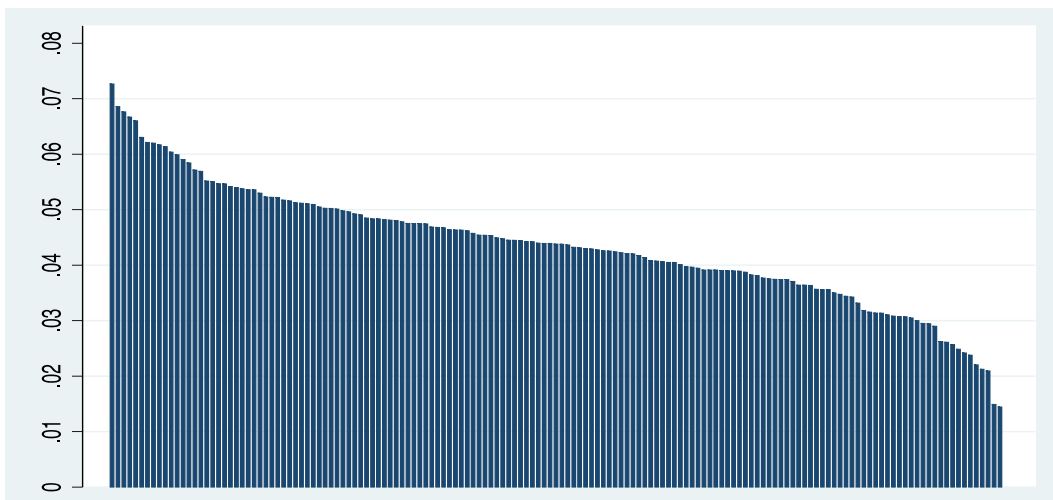
Data source: DWP, Attendance Allowance claimants at February 2013; ONS, Mid-2012 Population Estimates.

Figure 8. Share of Pension Credit claimants aged 80+ in population aged 65+ by Upper Tier LA



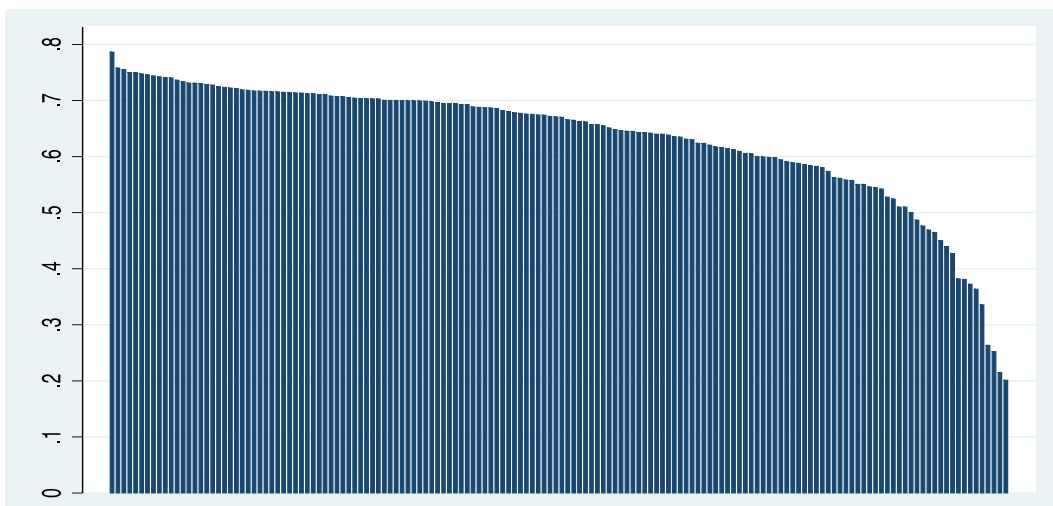
Data source: DWP, Pension Credit claimants at February 2013; ONS, Mid-2012 Population Estimates.

Figure 9. Concentration of care home beds for old age and dementia in population 65+ by Upper Tier LA



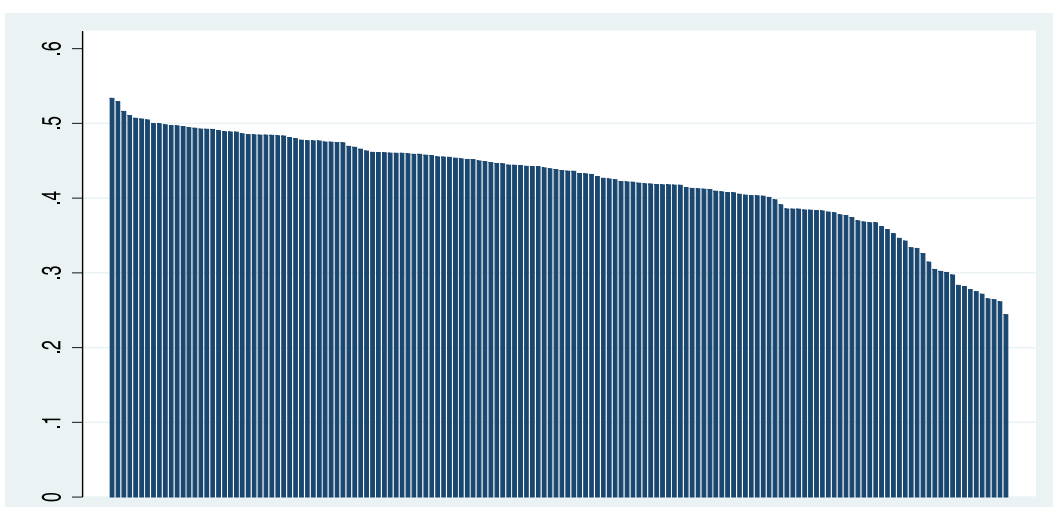
Data source: CQC, Care Directory Statistics February 2013; ONS, Mid-2012 Population Estimates.

Figure 10. Share of (outright) homeowner households 65+ in total households 65+ by Upper Tier LA



Data source: Census 2011, Table ID LC4201EW.

Figure 11. Share of households 65+ living as a couple in total households 65+ by Upper Tier LA



Data source: Census 2011, Table ID LC1102EW.

A3 Supply effects

Table 24. Negative binomial count models – endogenous and non- endogenous estimations

	Count model - random effects				Count model - fixed effects			
	Non-IV		IV model (predicted supply)		Non-IV		IV model (predicted supply)	
	Coeff	Z-stat	Coeff	Z-stat	Coeff	Z-stat	Coeff	Z-stat
Attendance Allowance claimants 65+ per capita 65+	2.106***	9.35	1.980***	4.68	2.224***	5.64	2.168***	4.68
Limiting (significantly) condition 85+ per capita 65+	1.278***	3.35	1.351**	2.28	1.210**	2.18	1.215*	1.90
Home owner households 65+ per households 65+	-0.424***	-5.99	-0.429***	-2.94	-0.425***	-2.81	-0.425***	-2.72
Pension Credit Claimants 80+ per capita 65+	2.023***	6.12	2.032***	5.27	1.986***	4.48	1.988***	4.67
Living arrangements: couple households per h'holds 65+	-0.654***	-5.18	-0.666***	-4.52	-0.668***	-4.83	-0.687***	-4.72
Population 65+ (log)	0.845***	37.07	0.846***	28.52	0.839***	28.00	0.839***	27.66
Total MSOA care home beds per MSOA pop 65+	0.856***	4.92	1.394	1.46	0.853***	3.98	1.164	1.04
			Stat	Prob			Stat	Prob
Weak instruments (F-test)			82.35	<0.001			82.35	<0.001
Over-identification (F-test)			NA	NA			1	0.39
Hausman endogeneity test (difference, Z-stat)			-0.54	0.56			-0.31	-0.48

Table 25. Fixed effects models with log resident count – endogenous and non- endogenous estimations

	Fixed effects (non-endogenous)		IV FE model (endogenous)	
	Coeff	Z-stat	Coeff	Z-stat
Attendance Allowance claimants 65+ per capita 65+	1.075***	4.63	0.884***	3.17
Limiting (significantly) condition 85+ per capita 65+	1.106***	4.07	1.264***	4.15
Home owner households 65+ per households 65+	-0.223***	-3.29	-0.237***	-3.47
Pension Credit Claimants 80+ per capita 65+	0.974***	5.53	1.008***	5.98
Living arrangements: couple households per households 65+	-0.379***	-4.86	-0.359***	-4.72
Population 65+ (log)	0.376***	16.83	0.377***	17.43
Total MSOA care home beds per MSOA pop 65+	0.541***	4.42	1.250*	1.96
			Stat	Prob
Under-identification			38.40	<0.001
Weak instruments (F-test)			24.11	0.00
Over-identification (chi-sq)			0.23	0.89
Hausman endogeneity test			1.33	0.25

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