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Synopsis

Accounting for unmet need in equitable healthcare resource allocation: Synopsis

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Abstract

Background: The National Health Service uses formulae based on historic patterns of service use to distribute funding locally. These formulae are adjusted using avoidable mortality rates, to account for unmet needs and address health inequalities. We do not know whether this approach accurately reflects variation in unmet need between areas.

Methods: We define need for National Health Service resources as the expected expenditure required to provide all standard National Health Services from which a population can benefit. We clarify the two components required to measure need: the relevant characteristics of the population living in each area and the cost weights indicating the expected needed expenditure associated with each of these characteristics. Four public advisor workshops were conducted to support the plain English description of the aims and methods used in the National Health Service resource allocation process. These led to the production of an animation to support public understanding of National Health Service resource allocation procedures.

We developed four adjustments to the current National Health Service allocation formulae to better account for unmet need using electronic health records for England from 2010 and 2018 and linked primary care, hospital and mortality data from 2008 to 2020 from the Clinical Practice Research Datalink.

Findings: Our responsiveness adjustment provides a method for more accurately estimating cost weights from regression models by only using data from those geographical areas that are better at aligning resources with patient need. Our longitudinal adjustment provides a new method for improving the way the utilisation formula accounts for supply-induced variation in utilisation, by using longitudinal data on people as they move between geographical areas. The primary care diagnosis adjustment shows how using linked data on primary care diagnosis improves the prediction of secondary care utilisation. Using data on people who have died from conditions, but who were not previously diagnosed, we estimate the proportion of people with 11 chronic diseases who were undiagnosed in each geographical area in England, providing an approach for adjusting National Health Service resource allocation formulae for unmet need due to underdiagnosis. Finally using instrumental variable methods we show that healthcare expenditure has larger effects on mortality in the middle deprivation groups, and smaller impacts in the top and bottom deprivation groups. These estimates indicate that some of our adjustments for unmet need may increase health inequalities. This highlights the need to maintain a 'health inequalities adjustment' that allocates more

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resources to socioeconomic groups with poor health outcomes to ensure that the National Health Service continues to help reduce health inequalities.
Limitations: Limitations in the data available and a lack of coherence between adjustments for unmet need, derived from this research, indicate that a great deal of uncertainty remains. Further work is needed to enhance the availability of linked electronic health records and survey-based symptom and biomarker data to support the modelling of unmet needs.
Conclusions: This programme of research has developed four adjustments targeting separate facets of unmet needs that can be implemented with the National Health Service resource allocation process as well as providing a tool that can be used to model the impact on health inequalities of any adjustment.
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Introduction

The Accounting for Unmet Need in Equitable Healthcare Resource Allocation research project aimed to advance methods for allocating NHS healthcare funding between geographical areas of England. Our remit was to refine the NHS resource allocation formulae used currently by the NHS to better account for 'unmet needs' in different parts of the country.

Many countries use geographical funding formulae to distribute public funds for health care to provinces, regions or planning areas.[1,2] The primary aim is to determine the target, relative, geographical distribution of public funding for health care between geographical health planning areas, such that each area receives funding in proportion to its needs. This is seen as necessary to achieve the objective of 'equal access for equal need'.[3] There is, however, much debate about what is meant by need for healthcare resources and how it should be measured for the purposes of geographical resource allocation.[3]

The current formulae used by the NHS to estimate relative differences in need between geographical areas are based on the 'utilisation approach'.[4] This uses data from electronic health records along with estimates of healthcare costs and measures of healthcare supply to estimate need as the predicted annual healthcare cost for each individual, conditional on supply (i.e. holding supply constant). In the first stage, a regression model is fitted to the data, with individual annual healthcare cost for each person as the outcome, and explanatory variables, including individual and area characteristics thought to be associated with needed expenditure and measures of healthcare supply. In the second stage, the coefficients on the need variables from this model are used to predict the expected needed expenditure for each individual in the population, holding supply constant. A frequent criticism of this approach is that, as it relies on data from people who have accessed health care, it will only reflect the distribution of needs that are usually met by the health system, and this may differ from the distribution of all needed expenditure if some groups systematically have unmet needs or overmet needs, that are not accounted for by observable differences in supply, for example, if they are undiagnosed, undertreated or overtreated.[5–7]

Unmet need for health care may arise because there are insufficient services available to some populations (supply side factors), or because despite the availability of services, they are not accessed (demand side factors).[8] In practice, however, many 'demand side' factors will be influenced by supply side characteristics, such as the acceptability and quality of care. Both supply and demand side factors have consequences for resource allocation policy. Supply side factors are likely to be more responsive to the allocation of additional resources, while addressing demand side factors may have cost consequences, for example, increasing awareness of a service will increase utilisation and increase costs. If a population is not allocated sufficient funds to cover these increased costs, this could disincentivise activities to increase access. Systematic biases in estimating relative differences in the amount of need between geographical areas will mean resource allocation fails to respect the fair share principle of distribution in proportion to need and may lead to discrimination against various groups of people – for example, by socioeconomic status, ethnicity, age, rurality and other equity-relevant characteristics – being baked into and perpetuated by resource allocation policy.

The aim of addressing unmet need in resource allocation policy is to allocate sufficient resources to each geographical area so that they can provide equal access for equal need. Measuring these unmet needs is, however, a challenge. A recent systematic review concluded that there is little useable evidence for measuring variation in unmet need between geographical areas that could inform resource allocation.[8] In the NHS, a simple formula adjustment using avoidable mortality, applied to 10–15% of the budget, aims to adjust for both unmet needs and to address avoidable health inequalities.[2] This is variously

referred to as an unmet needs adjustment and/or a health inequalities adjustment. However, there are no empirical grounds to indicate whether patterns of unmet need are associated with the geographical distribution of premature mortality.[9] Addressing unmet needs relates to the NHS objective of 'equal access for equal need', while a health inequalities adjustment aims to allocate more resources to socioeconomic groups with poor health outcomes in order to reduce the health gap between more and less disadvantaged groups. As highlighted below, these are different and potentially contradictory objectives.

One approach to address the issue of unmet needs has been to better account for unmet need within the utilisation model, and some improvements have been made based on previous reviews.[10] For example, by better adjusting for measures of healthcare supply, some supply-induced unmet need can accounted for. The formulae also include some counterintuitively signed coefficients (e.g. a negative sign for some minority ethnic groups indicating lower utilisation than White individuals) that are thought to indicate unmet need. These coefficients are set to zero in the prediction model – a process referred to as sterilisation. This means that, for example, even though some ethnic minority populations have lower-than-expected levels of utilisation, they do not end up with lower-needs weightings.[10] There is not, however, any systematic identification of population groups with consistent underutilisation, and the inclusion of these groups in the formula estimation could mean that the existing utilisation approach reinforces unmet need. Similarly, if there is systematic underdiagnosis among some population groups, the formulae may underestimate need in these groups. As Morris *et al.*[10] highlighted, as the utilisation approach is based on the average relationship between need variables and utilisation, rather than the relationship in the best performing areas, the coefficients are likely to be biased by under- and overutilisation.

A second approach has been to directly estimate the numbers of people with specific health conditions (diagnosed and undiagnosed) from epidemiological data (e.g. population surveys, risk factor measurements and mortality data) – referred to as the epidemiological approach.[11,12] These approaches have previously estimated the total undiagnosed and diagnosed prevalence of chronic diseases within small areas using representative national survey data [e.g. the Health Survey for England (HSE)]. This has then been compared to the diagnosed prevalence of disease as recorded in clinical data sets (e.g. the Quality and Outcomes Framework) to provide estimates of the undiagnosed prevalence.[11,12] There are, however, a number of major limitations with this approach for assessing met and unmet need. Firstly, the approach has been criticised, due to data limitations leading to uncertain estimates with limited disaggregation (e.g. by place, age, sex, social class, ethnicity, disease severity, and so on).[5] Secondly, many of the population prevalence estimates available[11,12] derived from national surveys are based on self-reported measures that in turn will be influenced by a respondent's access to diagnosis and treatment. Comparisons between these estimates and prevalence in clinical records may not, therefore, reflect the level of undiagnosed conditions. Work for the UK Advisory Committee on Resource Allocation (ACRA) exploring this[13] only identified prevalence estimates for depression, diabetes and hypertension, that could be used to estimate the prevalence of undiagnosed conditions in small areas. A limitation of previous approaches is that they have not utilised recent advances in disease epidemiology modelling that triangulate between multiple data sources (e.g. survey data, utilisation data and mortality statistics) to enable calculation of an internally consistent description of disease epidemiology from partial data.[14] While more recent methods using cross-sectional microsimulation methods[11] have led to more stable small area measures, they have not reduced the biases related to the limitations of the source survey data.

In order to provide a measure of need over a population, the number of cases estimated in epidemiological models for each population segment need to be weighted by an estimate of the needed costs associated with each condition.[5,6] It is unclear what cost weights should be applied when aggregating across cases. Vallejo-Torres and colleagues[5] criticise the epidemiological approach for assuming costs are undifferentiated across different types of cases, when they likely vary, for example, due to differences in severity. This is not, however, a necessary assumption of the epidemiological approach but, rather, follows on from the limitations of sparse data. In theory, if epidemiological approaches could estimate case prevalence with sufficient granularity (e.g. by age, sex, social class, ethnicity, region, severity, comorbidity, and so on) and appropriately differentiated cost weights could be applied, then this criticism would no longer hold.

We, therefore, sought to develop new methods for adjusting the current utilisation formulae used in the NHS in combination with new epidemiological approaches that better account for unmet needs between geographical health planning areas. For the purposes of this report, we use 'Clinical Commissioning Groups' (CCGs) as the unit of analysis, as these were the relevant local areas during the study period, although they have

now been replaced by larger regions – integrated care boards (ICBs). Although we sometimes refer to 'the' NHS formula in the singular, there are, in fact, seven different NHS formulae covering seven different NHS healthcare funding streams – 'General and Acute (G&A)', 'maternity', 'community', 'mental health', 'primary care', 'prescribing' and 'specialised services'. Altogether, these seven formulae cover approximately 66% of NHS healthcare expenditure in England. In this research programme, we have focused mainly on the general and acute formulae, and to a lesser extent, the mental health formulae. Our estimates of underdiagnosis also have implications for the primary care formula. These formulae represent those that are well established, while other formulae are still being developed and often subject to change as new data becomes available (e.g. community services and maternity services). They also represent the largest areas of funding that are allocated using area-based resource allocation formulae. The scope of the work was only NHS funds that are distributed to local areas (CCGs and ICBs), using these formulae, and the G&A formula accounts for about 50% of these, when including the mental health and primary care formulae these account for 77% of the funds allocated geographically to local areas.

Structure of the report

This report aims to outline the key findings from the project, strengths and limitations of the approaches and recommendations for how the findings can be applied in NHS resource allocation. Further detail is provided in a set of journal papers relating to each section, outlined in *Table 1*.

The project consisted of four work packages (WPs) as shown in *Figure 1*.

The report is structured as follows. *Understanding what we mean by unmet need for health care* outlines the work of WP1 clarifying definitions of need for health care relevant to the geographical allocation of resources and presents our framework for thinking about estimating relative need in geographical healthcare resource allocation, incorporating both epidemiological and utilisation approaches. *Enhancing the utilisation approach* presents the methods, key findings, strengths and limitations of WP1, outlining three of the four proposed adjustments, that enhance the existing utilisation approach to address specific gaps related to unmet need. The *responsiveness adjustment* (see *Responsiveness adjustment: an adjustment for unmet needs based on variations in responsiveness of expenditure to need*) seeks to correct the cost weights (i.e. coefficients) currently assigned to certain need characteristics, which may not accurately reflect the actual relative expenditure required. This adjustment aims to align these weights more closely with true need. The *longitudinal adjustment* (see *Longitudinal adjustment: adjustment accounting for time-invariant unobserved patients' need*) addresses the misclassification of need as supply in some areas – resulting in underestimation of need – and the opposite in others, where supply-related utilisation is incorrectly classified as need, leading to overestimation. The *primary care diagnosis adjustment* (see *The primary care diagnosis adjustment: an adjustment accounting for diagnoses in primary care*) responds to the absence of primary care diagnostic data in the general and

TABLE 1 Research project outputs

Journal paper
Barr B, Kypridemos C, Head A, Asaria M, Anselmi L, Sutton M, *et al*. Accounting for needs in geographical health care resource allocation [published online ahead of print April 1 2026]. *Health Soc Care Deliv Res* 2026. https://doi.org/10.3310/GJBB0820
Urwin S, Anselmi L, Mentzakis E, Lau YS, Sutton M. Adjusting the risk-adjustment: accounting for variation between organisations in the responsiveness of their expenditure to need. *Soc Sci Med* 2024;**361**:117346. https://doi.org/10.1016/j.socscimed.2024.117346
Urwin S, Anselmi L, Lau YS, Barr B, Sutton M. Are geographic variations in secondary hospital expenditure caused by supply and demand factors? Evidence from migration in England. *Soc Sci Med* 2025;**383**:118439. https://doi.org/10.1016/j.socscimed.2025.118439
Wang S, Lau YS, Sutton M, Anderson M, Kypridemos C, Head A, *et al*. Inequalities in the prevalence recording of 205 chronic conditions recorded in primary and secondary care for 12 million patients in the English National Health Service. *BMC Med* 2024;**22**:570. https://doi.org/10.1186/s12916-024-03767-4
Anosova O, Head A, Collins B, Alexiou A, Darras K, Sutton M, *et al.* Estimating the burden of underdiagnosis within England: a modelling study of linked primary care data. *PLOS ONE* 2025;**20**:e0313877. https://doi.org/10.1371/journal.pone.0313877
Barr B, Head A, Collins B, Kypridemos C. Unveiling the hidden burden: estimating the proportion of undiagnosed depression, hypertension and diabetes – a modelling study using survey data from adults in England, 2011–2019. *BMJ Public Health* 2025;**3**(2):e001919. https://doi.org/10.1136/bmjph-2024-001919
Anaya-Montes M, Grašič K, Lomas J, Anselmi L, Asaria M, Kypridemos C, *et al*. Do the poor gain more? The impact of secondary care expenditure on health inequality. Appl *Health Econ Health Policy* 2025 Dec 16. https://doi.org/10.1007/s40258-025-01016-0

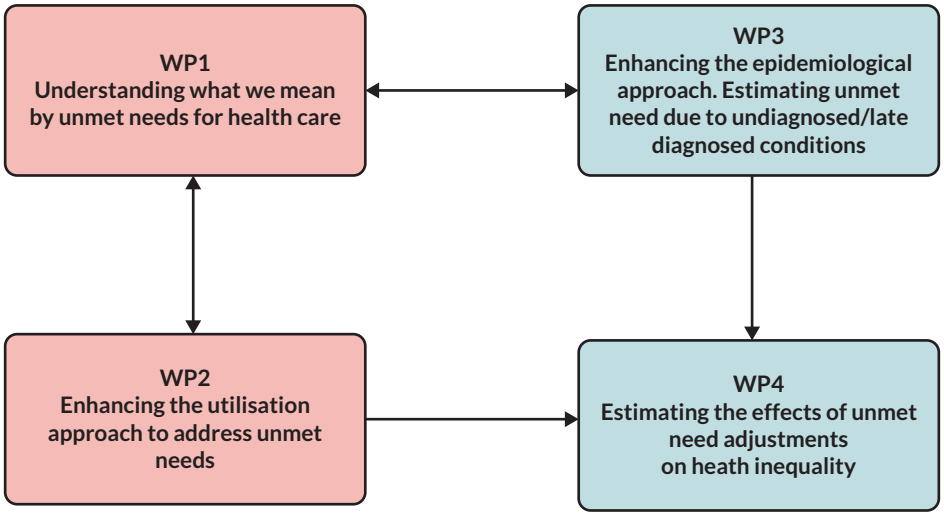


FIGURE 1 Components of the project.

acute formula. Since these data are a significant predictor of secondary care needs, its exclusion contributes to underallocation of resources in some areas relative to need.

The epidemiological approach: underdiagnosis adjustment outlines the work of WP3 applying a new *epidemiological adjustment* aimed at accounting for underdiagnosis, which is not currently captured by utilisation-based resource allocation models. This *underdiagnosis adjustment* (see *The epidemiological approach: underdiagnosis adjustment*) addresses the issue that undiagnosed conditions – despite representing genuine healthcare needs – are missing from existing formulae and thus from the allocations based on them. Together *Enhancing the utilisation approach* and *The epidemiological approach: underdiagnosis adjustment* present the methods, key findings, strengths and limitations of our four proposed adjustments that each address separate aspects of unmet need and can be incorporated alongside each other into the existing resource allocation process.

Estimating the effects of adjustments to resource allocation on health and health inequality outlines the estimates from WP4, based on instrumental variable analysis of the causal effect of variations in NHS funding on mortality and how this differs between places of differing levels of deprivation. These estimates are used to explore the likely distributional effects on heath of each of the proposed unmet need adjustments. *Overview* outlines how the adjustments can be combined and implemented, and *Implications for policy makers* provides recommendations for their use.

Objectives

This programme of research aimed to address the following objectives:

1. to improve our understanding of the concept of need and unmet need relevant to the geographical allocation of NHS resources
2. to examine whether the methodology of the utilisation approach used in the national resource allocation formulae can be enhanced to address unmet need
3. to estimate variation in unmet need by assessing the healthcare costs of diagnosing and treating the estimated prevalent cases of undiagnosed chronic conditions in each CCG
4. to estimate the heath impact and health inequalities impact of alternative adjustments for unmet need.

Findings

Understanding what we mean by unmet need for health care

Defining need for health care in resource allocation

One of the objectives of NHS resource allocation policy is to allocate resources in proportion to need, sometimes referred to as 'equal access for equal need'.[3] Distribution of resources in proportion to need is not the only objective of geographical public healthcare funding policy. Other objectives include reducing health inequalities (differences

in health between more and less socially advantaged groups that are systematic, avoidable and unfair[1]) and efficiency (maximising the health benefits from the overall budget). For the purposes of adjusting resource allocation for unmet need, however, we are only concerned with the first objective – improving the extent to which estimated target relative allocations are in proportion to needs (met and unmet). We do, however, outline the implications for health inequalities of adjustments for unmet need.

To allocate resources between places in proportion to need, we need to have an estimate of the proportional distribution of need between these places. Those proportions can then be applied to the total budget, so that each place gets the proportion of the national budget that is equal to their proportion of national needs; that is, a place estimated to have 5% of the needs would receive 5% of the national budget. As the budget is unlikely to be sufficient to address all needs for health care, allocating in proportion to need means aiming to equalise the proportion of needs that are met (and the proportion that are unmet) between NHS areas. The logic of proportionality means that everyone's needs should be met to some extent; this can be distinguished from the logic of maximisation (e.g. maximising overall health, or equality in health), which could mean that some people's needs could not be met at all, if it is more cost-effective to meet other people's needs, for example.

Allocating NHS resources in proportion to need requires a concept of what we mean by need for NHS care and how we quantify that need. To inform this discussion, an initial literature review was completed outlining the concepts of need as related to the geographical allocation of healthcare resources (see *Report Supplementary Material 1*). A useful starting point for defining the need for healthcare resources is the concept of 'capacity to benefit'.[6] This is a necessary condition of need; however, it does not tell you *how much* health care someone needs. One could define the total need for health care as the resource required to exhaust the capacity to benefit.[6] But this would include many forms of care that have some benefit (potentially for very high cost), which would not be available through the NHS. We, therefore, need to have a concept of care that is, or should be, available through the NHS. We can do this by recognising that there is a standard set of health services that are (or should be) available to all citizens through the NHS and a set of quality standards for appropriate clinical best practice. In practice, what is or is not included in the standard package is a political decision and is not explicitly defined within the NHS. Often, it is assumed that whatever is currently provided in the NHS is de facto the standard.[3] Cost-effectiveness may be a criterion for inclusion of a treatment in that standard package of care through the assessment of the National Institute for Health and Care Excellence, but cost-effectiveness is not currently used, to determine relative amounts of need in different local areas, and consequently does not influence allocations to local areas in proportion to those needs.

At the individual level, therefore, the 'absolute needed NHS healthcare expenditure' can be defined as the expected expenditure required to provide all the services, within the NHS standard package, that the individual can benefit from, to the current best practice clinical standards. This definition has some implications for resource allocation. As long as an individual meets these necessary conditions – that is, they can benefit from something the NHS provides (or should provide) – their amount of need is the cost of providing that care. This means that where that provision costs £1000 each for two people, they have the same amount of need, regardless if one person would benefit a lot more than other, or if one is from a deprived population with low life expectancy and the other is from an affluent population with high life expectancy.

The level of 'absolute needed NHS healthcare expenditure' in a population is the sum of these individual needs. The level of unmet need is the difference between this needed healthcare expenditure as defined above for a population and actual expenditure based on actual utilisation.[3] An important point here is that the aggregation of utilisation and consequent expenditure across a population may mask some unmet needs at the individual level, as these are, in effect, cancelled out by overmet needs in that population. So, for example, you could have a population where the actual expenditure is equal to the needed expenditure, so the level of aggregate unmet need is zero as defined above; however, there are unmet needs at the individual level as some people have unmet needs, while others have overmet needs (i.e. they are using more health care than they need, or health care from which they do not benefit). As the aim of resource allocation formula is, however, to allocate sufficient resources to each population to meet the same proportion of needs, how those resources are used at an individual level within that population is a secondary issue, and beyond the scope of resource allocation formulae. In other words, we would not vary the allocation of resources (and the share of needs they are sufficient to cover) just because some places are more likely to overmeet some people's needs compared to others. The systematic overmeeting of needs for some population groups could, however, have implications for using utilisation data in the estimation of the distributions of needs as outlined below.

Our starting point in understanding any adjustment of resource allocation for unmet need is, therefore, that it is aiming to allocate resources so that each place has sufficient resources to equalise the proportion of unmet need between places. As shown in *Figure 2*, the purple line is the gradient of absolute needed expenditure in each place (i.e. the resources required to provide everyone with everything in the standard package of care that they can benefit from), where each CCG is ranked by this measure of need. The orange line is the current resource distribution. In this example, this is not distributed proportionally; that is, in place A, it is sufficient to meet 75% of total needs; while in place B, it is sufficient to only met 60% of needs. An adjustment for unmet needs would aim to shift that distribution towards the black line, where this proportion is equalised, so that each CCG has sufficient resource to meet 65% of needs (35% are unmet).

Measuring the proportional distribution of need

Measuring the distribution of absolute need as defined above can be decomposed into two components (1) a *vector of characteristics* for each individual in each local NHS area indicating, for example, age, sex, morbidities, social characteristics and area- or practice-based characteristics of residence and a (2) *vector of cost weights* indicating the expected needed expenditure associated with each of these characteristics. Approaches for estimating the distribution of need generally involve these two components. The utilisation approach uses electronic health records linked to administrative data as the *vector of characteristics*. The epidemiological approach recognises that these are missing data on people with undiagnosed diseases and aims to estimate this from epidemiological models and survey data. Both approaches then need to use an estimate of the expected healthcare costs associated with each of those characteristics. The current utilisation approach is to use a regression formula to estimate these based on historical usage, conditional on supply.

However the vector of characteristic is estimated, similar cost weights are needed in applying an epidemiological approach, with the added challenge that assumptions need to be made about the cost of diagnosing and treating currently undiagnosed conditions. The costs associated with each characteristic are then added up for each local NHS area, and the proportion of need in each place is estimated as its total as a proportion of the national total, and this forms the target fair share. The implication of this simple conception of the estimation of fair shares is that it highlights that the utilisation and epidemiological approaches can be combined, utilising the strength of both – for example, supplementing electronic health records with estimates of undiagnosed conditions, then using these combined data within a standard utilisation approach.

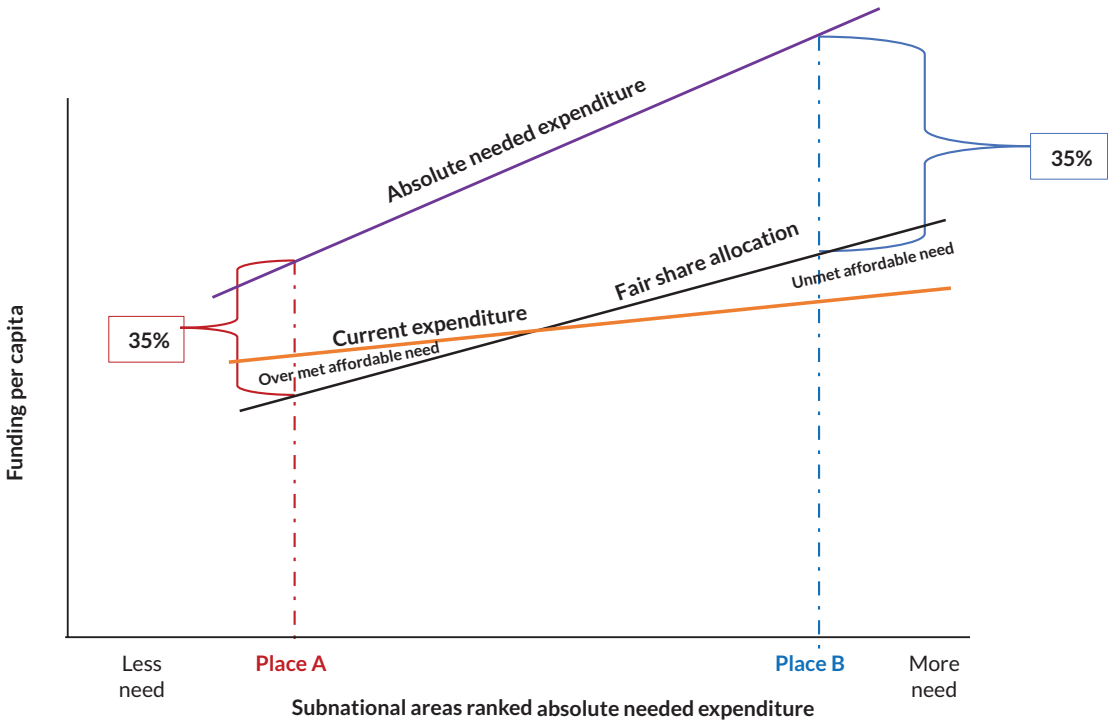


FIGURE 2 Absolute needed NHS healthcare expenditure, fair share allocation based on the proportional approach, overmet and unmet affordable need, relative to a hypothetical current allocation.

Unmet need and errors in the estimation of need

The problem with unmet need can, therefore, be understood as a measurement error and missing data problem. The extent that estimated shares reflect the target fair share distribution (as in *Figure 2*) – that is, distribution in proportion to need – will depend on whether the *vector of characteristics* includes all relevant characteristics of individuals that influence their need for health care and/or whether *the vector of cost weights* reflects the needed cost associated with each of those characteristics. For example, while the utilisation approach for estimating cost weights does adjust for some biases that could result from some groups (e.g. defined by sociodemographic characteristics, geographical locations or morbidities), overusing or underusing health care, where these are driven by differences in supply, it will be biased by systematic differences in underuse or overuse that are not accounted for by measures of supply. For example, if on average diabetic patients tended to underuse health care while cancer patients tended to overuse health care, the cost weights estimated through the utilisation method associated with diabetes would be underestimated, while those associated with a cancer diagnosis would be overestimated. There are several ways in which the current formulae are likely to include errors in these components, and our proposed adjustments outlined in *Enhancing the utilisation approach* and *The epidemiological approach: underdiagnosis adjustment* aim to address some of these errors. See our associated paper for a fuller discussion of the conceptual issues underlying unmet need.[15]

Enhancing the utilisation approach

In WP2, we considered whether unmet need can be addressed by adapting the current utilisation approach. This WP proposes three adjustments that address key issues with the two components outlined above – *the vector of characteristics* and *the costs weights* building on the review by Morris *et al.*[10] and exploiting new data sets and new linkages at the person level.

Responsiveness adjustment: an adjustment for unmet needs based on variations in responsiveness of expenditure to need

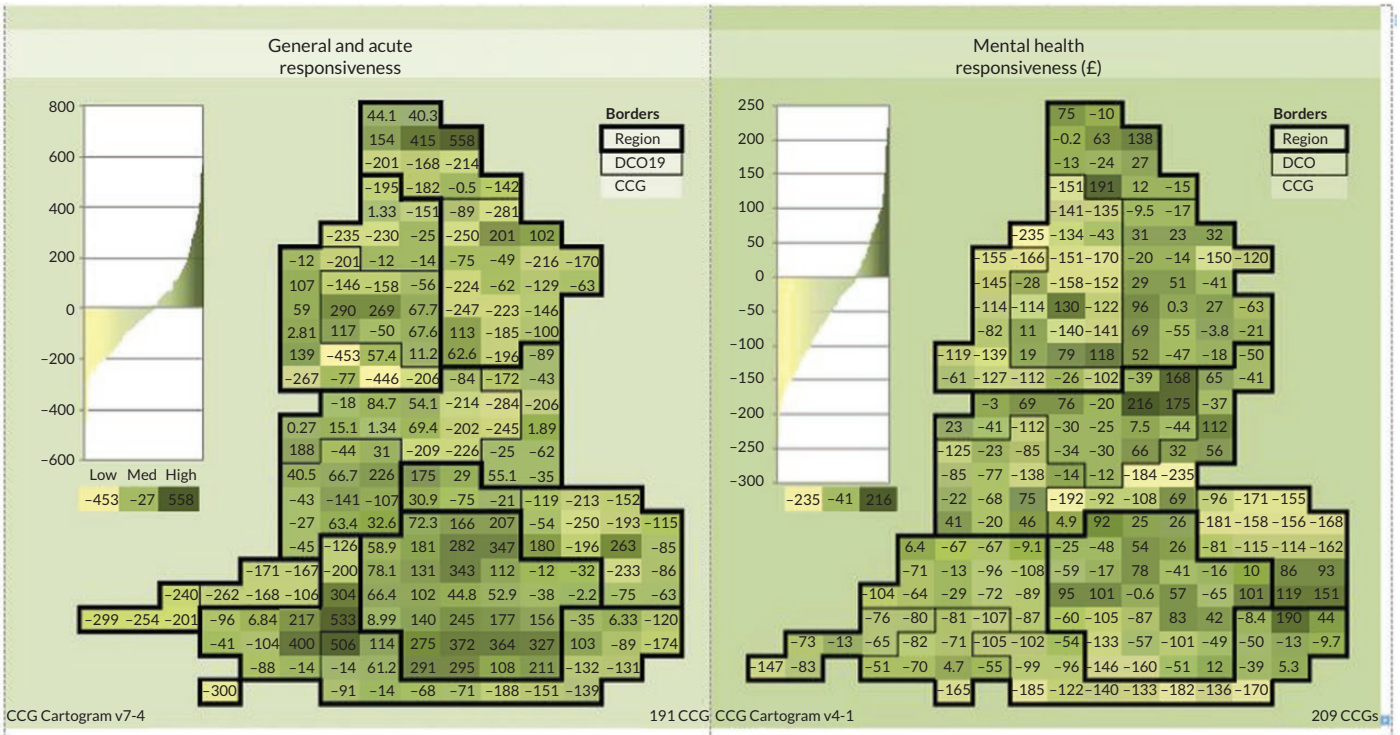
Method: At present, the utilisation formulae are estimated using data from the whole population of England. If there is unmet need (or overmet need) in use of healthcare services planning and delivery, it is likely to be more prevalent in some care systems than others. These systems will manifest as areas in which utilisation is less responsive to variations in the need of populations. For this reason, we use the term 'responsiveness' to describe the extent to which variations in need *within* a CCG are associated with variations in expenditure. We estimate the responsiveness of each CCG based on the association between individual needs indices and individual utilisation within each CCG, calculating a needs-based slope index of inequality.[16] Once identified, the less-responsive CCGs are then removed, and the formula re-estimated using data from the remaining CCGs. The estimation of the formula then provides coefficients that are applied throughout England to generate service-need predictions which better reflect need. Further details are given in our associated paper.[17]

Findings: Figure 3 shows the variation in responsiveness between CCGs. The level of responsiveness for general and acute varies from −453 to 558, indicating how much more or less a CCG spends on the highest need patients compared to its lowest-need patients, relative to the differences in need between these patients. In other words, the least-responsive CCG spends £453 less than expected on its highest need patients, while the most responsive CCG spends £558 more than expected on its highest need patients.

We find that higher levels of responsiveness are typically in areas with younger and less deprived populations. Generally, we find that responsiveness is associated with favourable outcomes, that we would expect to be associated with better targeting of resources to higher needs. Including lower avoidable mortality, higher proportion of early cancer diagnosis, higher chance of treatment within 52 weeks, shorter waits from referral to treatment and for a diagnostic test, lower suicide rate, higher Improving Access to Psychological Therapies recovery rates, a higher percentage of treatment started for psychosis within 2 weeks of a referral. However, most of these relationships were not statistically significant at the 5% level. Counterintuitively responsiveness was related to a higher waiting lists and a lower proportion of early cancer diagnoses. We found that higher responsiveness in secondary care was associated with higher responsiveness in primary care. Responsiveness in planned care was also associated with responsiveness in unplanned care. This suggests that more responsive systems tend to generally be better at aligning resources with patient need.

To illustrate the effect of removing different numbers of less-responsive CCGs, when calculating the cost weights associated with each patient characteristic in the general and acute and mental health formulas, we show how the needs index changes when removing:

1. the two general and acute and three mental health outlier CCGs with lowest responsiveness of expenditure to need



Note: 191 CCGs. Figures for 99P NHS Northern, Eastern and Western Devon CCG and 99Q NHS South Devon and Torbay CCG merged into 15N NHS Devon CCG.

Note: figures for 00F-NHS Gateshead, 00G NHS Newcastle North and East CCG and 00H NHS Newcastle West CCG are merged into 13T NHS Newcastle and Gateshead CCG

FIGURE 3 Geographical distributions by CCG of general and acute responsiveness, and mental health responsiveness.

2. the 5% CCGs with the lowest responsiveness of expenditure to need
3. the 10% CCGs with the lowest responsiveness of expenditure to need
4. the 25% CCGs with the lowest responsiveness of expenditure to need.

To indicate the distributional effect of this, we present the percentage change between the need index derived when less-responsive CCGs are removed, and the need index derived when all CCGs are included in the formula. *Table 2* shows this by CCG mean age and deprivation quintiles. Overall, applying the responsiveness adjustment to the general and acute formula tends to suggest greater need in more deprived CCGs compared to the baseline scenario. Applying the adjustment to the mental health formula suggested greater need in more deprived and younger populations compared to the baseline scenario. The relationship with age for the general and acute adjustment varies depending on the number of non-responsive CCGs removed. The adjustment indicates higher need (compared to baseline) in CCGs with more deprived and older populations when outliers and 25% less-responsive CCGs are removed and with more deprived and younger populations when 5% and 10% of the less-responsive CCGs are removed.

Figures 4 and *5* show the percentage change in the need index by CCG that would result from removing different numbers of non-responsive CCGs. In general, the North of England would gain more from applying the responsiveness adjustment in both the general and acute and mental health formula. London would benefit from removing up to 10% of less-responsive CCGs for the general and acute adjustment, but this switches, when removing 25% of less-responsive CCGs, reflecting the greater weight that is given to CCGs with more deprived and older populations, as shown in *Table 2*. The geographical pattern remains similar when adjusting for mental health responsiveness, regardless of the number of CCGs removed, London and the North would gain the most.

The responsiveness adjustment provides a relatively simple approach for ensuring that the formula cost weights are calibrated excluding data from the care systems that are less successful at aligning their resources with need. It is likely that some unmet needs are not adequately accounted for in the current utilisation formula, where the

TABLE 2 Percentage change in needs index derived when less-responsive CCGs are removed, compared to the need index derived when all CCGs are included in the formula, across age and deprivation quintiles

Deprivation quintile (D1 = least deprived, D5 = most deprived)	a. General and acute					b. Mental health				
	Age quintile (A1 = youngest, A5 = oldest)					Age quintile (A1 = youngest, A5 = oldest)				
	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5
Remove outliers less responsive										
D1	−0.04	−0.01	−0.02	−0.01	−0.01	−0.15	−0.14	−0.17	−0.10	−0.12
D2	−0.01	−0.01	0.01	0.02	0.00	−0.06	−0.06	−0.07	−0.05	−0.05
D3	0.00	−0.01	0.01	0.00	−0.01	0.01	−0.01	0.01	−0.01	0.00
D4	0.00	0.00	0.02	0.02	0.01	0.01	0.06	0.06	0.09	0.01
D5	0.00	0.01	0.02	0.02		0.10	0.10	0.12	0.13	
Remove 5% less responsive										
D1	−0.21	−0.14	−0.23	−0.19	−0.14	−1.31	−1.10	−1.51	−0.99	−0.98
D2	0.14	0.02	0.03	−0.10	−0.09	−0.26	−0.56	−0.79	−0.41	−0.42
D3	0.18	0.12	−0.02	−0.05	−0.08	0.56	−0.35	0.27	−0.27	0.07
D4	0.36	−0.06	0.01	−0.02	0.06	0.53	0.39	0.16	0.53	−0.01
D5	0.26	0.17	−0.04	0.05		0.86	0.72	0.52	0.88	
Remove 10% less responsive										
D1	−0.39	−0.31	−0.42	−0.35	−0.24	−4.49	−3.90	−5.14	−3.36	−3.52
D2	0.14	−0.07	−0.06	−0.14	−0.12	−0.69	−1.88	−2.65	−1.68	−1.66
D3	0.28	0.29	0.04	−0.09	−0.07	1.98	−0.90	0.60	−0.83	−0.15
D4	0.41	−0.04	0.02	0.10	0.19	2.02	1.26	0.73	1.70	−0.13
D5	0.41	0.28	0.03	0.25		3.20	2.48	2.05	2.78	
Remove 25% less responsive										
D1	−1.90	−1.45	−1.02	−0.37	0.39	−8.35	−7.28	−9.32	−6.04	−6.20
D2	−2.32	−0.72	0.31	0.85	0.96	−2.04	−3.47	−4.48	−2.83	−2.73
D3	−1.97	0.56	0.53	0.53	1.05	2.68	−1.69	1.17	−1.25	0.13
D4	−2.10	−0.20	0.92	1.64	2.05	2.65	2.51	1.79	3.73	0.24
D5	−0.95	0.68	1.26	1.97		5.51	4.84	4.36	5.79	

coefficients for some conditions and characteristics do not adequately reflect the cost associated with meeting those needs. These coefficients could be biased due to systematic patterns of underuse or overuse of health care associated with particular characteristics. This adjustment potentially addresses that problem, by deriving coefficients from a subset of areas where these systematic patterns of overuse or underuse of health care are less pronounced. It provides an approach that can be updated regularly and can be adapted based on new data indicating which local areas are better at allocating resources in proportion to need.

Longitudinal adjustment: adjustment accounting for time-invariant unobserved patients' need

Method: The utilisation formula currently adjusts for some unmet need for healthcare by accounting for differences in healthcare supply. This is done by including some measures of waiting times and by including 'fixed effects' for local NHS areas. These fixed effects adjust for unexplained differences in average use of health care between areas and ensure that the cost weights are based on differences within rather than between NHS areas. An assumption of this approach is that all variation in healthcare utilisation between NHS areas which is not captured by

FIGURE 4 Percentage change in general and acute needs index derived when the less-responsive CCGs are removed compared to need index derived when all CCGs are included in the formula, by CCG.

the need variables is interpreted as supply-side causes of variation in healthcare use. With longitudinal data, however, it is possible to estimate a formula that better accounts for individual needs by using indicators for each specific patient.

As the longitudinal data set includes people who are observed living in different NHS areas, we can more accurately separate the effects of different levels of supply on levels of utilisation from the effects of different levels of need. If, for example, we see that individuals with the same observed measures of need (e.g. diagnoses, and so on) systematically have higher levels of healthcare utilisation when they live in one NHS area compared to others, we can be more sure that this is due to higher level of healthcare supply in that area. In other words, we can be more confident that the higher level of healthcare utilisation in that area is not because the people who live there have higher needs, but rather is due to greater supply.

To explore the feasibility of this approach, we used person-level healthcare activity data on admitted patient care, outpatient visits, and accident and emergency attendances between 2010 and 2018. As we were not able to access linked data on all registered patients from the National Health Application and Infrastructure System (NHAIS) we only observe individuals living in a particular CCG when they use hospital services and had to make assumptions about where patients were living in the years when they did not use services.

FIGURE 5 Percentage change in mental health needs index derived when the less-responsive CCGs are removed compared to need index derived when all CCGs are included in the formula, by CCG.

We generated observations for these years with zero costs based on the following process:

- for all years prior to the first observed instance of healthcare utilisation, assuming that the individual had lived in the CCG where they were first observed
- for all years after the last observed instance of healthcare utilisation, assuming that the individual lived in the CCG where they were last observed
- for all years in between instances of healthcare utilisation, we assumed individuals continued living in their last CCG until they were next observed.

Following this process, each individual had 9 years of data, unless they were born or died during this period, in which case they were in our data set for the number of years alive between 2010 and 2018. The resulting data set contained 436,747,574 patient-year observations on 57,351,365 patients, of whom 6,155,033 (11%) lived in at least two different CCGs. We checked the distribution of individuals in our data set by sex, age and general practice (GP) against national patient registrations data and found these were broadly consistent. As we needed to make various assumptions outlined above, about where patients were living in the years when they did not use services, we repeated our analysis only using data for years when patients used some hospital services; this gave a data set of 192 million patient-year observations.

We modelled patient-level annual hospital costs as a function of sex, age, diagnostic information from the previous 2 years (as in the current general and acute

model), and financial year indicators. In addition, we included both patient-level fixed effects and CCG-level fixed effects. The coefficients on the CCG-level fixed effects represent differences in annual hospital costs per person *when* patients live in different CCGs after accounting for observed and time-invariant unobserved differences in need. They are a more reliable indicator of differences in supply between CCGs than the CCG effects estimated in the single-year cross-sectional models used for the general and acute formula.

To assess the sensitivity of the results to some of the required assumptions, we also estimated models in which we included indicators for the years before and after a patient moved to account for changes in care costs associated with moving (e.g. care disruption, new health checks). We also interacted these indicators with a variety of need measures in sensitivity analysis to account for variation in types of moves between CCGs. Further detail is given in our associated paper.[18]

Findings: The CCG fixed effects from our model are given in *Figure 6*. These indicate estimated differences in hospital costs in each CCG, compared to the all-England average, after accounting for observed and time-invariant unobserved needs. In other words, our estimate of additional supply-induced utilisation in each CCG. The left panel is our main analysis based on the data set containing patient-year observations with zero costs, while the right panel is based on the data set only containing observations for years when patients used some hospital services. These can be interpreted in comparison to the all-England average hospital costs per person per year over this period of £467 in the model using zero-cost observations (left panel), and in relation to the all-England average hospital costs per person per year of £1070 in the model only using data for person-years that had some hospital utilisation (right panel).

Taking account of years in which people do not use any services, by assuming they stay in the same CCG unless there is information to the contrary we find that the North-West is a high-use region (+ £26, 5.6%) and the South-East a low-use region (− £16, −3.4%) with the South-West no different than the national average and London estimated to have lower than expected use (− £16, −3.4%). When we focus only on years in which people use some hospital services, we find some important regional differences – in particular, in London, our estimates now suggest high unexplained use £17 (1.6%). In this model, similar to our main model high use is seen in the North West £36 (3.4%) and low use in the South East (− £26, 2.4%), while the South West is now estimated to have low use (− £33, 3.1%). These changes suggest that our results may be sensitive to patterns of migration in and out of London among people with zero use of hospital services.

This method utilises longitudinal data to provide an incremental improvement in the current utilisation approach, by including individual fixed effects to account for individual time-invariant unobserved needs. It can be applied in conjunction with other changes to the formula and updated through the same processes currently used.

The primary care diagnosis adjustment: an adjustment accounting for diagnoses in primary care

Method: Currently the general and acute formula only includes information on diagnoses if they have been recorded in secondary care records in the previous 2 years. This means it is missing information on people who have a diagnosis in primary care, but they have not had contact with secondary care in the past 2 years, or they have had contact, but their diagnoses have not all been recorded. It is likely that diagnoses in primary care are predictive of future secondary care utilisation even in people have not used secondary care. If the primary care diagnoses are predictive of secondary care use and the geographical distribution of primary care diagnosis differs from the distribution of secondary care diagnosis, then including primary care diagnostic flags in the general and acute formula would better reflect the distribution of overall healthcare need.

Using linked primary and secondary care data over three financial years (2016/7–2018/9) for 12.8 million patients registered with 1406 GP, we investigate the effect on the distribution of estimated need of adding primary care diagnostic data to the general and acute formula. In these data, a large proportion of diagnoses were only captured in primary care (78%). We compared the current formula using just secondary care data with models additionally including primary care diagnostic data in various ways. Firstly, just including primary care diagnosis and no secondary care diagnoses, secondly includes one set of variables indicating whether conditions had been diagnosed in either secondary or primary care, and thirdly including two sets of variables indicating whether conditions had been recorded (1) in secondary care and (2) in primary care only. Further, detail is given in our associated paper.[19]

Findings: *Tables 3* and *4* show the effect of adding primary care diagnostic information to the general and acute formula, on the distribution of estimated need by age and deprivation and between regions. Each of

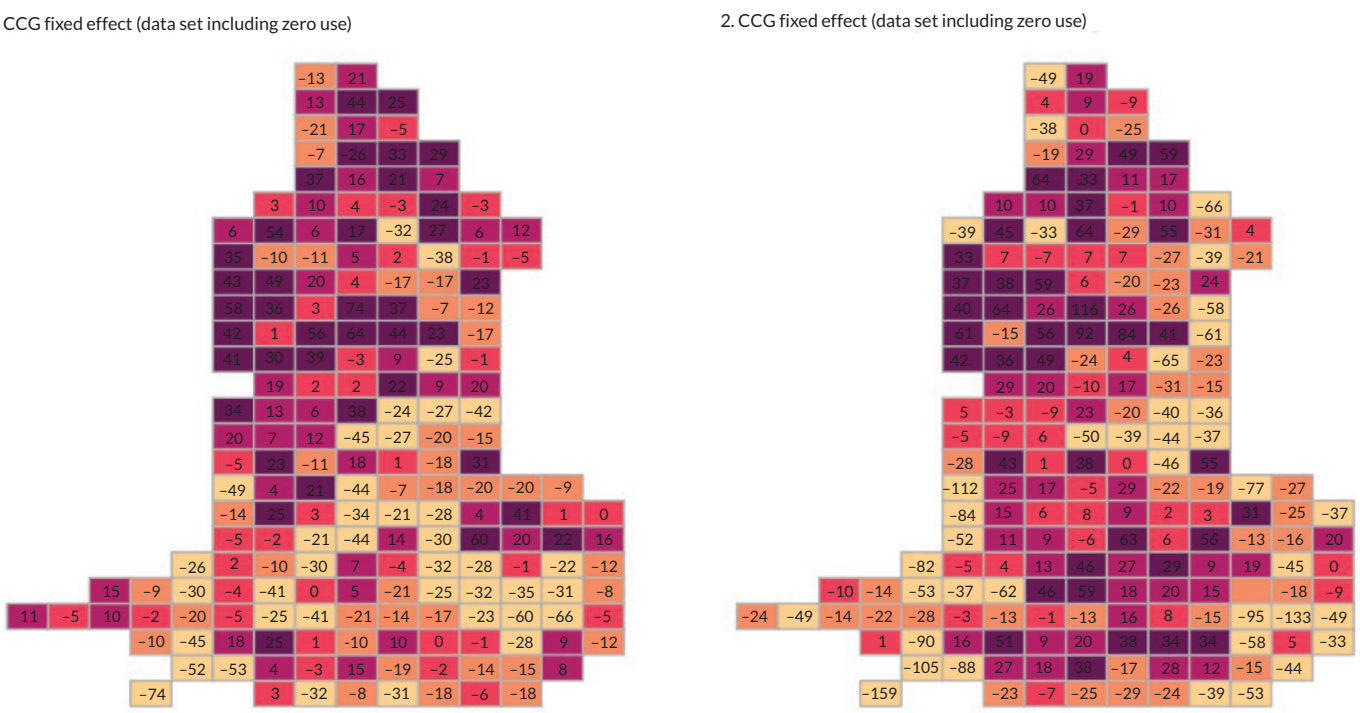


FIGURE 6 Differences in annual hospital costs per person per year for each CCG relative to the all-England average. Left panel is based on data set containing observations only for years when patients used some hospital services. Right panel is based on data set also containing patient-year observations with zero costs.

TABLE 3 Percentage change in need indices for three approaches for including primary care diagnoses in general and acute formula compared with current G&A model

Deprivation quintile (D1 = least deprived, D5 = most deprived)	Age quantile (A1 = youngest, A5 = oldest)				
	A1	A2	A3	A4	A5
Primary care diagnoses only					
D1	1.84	3.25	−0.36	−2.09	−0.16
D2	0.86	2.84	−0.02	−0.89	−0.12
D3	−0.17	1.48	−0.98	−0.85	0.09
D4	−1.53	0.01	−1.26	0.18	0.29
D5	−2.45	−2.29	0.15	1.73	1.18
Secondary or primary care diagnoses					
D1	7.17	8.17	1.75	−3.05	−1.12
D2	3.18	4.71	0.91	−1.82	−0.57
D3	0.45	1.33	−1.33	−1.36	−0.04
D4	−2.33	−1.88	−2.33	0.48	0.92
D5	−6.07	−4.12	−0.38	3.25	2.58
Secondary and primary care only diagnoses					
D1	7.54	7.23	1.29	−2.66	−1.33
D2	3.51	3.69	0.57	−1.68	−0.64
D3	0.88	0.82	−0.84	−1.03	−0.15
D4	−1.97	−1.96	−1.56	0.56	0.96
D5	−5.72	−3.67	−0.07	2.92	2.51

TABLE 4 Percentage change in need indices for three approaches for including primary care diagnoses in general and acute formula compared with current G&A model

	Primary care diagnoses	Secondary or primary care diagnoses	Secondary and primary care only diagnosis
North East	4.04	3.47	2.26
North West	0.00	0.91	1.00
Yorkshire and the Humber	5.04	4.82	1.70
East Midlands	3.54	3.16	1.15
West Midlands	0.74	−0.01	−0.19
East of England	−0.35	−0.49	−0.04
South West	1.31	1.18	0.30
South East	−0.45	−0.69	−0.70
London	−3.47	−3.15	−1.36

the three approaches show a similar pattern. Compared to the current approach they shifted need from the younger in more deprived areas and older in less deprived areas towards younger in less deprived areas and older in more deprived areas. On a regional level, this would shift resources from London and the South East to the North East, Yorkshire and the Humber of the East Midlands. This probably reflects that London has a younger deprived population compared to the North East, Yorkshire and the Humber of the East Midlands. Adding primary care diagnoses to the formula made very little difference to the distribution of estimated need between ethnic groups.

It is clear that including primary care diagnostic information provides additional information on the distribution of need and would be relatively easy to implement once this data becomes available nationally.

The epidemiological approach: underdiagnosis adjustment

Dynamic state model: estimating the number underdiagnosed

Method: In this adjustment, we estimate number of people with undiagnosed conditions differentiated by sociodemographics. We focus on 11 diseases with a high burden on the UK population according to the Global Burden of Disease project, namely: coronary heart disease (CHD), stroke, hypertension, chronic obstructive pulmonary disease (COPD), type 2 diabetes mellitus, dementia, breast cancer, prostate cancer, lung cancer, colorectal cancer and depression/anxiety. Not all NHS expenditure can be attributed to specific diseases. The last exercise that attempted to do this was the 2013–4 programme budgeting exercise and based on that data, these conditions account for 80% of all NHS expenditure that could be attributed to specific diagnoses.[20]

We estimate numbers undiagnosed using a dynamic state model as shown in *Figure 7*. We use linked primary care, hospital and mortality data, on approximately 1.3 million patients registered for more than 1 year during the study period of 1 April 2008–31 March 2020 from Clinical Practice Research Datalink (CPRD). We identify people who have died from a condition (or where it has been a contributing factor), but who were not previously diagnosed, or had only recently been diagnosed. This gives an indication of the extent of underdiagnosis in the population. In combination with observed data on the incidence of diagnosis, the case fatality rate (CFR) in the diagnosed, and an assumption about how that CFR varies with diagnosis, we can estimate the number of undiagnosed cases of disease in each population group. For our main model, we assume the CFR in the undiagnosed is the same as in the diagnosed in the first year of diagnosis. The data available have allowed us to stratify this by age group, deprivation, sex and region (i.e. 450 groups), providing an estimate of the numbers undiagnosed and the proportion of cases of each disease undiagnosed [i.e. number undiagnosed/(number undiagnosed + number diagnosed)]. As there were relatively small numbers within each strata and in some we observed no undiagnosed deaths we use logistic regression to smooth the probability of undiagnosed deaths across the strata. We also define deaths that occur within 1 year of diagnosis as 'undiagnosed' deaths, as it is

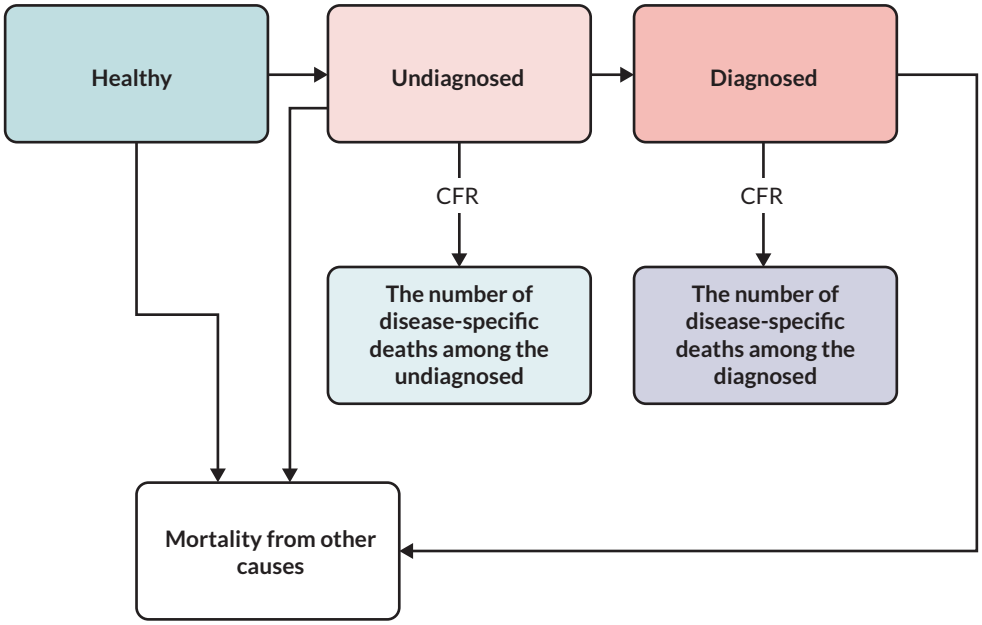


FIGURE 7 Dynamic state model used to estimate undiagnosed populations.

likely that diagnosis so close to death, still indicates that the individual was living with the condition for some time prior to diagnosis.

We then use microsimulation to apply these estimates to population segments in 2018 to produce estimates of the number of people undiagnosed and diagnosed with each condition in each CCG. We first use Office for National Statistics mid-year population statistics to construct a microdataset for all ≈28 million people aged 30 and over in England in 2018, for each age group and sex, within small neighbourhoods, known as Lower Support Output Areas (LSOA), with their associated level of deprivation [Index of Multiple Deprivation (IMD) quintile], nested within CCGs, that lie within 9 English regions. We then estimated a set of flags indicating whether individuals had each of the 12 conditions, and whether those were diagnosed or undiagnosed based on the estimates derived from the dynamic state model. These were then aggregated up for each CCG giving an estimate of the proportion of cases undiagnosed for each CCG.

Further detail is given in our associated paper.[21]

To investigate whether our estimates of the percentage of conditions undiagnosed reflect other indicators of late diagnosis we compare our estimates to emergency unplanned admissions for each of these conditions. If levels of under or late diagnosis are high in a CCG, we might expect that this would lead to higher levels of unplanned emergency admissions, as these undiagnosed conditions would not be managed by existing healthcare services. For our estimates of undiagnosed cancers, we compare our estimates of percentage of cancers that are undiagnosed to the proportion of cancers in each place that are late diagnosed (stage 3 or 4). We would expect that places with higher levels of undiagnosed cancer would also have a higher proportion that are presenting with later stage disease. We also compare our estimates to those derived from survey data.[22]

Findings: *Table 5* shows the probability of being undiagnosed for each disease estimated from the model, for groups of CCGs split into 5 groups based on deprivation and 5 groups based on mean age (i.e. 25 groups in total). The relationship between age, deprivation and the probability of being undiagnosed varies greatly between diseases. For many diseases, however, this increases for places with older populations (for depression/anxiety, CHD, dementia, hypertension, breast cancer, prostate cancer, diabetes). For COPD and stroke, however, the model estimates higher underdiagnosis in places with younger populations. There is an inconsistent pattern with deprivation. For some conditions, underdiagnosis is estimated to be higher in less deprived places (depression/anxiety, stroke), in others it is estimated to be higher is more deprived places (CHD, diabetes), for other diseases there is no obvious relationship.

Figure 8 shows the distribution of the estimated probability of not being diagnosed by CCG. The spatial pattern varies by disease. As an example of the extent of regional differences, some diseases are estimated to be more likely to be undiagnosed in London (COPD and stroke) while others appear to be less likely to be undiagnosed (CHD, dementia, hypertension, prostate cancer and diabetes).

TABLE 5 Estimated proportion of conditions undiagnosed by groups of CCG grouped by age and deprivation (2018)

	Deprivation quintile (D1 = least deprived, D5 = most deprived)	Age quantile (A1 = youngest, A5 = oldest)				
		A1	A2	A3	A4	A5
Diabetes	D1	0.20	0.23	0.23	0.23	0.23
	D2	0.20	0.22	0.24	0.25	0.26
	D3	0.21	0.26	0.26	0.24	0.27
	D4	0.21	0.27	0.26	0.26	0.28
	D5	0.24	0.27	0.28	0.28	0.28
Hypertension	D1	0.31	0.33	0.33	0.30	0.32
	D2	0.28	0.28	0.31	0.29	0.31
	D3	0.28	0.28	0.32	0.29	0.27
	D4	0.27	0.32	0.29	0.30	0.31
	D5	0.29	0.30	0.31	0.30	0.35
Depression/anxiety	D1	0.38	0.37	0.37	0.37	0.38
	D2	0.36	0.34	0.34	0.34	0.36
	D3	0.33	0.32	0.32	0.31	0.33
	D4	0.30	0.30	0.28	0.31	0.30
	D5	0.25	0.27	0.28	0.27	0.30
CHD	D1	0.44	0.47	0.47	0.47	0.47
	D2	0.44	0.46	0.47	0.46	0.47
	D3	0.45	0.46	0.48	0.48	0.45
	D4	0.46	0.48	0.46	0.46	0.48
	D5	0.49	0.47	0.46	0.44	0.49
Stroke	D1	0.17	0.17	0.16	0.16	0.16
	D2	0.18	0.17	0.17	0.16	0.17
	D3	0.18	0.16	0.16	0.16	0.16
	D4	0.18	0.16	0.15	0.16	0.17
	D5	0.17	0.16	0.15	0.15	0.18
COPD	D1	0.26	0.26	0.26	0.26	0.26
	D2	0.28	0.26	0.26	0.26	0.27
	D3	0.28	0.27	0.26	0.25	0.26
	D4	0.29	0.25	0.23	0.25	0.27
	D5	0.27	0.25	0.23	0.22	0.27

continued

TABLE 5 Estimated proportion of conditions undiagnosed by groups of CCG grouped by age and deprivation (2018) (*continued*)

	Deprivation quintile (D1 = least deprived, D5 = most deprived)	Age quantile (A1 = youngest, A5 = oldest)				
		A1	A2	A3	A4	A5
Colorectal cancer	D1	0.28	0.27	0.26	0.28	0.27
	D2	0.27	0.27	0.27	0.27	0.27
	D3	0.26	0.26	0.28	0.30	0.26
	D4	0.27	0.28	0.27	0.26	0.26
	D5	0.26	0.26	0.27	0.28	0.22
Breast cancer	D1	0.64	0.66	0.68	0.68	0.69
	D2	0.63	0.67	0.65	0.65	0.67
	D3	0.63	0.62	0.67	0.72	0.62
	D4	0.62	0.68	0.65	0.66	0.66
	D5	0.65	0.65	0.67	0.64	0.66
Lung cancer	D1	0.35	0.36	0.37	0.37	0.36
	D2	0.36	0.38	0.38	0.37	0.37
	D3	0.37	0.37	0.38	0.39	0.36
	D4	0.37	0.31	0.35	0.36	0.37
	D5	0.38	0.37	0.32	0.33	0.38
Dementia	D1	0.20	0.23	0.25	0.23	0.24
	D2	0.20	0.22	0.23	0.23	0.24
	D3	0.20	0.22	0.23	0.23	0.24
	D4	0.18	0.21	0.24	0.25	0.25
	D5	0.21	0.23	0.22	0.25	0.27
Prostate cancer	D1	0.66	0.68	0.67	0.68	0.68
	D2	0.66	0.68	0.68	0.69	0.69
	D3	0.65	0.69	0.70	0.68	0.70
	D4	0.64	0.69	0.70	0.71	0.69
	D5	0.66	0.71	0.70	0.72	0.67

The probability of being undiagnosed from our estimates was positively associated with emergency CHD admissions, dementia emergency admissions, prostate cancer, breast cancer and diabetes, but negatively associated with emergency admissions for stroke and COPD. For stroke this could be because many strokes will be first diagnosed through emergency admissions. We find a weak correlation between the probability of being undiagnosed with lung and prostate cancer and the proportion of diagnosis at a late stage. When comparing our estimates from the dynamic state model to survey-based estimates derived from the HSE[23] and understanding society (US)[24] (see *Survey-based estimates of the probability of being undiagnosed*), we find that for diabetes there is a strong negative correlation. This is because in our estimates the probability of being undiagnosed increases with age and deprivation while in the HSE the probability of being undiagnosed decreases with deprivation and is unrelated to age. We see a similar negative association between our measures of depression and anxiety prevalence and those derived from US.[21] This is largely because our estimates indicate a decreasing probability of being undiagnosed with increasing deprivation while US indicates that the probability of being undiagnosed increases with deprivation. For hypertension there is no association between our estimates and those derived from HSE. This is partly because our estimates indicate increasing

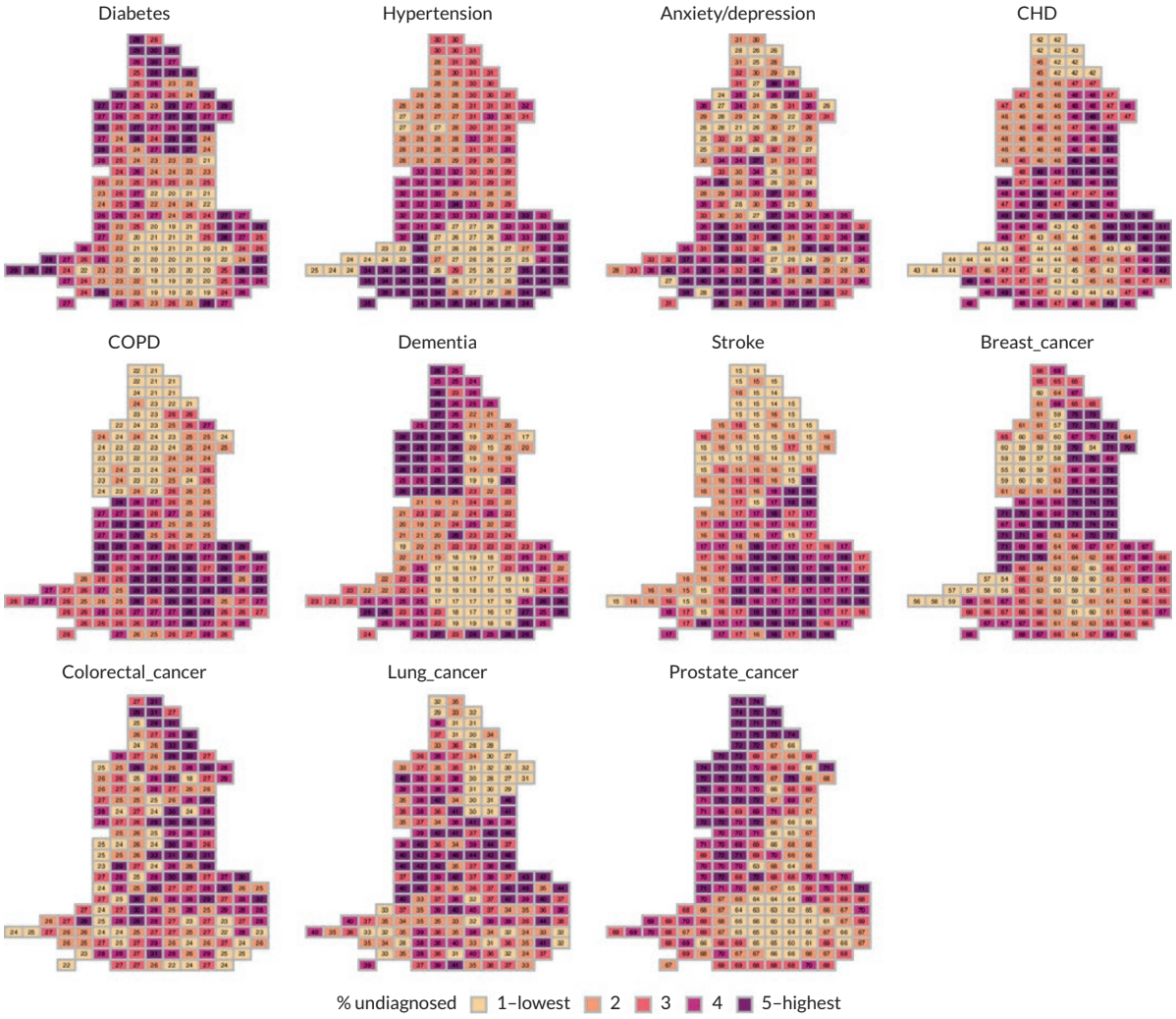


FIGURE 8 Estimates percentage of conditions undiagnosed by CCG, 2018. Reproduced from Anosova *et al.*[21] This is an Open Access article distributed in accordance with the terms of the Creative Commons Attribution (CC BY 4.0) licence, which permits others to distribute, remix, adapt and build upon this work, for commercial use, provided the original work is properly cited. See: https://creativecommons.org/licenses/by/4.0/. The figure above includes minor additions and formatting changes.

probability of being undiagnosed with deprivation, while HSE indicates a weak negative relationship with deprivation – that is that more deprived people with hypertension are more likely to be diagnosed than less deprived.

Survey-based estimates of the probability of being undiagnosed

Method: To complement our estimates above in *Dynamic state model: estimating the number underdiagnosed*, we also estimated the total prevalence of diabetes, hypertension and depression/anxiety, and the estimated proportion undiagnosed for each age group, deprivation quintile, sex and region (i.e. 450 groups) using a survey-based approach. For diabetes and hypertension, we use the HSE between 2010 and 2019, and for anxiety and depression, we use the US panel survey between 2010 and 2019. For each condition, we define people with undiagnosed disease as those with clinical signs indicating a condition (hypertension – systolic blood pressure > 140 mmHg and/or diastolic blood pressure ≥ 90, HbA1c ≥ 48 mmol/mol,[25] 12-Item short-form survey mental health component score < 42[26]), but report that they have not been diagnosed with the condition. The total prevalence is defined as those with either clinical signs or a reported diagnosis. We estimate the total prevalence of disease and the probability of people having a diagnosis conditional on having the disease, using logistic regression, including all two-way interactions between age group, deprivation quintile, sex, region and time period. We use stepwise model selection by Akaike information criterion to find the combination of interactions that provides the best-fit model for the data.[27]

We then use microsimulation as outlined in *Dynamic state model: estimating the number underdiagnosed* to apply these estimates to population segments in 2018 to produce estimates of the number of people undiagnosed and diagnosed with each condition in each CCG. See our associated paper for more details.[22]

Findings: *Table 6* shows the pattern of our estimates, by mean age and deprivation of each CCG. For these estimates, the probability of being undiagnosed with depression/anxiety is greatest in places with the youngest populations and increases with deprivation. According to responses from HSE, people with hypertension in places with older and more affluent populations are estimated to be less likely to be diagnosed than places with younger more deprived populations. This inverse relationship with deprivation is even more clear in HSE estimates for diabetes, with diabetics in more affluent areas being more likely to be undiagnosed.

Figure 9 shows these estimates by CCG. Most notable are the high-estimated levels of underdiagnosis for depression and anxiety in London and low levels of underdiagnosis in the South West. For hypertension, we see lower levels of underdiagnosis in London, higher in the South West and the North. For diabetes, the HSE estimates indicate low levels of underdiagnosis in the North and higher levels in the South.

Aggregating undiagnosed estimates across conditions

Method: To derive an adjustment for unmet need due to underdiagnosis across multiple conditions, we need an estimate of the needed cost associated with each undiagnosed case. It is not possible to observe what the cost would have been for each undiagnosed case had it been diagnosed. We, therefore, assume that the needed cost for each case of undiagnosed disease, within each age, sex, IMD quintile and region, is the same as the average cost for each diagnosed case in the same segment. We can then estimate our measure of unmet need due to underdiagnosis as the estimated costs of diagnosing and treating the undiagnosed as percentage of the total costs of diagnosing and treating all cases of these diseases. This is essentially the average probability of these conditions being undiagnosed, weighted for the average costs associated with each condition, differentiated by age, sex, deprivation and region. This approach can be used to provide an estimate of unmet need due to underdiagnosis across any group of conditions, potentially using different methods to estimate levels of underdiagnosis for different diseases.

We derive primary and secondary care costs using linked CPRD-Hospital Episode Statistics (HES) data. Firstly, we estimate the costs for each individual, then we fit linear regression models with the annual cost as the dependent variable and region, gender, age group, quintiles of IMD, disease diagnosis and the interactions of disease diagnosis with age group and quintiles of IMD as the predictors. We then predicted from these models the cost for cases for each disease within each region/gender/age group/

TABLE 6 Estimates percentage of conditions undiagnosed by CCG mean age and deprivation quintiles

	Deprivation quintile (D1 = least deprived, D5 = most deprived)	Age quantile (A1 = youngest, A5 = oldest)				
		A1 (%)	A2 (%)	A3 (%)	A4 (%)	A5 (%)
Diabetes	D1	24	24	24	24	24
	D2	24	23	23	23	23
	D3	23	23	22	23	23
	D4	22	21	21	21	22
	D5	20	20	20	20	21
Hypertension	D1	20	21	22	22	21
	D2	19	22	21	22	21
	D3	19	23	20	22	22
	D4	18	19	20	20	20
	D5	19	19	20	20	19
Depression/anxiety	D1	57	55	54	55	56
	D2	61	59	57	57	54
	D3	60	53	57	60	54
	D4	63	57	59	60	53
	D5	62	60	59	58	50

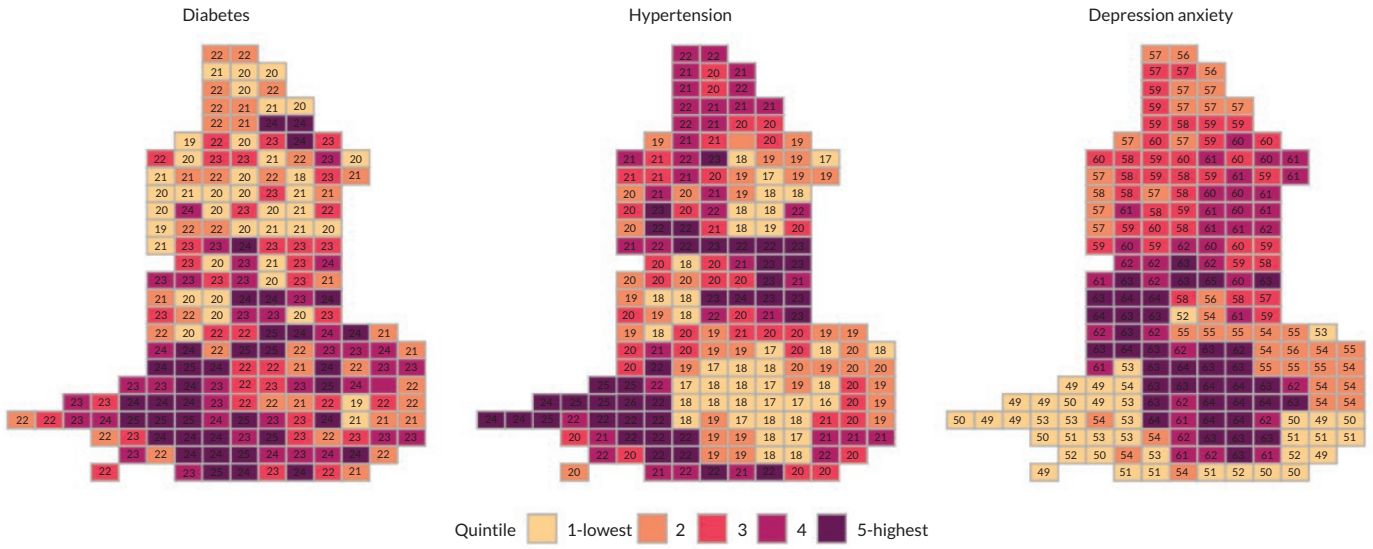


FIGURE 9 Estimates percentage of conditions undiagnosed by CCG (darker colour indicates high per cent undiagnosed).

quintiles of IMD stratum. See our associated paper for further details of methods.[15]

We first plot the estimated primary and secondary care costs per case, by age deprivation and disease, to explore how these costs vary across these dimensions. We then plot 2018 estimated expenditure on these groups of disease for each CCG, just including diagnosed conditions and then the total needed expenditure, including diagnosed and undiagnosed conditions, and compare the share of funding that each CCG in these two scenarios assuming a fixed budget. Essentially, this reproduces *Figure 2* in *Measuring the proportional distribution of need* using empirical estimates of diagnosed prevalence and our estimates of undiagnosed cases in each CCG. To investigate potential consequences for health inequalities for such an adjustment, we plot the change in funding each CCG would experience moving from the current funding to fair shares that account for undiagnosed cases, by the average IMD[28] of each CCG.

We then map the percentage unmet need due to underdiagnosis for each CCG in aggregate across all 11 conditions (CHD, stroke, hypertension, COPD, diabetes, dementia, breast cancer, prostate cancer, lung cancer, colorectal cancer and depression/anxiety). For each analysis, we use the estimates of the number undiagnosed from our dynamic state model and then we estimate the same results for a combined model, where we substitute the estimates for anxiety/depression, hypertension and diabetes with those from our survey-based estimates.

Findings: Figure 10 shows the distribution of primary care costs across age and deprivation groups for each disease. For most conditions, costs tend to increase with both age and deprivation, although the pattern is less clear for lung cancer. This may reflect that most costs for lung cancer are in secondary care. There appear to be particular high primary care costs for the most deprived 30- to 49-year-olds with colorectal cancer. The pattern of primary care costs was fairly similar across regions (data not shown).

Figure 11 shows the distribution of secondary care costs across age and deprivation groups for each disease. Similarly, for most conditions, costs tend to increase with both age and deprivation, although the pattern is less clear for hypertension, diabetes and breast cancer. There are also particular high secondary care costs for the most deprived 30- to 49-year-olds with colorectal cancer. The regional pattern shows higher costs in London across all conditions and, to a lesser extent, higher costs in the North West (data not shown).

Figures 12 and *13* show the absolute needed expenditure taking into account diagnosed and undiagnosed cases of disease (panel 1 – purple line) and the distribution of expenditure on diagnosed cases (panel 1– orange line). The total expenditure needed to treat all cases (diagnosed and undiagnosed) is obviously much higher than the expenditure required to just treat those currently diagnosed. Assuming a fixed budget, however, and sharing out the total national expenditure on diagnosed cases in proportion to the absolute needed expenditure for each CCG, gives the black line in panel 2. *Figure 12* shows these results just using the estimates from the dynamic state model, and *Figure 13* shows this for the combined model, where we substitute the estimates for

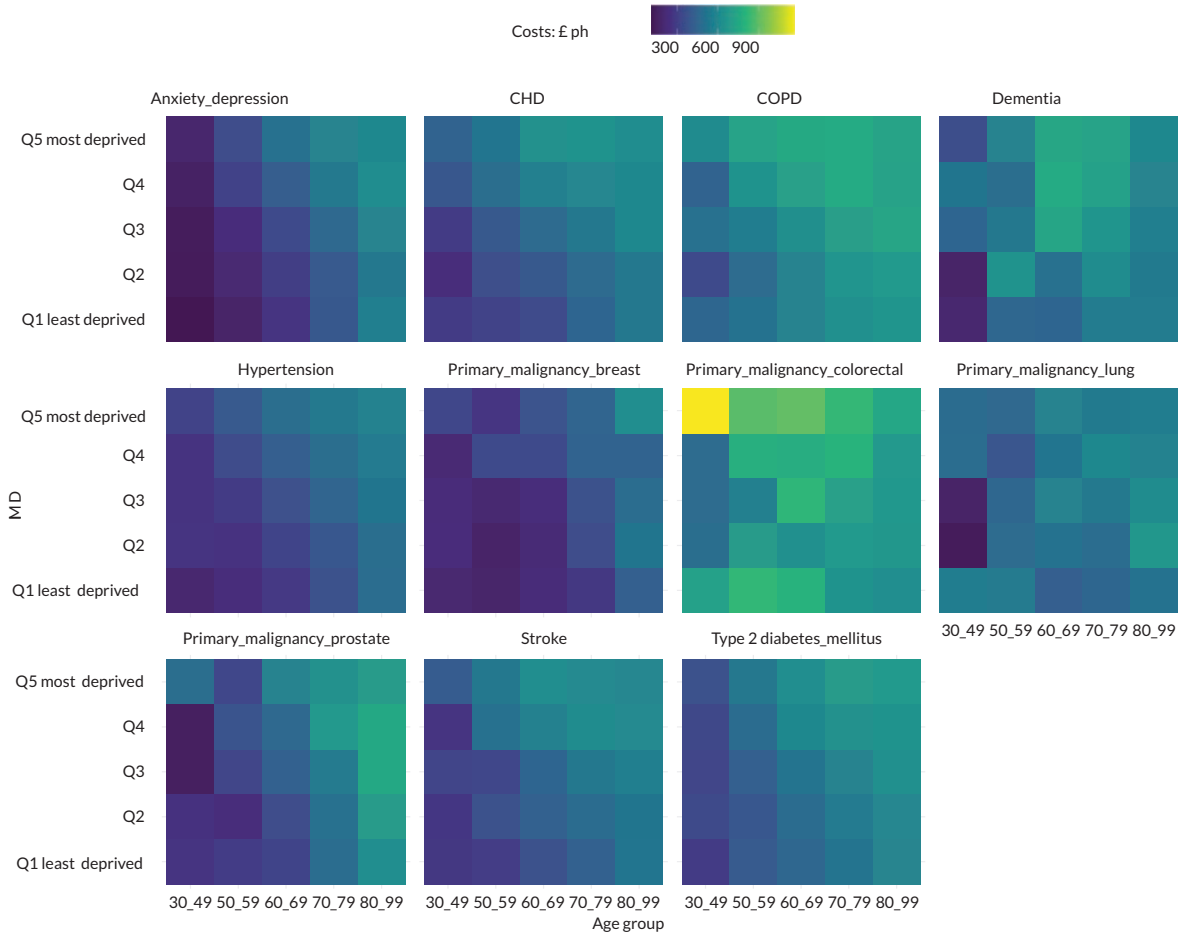


FIGURE 10 Primary care costs by age, deprivation and disease.

anxiety/depression, hypertension and diabetes with those from our survey-based estimates.

In both cases, the distribution of expenditure based on diagnosed cases is not hugely different from the fair share distribution, taking into account estimated undiagnosed and diagnosed conditions. Just using the dynamic state model estimates of underdiagnosis (see *Figure 12*), we find the fair share distribution taking account of the undiagnosed (black line – panel 2) is slightly lower than the actual expenditure shares in CCGs with the highest needs. This would mean that shifting resources so that they are in proportion to all needs (diagnosed and undiagnosed) would shift resources away from CCGs with high overall needs to those with lower overall needs. So high-need CCGs, in this example, are estimated to have overmet affordable needs, and mid- to low-need CCGs have unmet affordable needs. There is a strong negative relationship with deprivation. Moving to this fair share distribution would tend to benefit less-deprived CCGs and shift resources away from the most deprived CCGs. Adjusting allocations based on this analysis would lead to a 7% increase in the budget in the CCG with the highest unmet needs and an 8% reduction in the budget for CCGs with the least unmet needs due to underdiagnosis.

Replacing the estimates of underdiagnosis for anxiety/depression, hypertension and diabetes with estimates of underdiagnosis from survey data changes the fair share distribution taking account of the undiagnosed (*Figure 13*, black line – panel 2). In particular, the negative relationship with deprivation is now less pronounced. This is largely because the survey-based estimates suggest a higher prevalence of undiagnosed depression/anxiety, in more deprived areas (see *Table 6*).

Figure 14 shows the aggregate level of estimated unmet need due to underdiagnosis from the dynamic state and combined model across CCGs. Once we have aggregated up these estimates of underdiagnosis across CCGs and diseases the estimated level of unmet need does not vary hugely between CCGs, with the estimated proportion of needs unmet due to underdiagnosis varying between 32% and 41%. The dynamic state model indicates lower levels

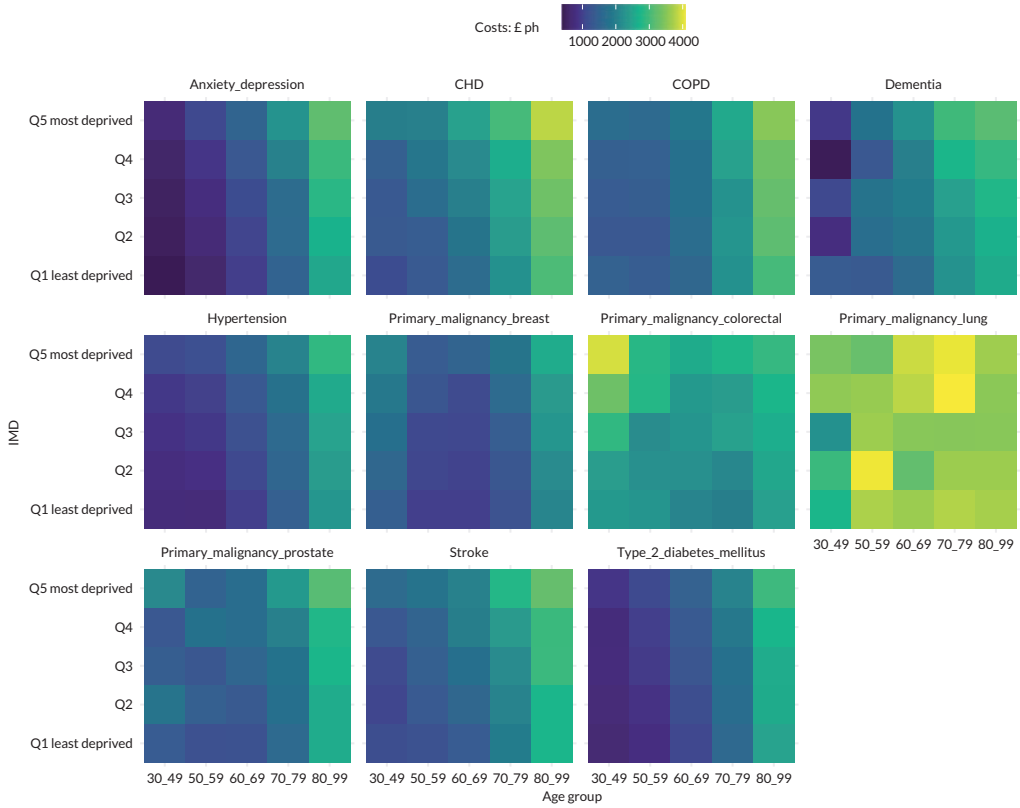


FIGURE 11 Secondary care costs by age, deprivation and disease.

of unmet need due to underdiagnosis in London and lower levels in the North West. The addition of the survey-based measures increases our estimates of unmet need in London and the East Midlands. This reflects the high levels of undiagnosed depression/anxiety estimated in London and high levels of undiagnosed hypertension estimated in the East Midlands when using the survey-based model.

Estimating the effects of adjustments to resource allocation on health and health inequality

Method: Applying the adjustments developed above should lead to a distribution of healthcare resources that is closer to one that is proportional to the total amount of need in each area, that is it would lead to levels of unmet need in each CCG that are more similar. In order to understand what effect that may have on health outcomes, we estimate the relationship between secondary healthcare expenditure and mortality and how this differs across levels of deprivation. We focused on secondary care expenditure (i.e. 'hospital' expenditure, for short) because this is the largest component of health expenditure in England and may potentially have a more immediate effect on mortality than primary care and public health expenditure focused on long-term prevention.

Our analysis employs data on deaths and population by sex and age for all 32,844 LSOAs in 2018 in England. These were used to calculate age/sex standardised all-age mortality rates for each LSOA, which were then linked to 2019 English indices of deprivation and to NHS funding allocations in the financial year 2018–9 for 195 CCGs mapped to LSOAs. Our study focuses on the main funding stream, known as 'Core Allocations', of which approximately two-thirds is assigned to general and acute hospital care, including hospital-based maternity services and mental health care, and one third to community-based mental health care, maternity services and prescribing.

Healthcare expenditure and mortality are potentially endogenous. That is, increased morbidity and mortality could lead to increased funding as well increased funding causing a reduction in mortality and morbidity. Therefore, we use instrumental variable techniques to estimate the causal effect of exogenous variation in this funding on mortality in 2018, in line with previous research.[29–32] Our main analysis uses *Distance From Target (DFT)* as the instrument. DFT is calculated by the NHS as a direct estimate of how much more (or less) funding a CCG has, than it should have, based on its level of need. It is the percentage difference between the funding a CCG is

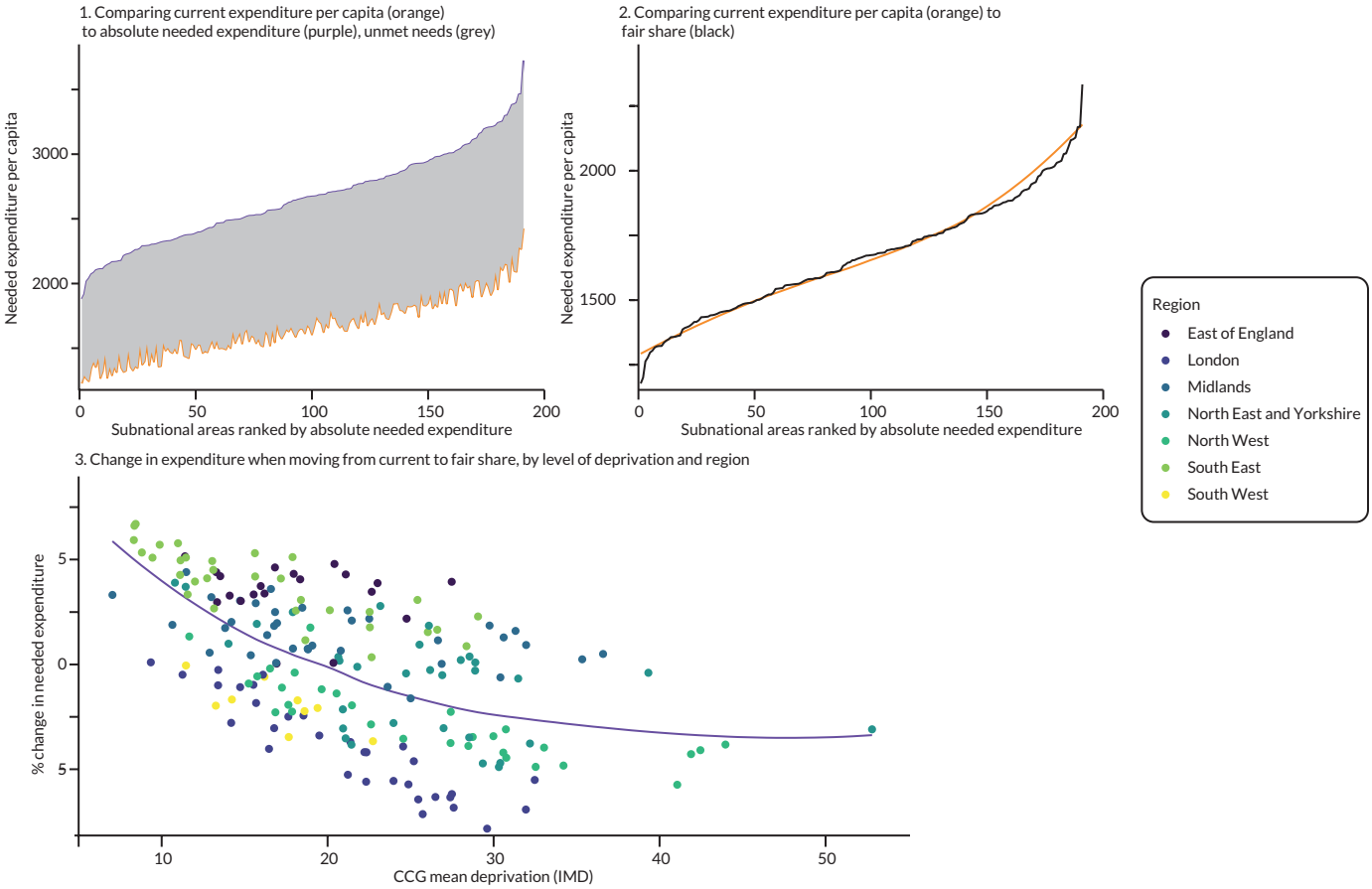


FIGURE 12 Dynamic state model – absolute needed expenditure and fair share accounting for expenditure on diagnosed and undiagnosed conditions compared to expenditure on diagnosed cases of 11 conditions (diabetes, hypertension and anxiety/depression, CHDs, stroke, hypertension, COPD dementia, breast cancer, prostate cancer, lung cancer and colorectal cancer). Proportion of conditions undiagnosed estimated using dynamic state model described in *Dynamic state model: estimating the number underdiagnosed*. Bold orange line in panel 2 and bold purple line in panel 3 are loess smoothed values.

estimated to need from the allocation formula and the actual funding it received in the previous year. We estimate the marginal effect of the allocation on mortality using a standard two-stage least squares method to instrument the logged allocation. This provides an elasticity of mortality with respect to expenditure allocation (i.e. the per cent change in mortality rate for a 1% change in expenditure). To analyse sub-group variation in the elasticity of mortality with respect to expenditure allocation by deprivation group, the instrumented allocation was interacted with deprivation quintiles. Further, details of methods are given in our associated paper.[33]

Findings: We find that a 1% increase in expenditure reduced age-standardised mortality by 0.83% [95% confidence interval (CI) 0.23% to 1.42%] overall, 0.46% (95% CI −0.18% to 1.10%) in the least deprived group of small areas and 0.64% (95% CI 0.11% to 1.16%) in the most deprived group (*Figure 15*). We find that the mortality effect of a marginal change in secondary care expenditure follows an inverted U shape with deprivation – larger in the middle deprivation groups, and smaller in the top and bottom deprivation groups (see *Figure 15*).

These estimates can be used to estimate the impact on health inequalities of alternative adjustments outlined above. We have developed an interactive tool that enables users to enter the relative change expenditure for each CCG indicating the potential impact of this on mortality and quality-adjusted life-years (https://darkpeakanalytics.shinyapps.io/unmetneeds_dev/).

Figure 16 shows the likely effect on mortality by deprivation quintile of two adjustments, the responsiveness adjustment removing the 25% least-responsive CCGs (i.e. as in *Figure 4*, panel 4) and the underdiagnosis adjustments, adjusting for levels of underdiagnosis based on dynamic state model estimates, (i.e. as in *Figure 12*).

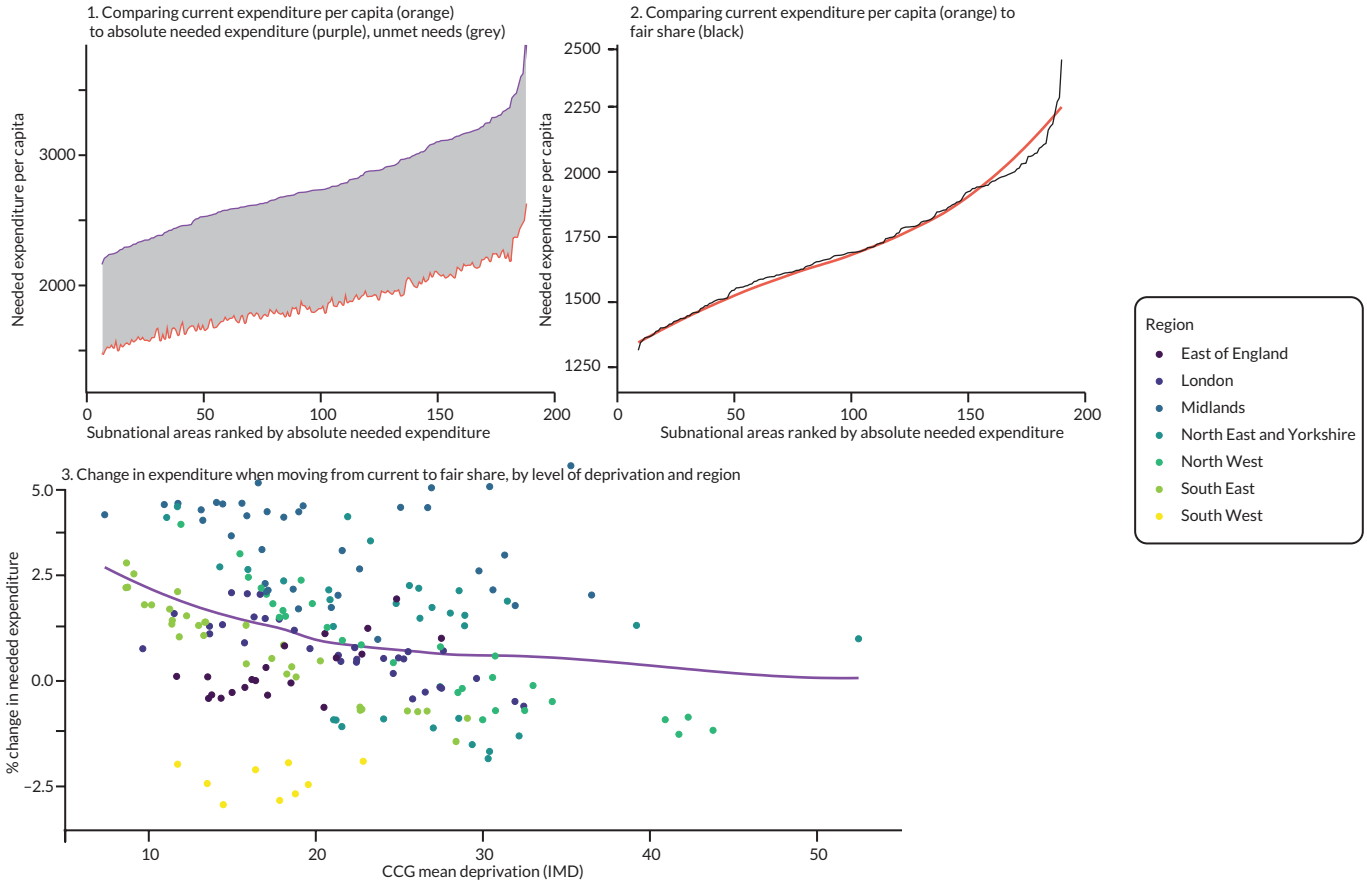


FIGURE 13 Combined model – absolute needed expenditure and fair share accounting for expenditure on diagnosed and undiagnosed conditions compared to expenditure on diagnosed cases of 11 conditions (diabetes, hypertension and anxiety/depression, CHDs, stroke, hypertension, COPD dementia, breast cancer, prostate cancer, lung cancer and colorectal cancer). Proportion of conditions undiagnosed estimated using dynamic state model described in *Dynamic state model: estimating the number underdiagnosed*, except for anxiety/depression, hypertension and diabetes, which are based on survey-based model outlined in *Survey-based estimates of the probability of being undiagnosed*. Bold orange line in panel 2 and bold purple line in panel 3 are loess smoothed values.

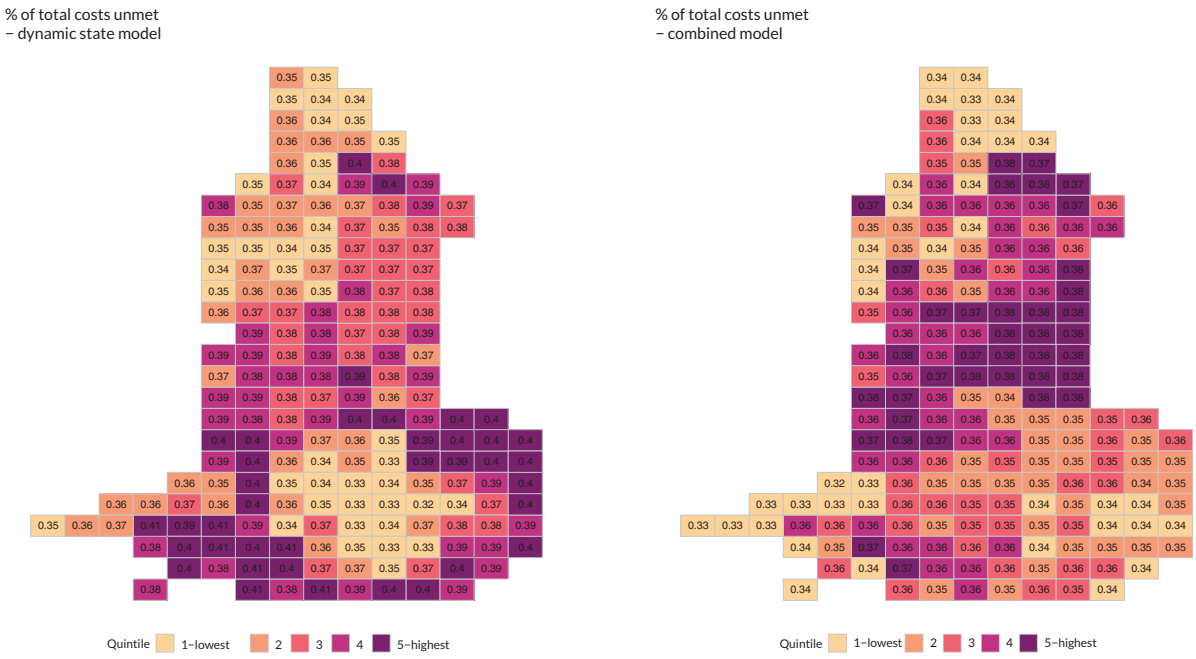


FIGURE 14 Estimates of relative unmet need due to underdiagnosis using (1) dynamic state model estimates of underdiagnosis (2) combination of dynamic state and survey-based estimates.

For the responsiveness adjustment this assumes that the initial distribution of resources reflects the distribution of the needs index estimated in the current general and acute formula, and the budget change is equal to the percentage change in the needs index following the responsiveness adjustment. For the underdiagnosis adjustment we assume the overall budget change is equal to the estimated percentage budget change for the 11 conditions included in the model, after adjusting for underdiagnosis as outlined in *Aggregating undiagnosed estimates across conditions*. For the responsiveness adjustment, the model estimates a negative effect (i.e. increasing mortality) across all quintiles apart from the most deprived, where mortality is estimated to decline due to the adjustment. In this scenario, overall mortality would be increased by the adjustment, but inequality (i.e. the gap between the most and least deprived) decreased. For the underdiagnosis adjustment, mortality declines in the least deprived quintiles and increases in the most deprived. Overall mortality decreases as a result of the adjustment, but inequality increases.

As outlined there are a number of limitations and uncertainties about these adjustments for unmet need, as well as the estimates of mortality impact (see below). This analysis highlights, however, that adjusting for unmet need could have negative effects on overall efficiency (i.e. change in overall mortality for a fixed budget) and/or on health inequality.

Discussion

Overview

Overview of the four adjustments

In *Understanding what we mean by unmet need for health care* we outline a framework for the measurement of need in NHS resource allocation formulae, highlighting how measurement can be decomposed into two components (1) a *vector of characteristics* for each individual in each local NHS area and a (2) *vector of cost weights* indicating the expected needed expenditure associated with each of these characteristics. The problem with estimating unmet need can therefore be understood as a problem with missing data and/or measurement error in these two components. We clarify that judgement of these inaccuracies in NHS allocation formula should be based on the extent to which they distribute sufficient resources to each area to meet an equal proportion of the total resources required to provide each individual in each area with all the services that the NHS normally provides from which they can benefit.

We have then outlined four adjustments that address different errors and types of missing data in the current approach used for NHS resource allocation formulae. The responsiveness adjustment (see *Responsiveness adjustment: an adjustment for unmet needs based on variations in responsiveness of expenditure to need*)

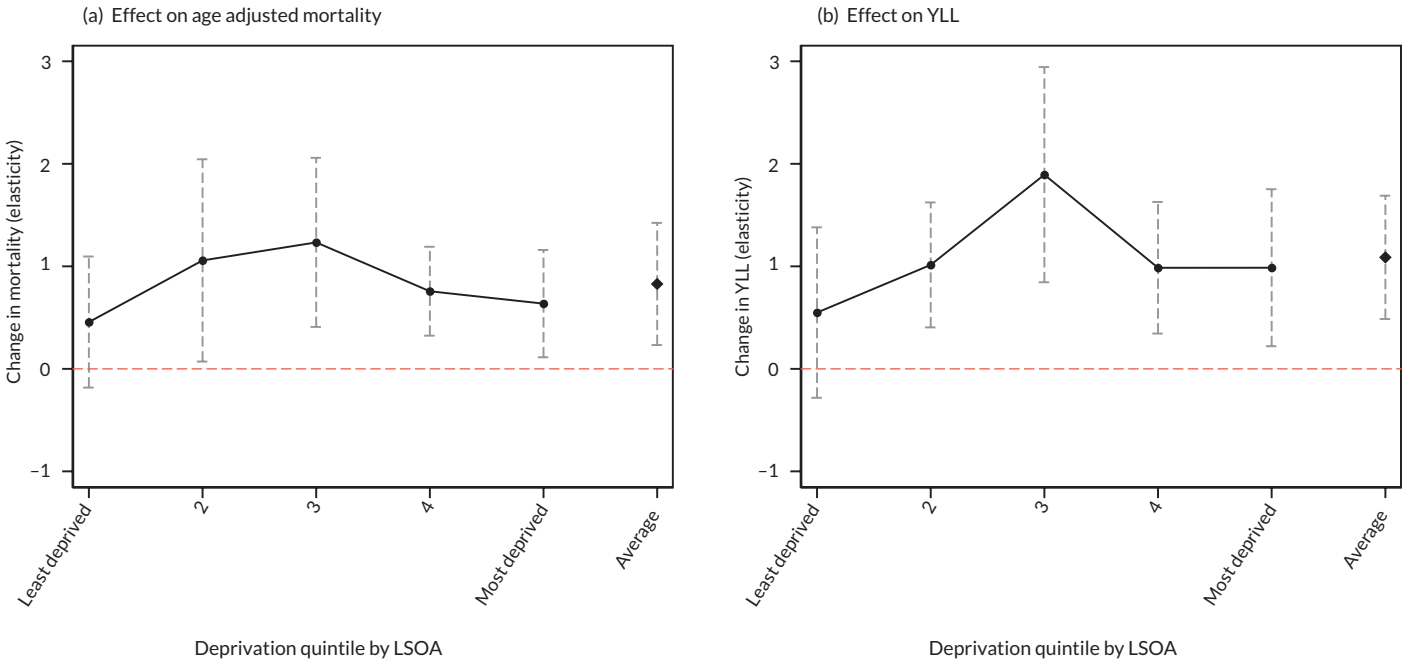


FIGURE 15 Estimated effect of healthcare expenditure on mortality by deprivation group. YLL, Years of Life Lost.

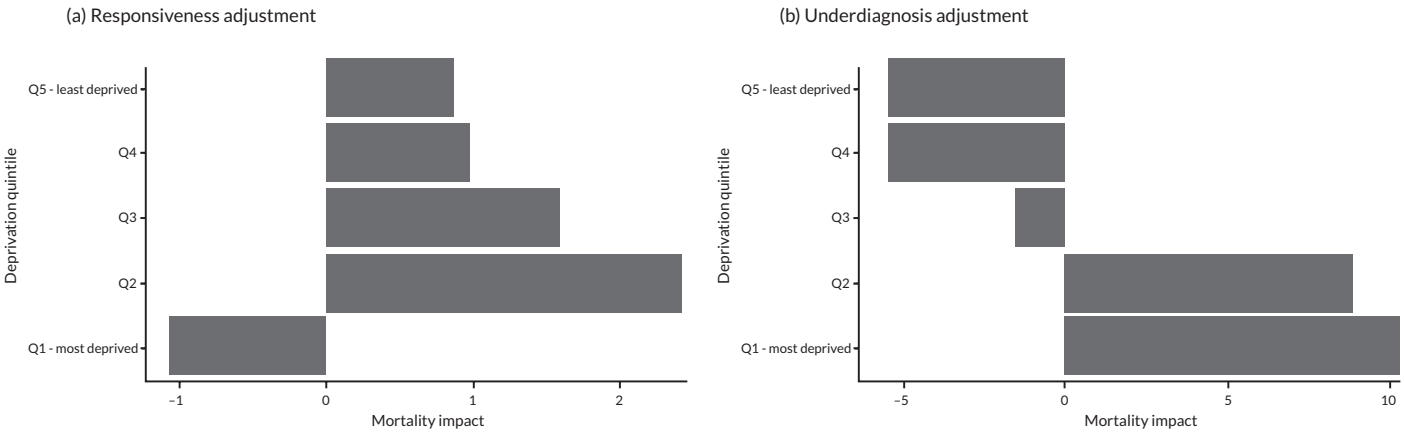


FIGURE 16 Estimated impact on mortality by deprivation quintile of two adjustments assuming a fixed budget. (a) Responsiveness adjustment, removing 25% of least-responsive CCGs (i.e. as in *Figure 4*, panel 4) and (b) Adjusting for levels of underdiagnosis based on dynamic state model estimates (i.e. as in *Figure 12*).

addresses issues with the second component (the *vector of cost weights)*, as these are currently estimated using data from across all NHS areas they may not reflect the actual relative needed expenditure associated with those characteristics. For example, some health conditions may, on average, be more likely to be undertreated compared to health conditions. We provide a method, for deriving more accurate cost weights, by estimating the formula on a subset of NHS areas that are more responsive to need, and show how this would affect the distribution of resources between NHS areas. The longitudinal adjustment (see *Longitudinal adjustment: adjustment accounting for time-invariant unobserved patients' need*) provides a further approach for more accurately estimating the cost weights. Currently cost weights are estimated based on the predicted costs associated with each characteristic, conditional on variation in healthcare supply. These will be inaccurate if variation in supply is not adequately accounted for. By using longitudinal individual data, we show how supply effects can be better accounted for, enabling the formula to be adjusted for inaccuracies in the current cost weights. The primary care diagnosis adjustment (see *The primary care diagnosis adjustment: an adjustment accounting for diagnoses in primary care*) addresses the fact that data are currently missing on primary care diagnosis from the first component (*vector of characteristics)*, used for the current general and acute formulae. We show that this missing data is a predictor of healthcare use and influences the distribution of resources so that the formula better reflect patterns of need. Finally, the underdiagnosis adjustment (see *The epidemiological approach: underdiagnosis adjustment*) aims to address the major factor missing from the first component (*vector of characteristics)*, in all the formulae, namely whether people have undiagnosed conditions. We provide a method that can be used to estimate the extent of this across population segments enabling the formulae to be adjusted for this missing data.

Combining adjustments

As each of the adjustments relate to different inaccuracies in the current approach they can be combined without duplication or double counting unmet needs. For example, as outlined in *Figure 17*, the responsiveness adjustment could be applied by removing less-responsive CCGs from the data used for formula estimation. These data could include linked primary care data to improve the estimation of need (i.e. the primary care diagnosis adjustment). Longitudinal data with patient fixed effects could then be used to calculate over or under estimation of supply effects from the pooled model for each place. Finally estimates for underdiagnosis could be applied to diagnostic flags in each population segment in the data used for predicting need. In the case of our model this would be region × IMD × age × sex segments, but more sophisticated models in the future could produce estimates at finer granularity. These estimates of underdiagnosis could be included within the current utilisation approach by weighting each diagnosed case of disease by the inverse probability of being diagnosed, that is in population segments with a higher-than-average probability of being diagnosed the weight would be < 1 and in population segments with a lower probability of being diagnosed the weight would be > 1, reflecting the levels of over or underdiagnosis. These weights would

then be used in the prediction stage of the utilisation approach in the same way diagnostic flags currently are. In other words if currently a case of diabetes is given a weight of £500 in the current formula (i.e. the coefficient on the diagnostic flag is £500), and it is estimated that only 80% of diabetics are diagnosed in this population segment, then the case – adjusting for underdiagnosis would we given a cost weight of £500*1/0.8 = £625 for each diagnosed case of diabetes. This would mean that the cost weighted utilisation in groups with lower probability of diagnosis would be inflated to account for higher levels of underdiagnosis. This approach would be making the same assumption as we have used in *The epidemiological approach: underdiagnosis adjustment* that the needed costs for the undiagnosed is the same as for the diagnosed. There are, however, likely differences in disease stage and severity between diagnosed and undiagnosed that might affect costs. There may also be additional costs for case-finding and diagnosing the undiagnosed to enable them to take up optimal treatment, that we are also not able to include. Alternative approaches could be applied to adjust the cost weights applied to undiagnosed cases to account for these differences. Predicted need from this approach could then be aggregated to the area level as with the current formula.

In practice, this approach of combining the four adjustments would rely on greater data requirements than is currently available and addressing limitations outlined below. The consequences in terms of the impact on resources distribution and effects on the distribution of health would need to be carefully assessed before implementation.

Assessing the health inequalities impact of unmet need adjustments

As outlined in *Understanding what we mean by unmet need for health care*, the aim of these four adjustments is to improve the NHS resource allocation formulae so that they more closely reflect the relative distribution of need. This is distinct from the other objective of NHS resource allocation which is to reduce health inequalities. Changing the distribution of resources to better reflect patterns of need, however, will influence health inequalities, by changing the distribution of health. In *Estimating the effects of adjustments to resource allocation on health and health inequality* we provide an approach for estimating this effect. We find that NHS expenditure tends to reduce mortality in the middle deprivation groups, and have a smaller effect in the top and bottom deprivation groups. These estimates imply that the responsiveness adjustment, would likely reduce health inequalities (i.e. the mortality gap between least and most deprived areas) while adjusting for underdiagnosis using the estimates we derive in *Dynamic state model: estimating the number underdiagnosed* would increase inequalities. This highlights the point we made in *Understanding what we mean by*

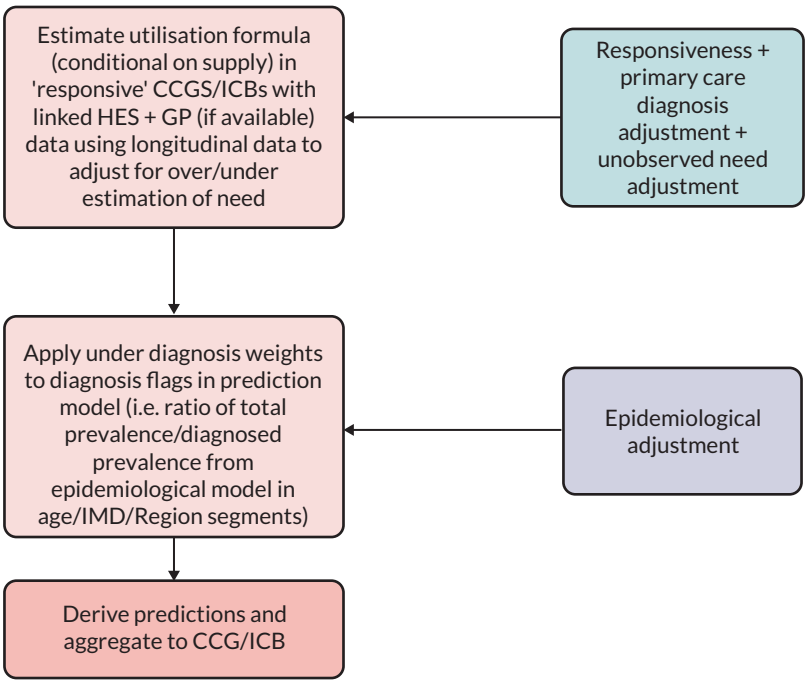


FIGURE 17 Showing how the outlined adjustments could be applied in practice.

unmet need for health care that improving the formulae by better accounting for unmet needs could lead to an increase in health inequalities.

Limitations

There are several limitations with the four adjustments we outline and the approaches we develop for assessing their impact on health inequalities.

First, our responsiveness adjustment relies on identifying those NHS areas that are better at aligning resources to need. We do this by identifying those areas that have a higher correlation between need (measured by the service need estimates derived from the formula) and expenditure within their populations. Concerns have been raised that the measure of need in this approach may not accurately reflect the distribution of need within an NHS area and the approach we use may exacerbate existing biases present in the formulae. However, it is not necessary for our measure of need to be a perfect measure of absolute need for our indicator of responsiveness to be unbiased. It only needs to reflect relative differences in need between people within a CCG. In other words the rank of need between individuals, based on the needs index, should broadly reflect the rank of absolute need, for this to be an unbiased measure, even if only a fraction of needs are met. As the measure of responsiveness we use reflects the association between need and expenditure *within* CCGs, it should not be biased by systematic *between* CCGs errors in the measure of need used. As long as the ranking by service need reflects the ranking by true need, the ranking of CCGs by responsiveness will be maintained. The actual measure of responsiveness may change but the less-responsive CCGs would be the same.

While we cannot know for certain whether the approach does identify those NHS areas that are better at aligning resources to need, a number of the robustness checks suggest this is the case. We tested the association between responsiveness and a broad range of performance and potential influences and consequences of unmet need, finding that responsiveness was generally associated with indicators that would be expected to indicate CCGs that were better at meeting unmet needs. We found no evidence of association between responsiveness and negative measures of performance.

One potential limitation with the longitudinal adjustment is that it only accounts for time-*invariant* individual needs and not time varying unobserved needs. Estimates could then be biased if time varying unobserved measures of need vary between places. Estimates could also be biased if movements between areas were related to differences in healthcare supply. However, we checked that individuals did not move systematically to higher or lower utilisation CCGs or to more or less rural, coastal or deprived regions. We also checked that the results were unaffected by controlling for interactions between moving and area based and individual characteristics. Additionally, if there is a lag between changes in healthcare utilisation and movements between areas, this could lead to underestimation of the supply differences between areas. This could happen, for example, where people have agreed a package of care in their origin NHS area that will not change soon after they move even if the supply conditions are different. While 'sticky' packages of care may still dampen the estimation of differences in supply, the longitudinal model would remain an improvement on the pooled model. It would just mean that some residual unmeasured needs would continue to be captured by the area supply effects. The key limitation to this approach is not having access to linked data on all people registered with GPs and, therefore, needing to make assumptions about where individuals are living in years when they do not use hospital services. This could be addressed by using HES data linked to NHAIS data.

The main limitation with the primary care diagnosis adjustment is the lack of access to such data nationally at present. As the data used here from CPRD do not include all practices and are not a random sample of primary care records, the results may not be generalisable to the whole population. In other words, the effect on the distribution could change if replicated using more representative data. It is unlikely that these differences would be large; however, CPRD data are broadly representative of the national population.[34] A further issue is how to include primary care diagnosis within the formula in combination with diagnoses in secondary care. Here we have outlined three approaches, but other options are possible. For each of the 205 conditions recorded in primary and secondary care used here, there are four possible combinations: (1) recorded only in primary care, (2) recorded only in secondary care, (3) recorded in both primary and secondary care and (4) recorded neither in primary or secondary care. Each of these combinations could indicate different levels of expected need, but to include them all would be adding 4 × 205, that is 820 variables to the model, which could overly complicate the model. Further investigation should be undertaken understand the most parsimonious combinations of primary and secondary care diagnosis to include in the general and acute formula while maintaining improvements in prediction.

While the underdiagnosis adjustment we outline, makes several advances on previous epidemiological approach, there are still several limitations that would need to be overcome for it to be implemented. While our dynamic state model does allow for greater granularity in analysis compared to survey based methods – our dynamic state modelling approach relies on using data on deaths without prior diagnosis. For many diseases, however, these are relatively rare events, leading to high levels of uncertainty within population segments (e.g. age group/sex/deprivation/region/year strata). This means that it is still only possible to directly estimate levels of underdiagnosis across a limited number of population segments.[21]

A major assumption we need to make for this model is how the CFR in the undiagnosed relates to the CFR in the diagnosed. In our main model, we assume the CFR in the undiagnosed is that same as in the first year of diagnosis. For each of these assumptions, however, we test whether they make a large difference to the distribution of the undiagnosed fraction of conditions between CCGs.[21] In most cases, changing these assumptions has a limited impact on this distribution.

A further limitation with the underdiagnosis adjustment is that we found an inconsistent relationship between our estimates and other indicators that might be expected to follow patterns of unmet need. This lack of consistency between measures leads to greater uncertainty about the validity of the estimates we derive.

A limitation with our approach that affects epidemiological approaches in general is that we are limited to a relatively small number of conditions. Our dynamic state model is an improvement on survey-based methods as outlined in *Survey based estimates of the probability of being undiagnosed*, that are limited to a few conditions where there is direct clinical measurement of conditions in representative survey data, generally just diabetes, hypertension and some mental health conditions.[21] Our dynamic state model can be applied across a larger number of conditions; however, it is limited to those conditions for which there is sufficient data available on deaths without prior diagnosis.[21]

The main limitation in the approach we apply for assessing the impact of formula adjustments on mortality is that like the many previous instrumental variable studies of the health effects of marginal changes in health expenditure, our methods are not as scientifically robust as a randomised controlled trial or natural experiment would be. We rely on the twin assumptions that our 'distance to target' instrument reflects variation in expenditure that is both (1) exogenous and (2) sustained for a few years before and during the current year in which mortality was observed. This latter assumption of sustained variation means that we can interpret the effect as a medium-term 'equilibrium' effect of sustained expenditure change on mortality, rather than a short-term effect of a short-term fluctuation in expenditure in the current period only. A second limitation is that as we do not have expenditure by small area we cannot tell how far our results are due to deprivation-related differences in (1) how changes in large area planning allocations are shared out between small area neighbourhoods within those large areas, versus (2) the mortality effect of a one unit change in small area level expenditure. However, this limitation does not bias or invalidate our main conclusions. The large area level is the relevant one for analysing the causal effects of changes in allocations on mortality outcomes, since secondary care expenditure is allocated to large planning areas and not directly to small areas.

Impact and learning

Each of the studies outlined in this research has initially been discussed with the Technical Advisory Group (TAG), and then with the ACRA, with some studies going through this process more than once. At each stage, this has involved refining the analysis, checking robustness and sensitivity testing based on the comments of external experts and the NHS England resource allocation team. In addition, findings have been reviewed annually by our oversight group. A final report was prepared for and presented to ACRA with a set of recommendations as outlined in *Implications for decision-makers*. This has ensured that users of the research are fully appraised on the strengths, limitations, and practicalities of implementation. ACRA has established an Unmet Need Task and Finish Group to consider the recommendations and how they can be implemented.

The research has potential for impact on several levels. Firstly, some of the adjustments as outlined can be implemented, in the short term, within the NHS resource allocations process, as data become available, in particular the responsiveness, primary care diagnostic and longitudinal adjustments. This would improve the current formula enabling it to better account for unmet needs. Secondly, the research provides conceptual and methodological advances that form the basis for further research that aims to address unmet needs and health inequalities through the geographical allocation of healthcare resources. The conceptual clarity with respect to need for health care, health inequalities and the components of needs estimates, as outlined in *Understanding what we mean by unmet need for health care*

will enable the formation of clearer research questions and improve the synthesis of findings for research allocation policy. The dynamic state model outlined in *Dynamic state model: estimating the number underdiagnosed* outlines a promising approach for identifying underdiagnosis, that with improved data and further validation could provide a crucial tool to inform national allocations that take account of underdiagnosis. Thirdly, the approaches outlined can be used by integrated care systems (ICSs) to allocate resources and target intentions to those with the greatest needs within their populations. The dynamic state model approach could provide ICS with a tool to identify population segments and diseases with high levels of underdiagnosis for targeted interventions and outreach to improve early diagnosis. The methods outlined in *Enhancing the utilisation approach* can be applied through regional secure data environments to inform resource allocation decisions between neighbourhoods within ICS regions. For example, a result of this project, the Cheshire and Merseyside ICS is using a utilisation formula to inform the staffing levels for neighbourhood community nursing teams.

Implications for decision-makers

This programme of research has developed four adjustments targeting separate facets of unmet needs, that can be implemented within the NHS resource allocation process. The responsiveness adjustment helps rectify under estimation of needed expenditure associated with patient characteristics, ensuring estimates better reflect the distribution of overall healthcare need between places. The longitudinal adjustment addresses misclassification of supply versus need-related variation in utilisation. The primary care diagnosis adjustment fills data gaps in the general and acute formulae, enhancing predictions of secondary care needs. The underdiagnosis adjustment accommodates undiagnosed conditions, currently not sufficiently accounted for in the resource allocation formulae.

Each of these adjustments can practically be implemented as adaptions to the current resource allocation process (see *Overview*). The adjustments outlined, however, have different issues related to uncertainty in the output and practicalities and are not all ready to be implemented. The responsiveness adjustment is ready for implementation. The longitudinal adjustment offers a robust methodological basis but requires refinement, replication, and stability checks with linked primary care registration data (e.g. NHAIS). The primary care diagnosis adjustment awaits available linked primary care data, but can be implemented as and when that becomes available. There remains fairly large uncertainty with respect to the estimation of undiagnosed disease and further work is needed to develop and validate the modelling approach before it can be considered for implementation within the resource allocation process.

Likely distributional effects on health vary among adjustments, with no consistent association between our estimates of unmet need and avoidable mortality – the current unmet need/health inequalities adjustment used in the resource allocation formula. Some of the adjustments reveal greater unmet needs in less deprived and older populations. We show that the distribution of NHS resources between places has a direct causal effect on mortality across levels of deprivation, with effects being greatest in the middle of the deprivation distribution and lower in the most deprived and least deprived areas. Our analysis indicates that the impact of applying some of the adjustments outlined would potentially increase health inequalities. Therefore, there are potential conflicts between allocating resource in proportion to need and health inequality reduction.

We make the following recommendations based on this research:

1. The responsiveness adjustment is implemented in the forthcoming resource 2025–6 allocation round. We recommend removing at least 10% and up to 25% of less-responsive CCGs to obtain an adjustment which sufficiently shifts resources to potentially address unmet needs.
2. The longitudinal adjustment is implemented following replication and checking the stability of estimates using data linked to primary care registrations which include more frequently recorded location information of patients when they are not using healthcare, enabling improved time varying information on area characteristics of residence.
3. Progressing the linkage of national primary care and secondary care data and making this available for resource allocation. When this is available, it should be used within the General and Acute resource allocation formula as we have outlined.
4. Progressing work to develop and validate the modelling approaches we outline for estimating the probability of not being diagnosed and incorporating this into the utilisation formula when measurement of underdiagnosis reaches an acceptable level of robustness.
5. Maintaining a health inequalities adjustment based on premature mortality and separately addressing this concern alongside unmet needs adjustments.

This synopsis should be referenced as follows:
Barr B, Anselmi L, Urwin S, Mentzakis E, Sutton M, Wang S, *et al*. Accounting for unmet need in equitable healthcare resource allocation: Synopsis. *Health Soc Care Deliv Res* 2026;**14**(17): 1–38. https://doi.org/10.3310/GJBB1722

6. Regularly assessing the impact of resource allocation changes on mortality distribution to gauge their effect on health inequalities, using the evidence and tool we have developed alongside similar causal evidence.

Patient and public involvement

Involvement of the public in this area of research has been a challenge due to the pandemic, the narrow technical nature of the work and the lack of public involvement in the overall NHS resource allocation process. The work has been an iterative collaboration with the NHS England Resource Allocations team and existing advisory structures designed to support that process. These include the ACRA[35] and its TAG. As yet, there is no formal public involvement or consultation procedure within the resource allocation formulae development process, which remains a primarily technical procedure. We recognise, however, that resource allocation decision-making is also a political and democratic process, and the distinction between technical and normative advice is not always clear. Public involvement and consultation should become part of the process of developing advice on NHS geographical resource allocation, with clear guidance on the aims and remit of lay advisors. Not least this could help with explaining and disseminating the advice in a way that is understandable to the public. Integrating public involvement into the NHS resource allocation process, however, has been beyond the scope of this work. Lay public advisors have, however, been involved throughout this research programme. This has primarily been through a panel of public advisors involved in the NIHR North West Coast Applied Research Collaboration and has focused on discussing, explaining and communicating the principles involved in NHS geographical resource allocation. Initially, in December 2020, two workshops were held with public advisors, outlining and discussing the NHS resource allocation process and our initial conceptual framework (see *Understanding what we mean by unmet need for health care*). This included interactive exercises where lay advisors could explore potential trade-offs between allocating resources to equalise access versus allocating resources to equalise health outcomes. Our public advisor panel had further online meetings throughout the project, leading to two further workshops in March and May 2023, where we have worked with public advisors to produce an animation to support public understanding of NHS resource allocation procedures (https://pldr.org/2025/09/07/how-the-nhs-decides-where-money-goes/). *Figure 18* highlights issues raised about the resource allocation process that are addressed through this animation.

Equality, diversity and inclusion

This research programme has sought to understand how unmet needs vary across population groups. Due to limitations in the data available, we have tended to focus on the dimension of age and socioeconomic deprivation (e.g. populations disadvantaged in relation to education, employment, income, housing). These dimensions are the major factors that influence need for health care and often also affect access to health care. They also tend to be inversely corelated across places; that is, more deprived populations tend to have younger populations and vice versa. This is partly due to health inequalities, in that lower life expectancy in more deprived population leads to fewer older people in these communities. This inverse relationship means there will be trade-offs between meeting the needs of groups defined by age and those defined by deprivation. In other words, allocating resources to improve access in older populations (e.g. over 75 seconds) will tend to move resources away from more deprived populations, all else being equal. Age and deprivation are, however, not the only relevant equality dimensions; where possible, we have also included analysis in relation to ethnicity and region. The utilisation approach that we have sought to enhance, as outlined in *Enhancing the utilisation approach*, uses a wide variety of variables relevant to different underserved groups, including multiple diagnostic flags, multiple area-based measures of socioeconomic deprivation, 16 ethnicity variables and an adjustment for the additional costs of providing hospital services in remote areas. Where variables for minority ethnic groups have negative signs – that is, they predict underuse of resources in these groups, relative to need – these effects are sterilised from the formula; in effect, this means the formula allocates greater resources to these groups than their predicted

FIGURE 18 Visual minutes from public involvement workshop on accounting for unmet need in NHS resource allocation.

utilisation, recognising that their utilisation may be low due to poor access.

The inclusion of these variables in the utilisation formula helps ensure that the needs of underserved groups are accounted for when allocating resources. There are, however, other groups for which there is insufficient robust data to assess and account for any additional needs they may have that are not already captured in the formula. These include homeless people, carers, looked-after children, Lesbian, Gay, Bisexual, Transgender and Queer +/sexual orientation groups. Further, work will be needed to improve data sources and analyse these data to assess unmet needs in these groups.

In *Unmet need and errors in the estimation of need*, we highlight how better meeting unmet needs in some equality and diversity groups, for example, by equalising access could lead to increasing inequalities in health outcomes between these groups. To enhance our understanding of these trade-offs, one section of our work aimed to estimate the mortality effects of shifting NHS resources from more to less-deprived populations (and vice versa). This will help the NHS better understand the equality and diversity impact of changes to resource allocation decisions.

Research recommendations

Priority areas for research should include:

- Enhancing the availability of linked electronic health records and survey-based symptom and biomarker data to enable enhanced estimates of the probability of diagnosis for multiple conditions and how this varies by population characteristics.
- Develop improved modelling techniques that can make best use of multiple imperfect data sources (electronic health records, survey data, registry data, biomarker data, and so on) to estimate dynamic models of disease incidence, diagnosis and progression, disaggregated by multiple population characteristics.
- Use long-term time series data on NHS resource allocation and utilisation data for small area populations to better understand the population health impact of NHS spend in different sectors (e.g. primary care, mental health services, and so on) and how this varies by population health characteristics (e.g. deprivation, age, ethnicity).
- Develop with ICS's new approaches for using small area needs-based capitation formulae to inform neighbourhood resource allocation, for example, for primary, community and social care teams, and evaluate the health impact of these approaches.

Conclusions

Many countries, including the UK, use funding formulae to distribute public funds for health care to geographical areas.[1,2] The NHS in England largely uses 'utilisation formulae' to estimate differences in need between places, enabling funding to be allocated in proportion to these needs. There are concerns that these formulae do not sufficiently take into account the level of unmet need. At present, a simple adjustment is applied to these formulae using avoidable mortality, which aims to account for both unmet needs and to address avoidable health inequalities.[2] However, there are no theoretical or empirical grounds to indicate that this adjustment has any relation to patterns of unmet need. The research programme, therefore, aimed to refine the NHS resource allocation formulae to better account for 'unmet needs' in different parts of the country.

First, we clarified what we mean by need and unmet need for health care. Need in this context was defined as the expected expenditure for the population of a geographical area that is required to provide all services that it is appropriate for the NHS to provide (i.e. within the standard package) that this population can benefit from. The level of unmet need is the relative difference between this amount of resource and the actual funding the geographical area receives. The aim of the utilisation formula and any adjustment for unmet need is to allocate resources in proportion to these needs. In other words, the aim is to equalise the proportion of needs that are unmet between geographical areas. To estimate the level of need in each geographical area, we need to identify all the relevant characteristics of the population living in each area and the cost weights indicating the expected needed expenditure associated with each of these characteristics. We develop four refinements to the allocation formulae focused on improving these two components, measuring the relevant characteristics of the population and deriving accurate cost weights associated with those characteristics.

Second, the responsiveness adjustment provides a method for better estimating the cost weights, by estimating the regression models in the current utilisation formulae, using only those geographical areas that are generally better at aligning resources with patient need. These areas are identified as being those where there is a greater association between individual needs indices and individual utilisation within each area. We find that higher levels of responsiveness are typically in areas with younger and less-deprived populations. Generally, we find that responsiveness is associated with favourable outcomes, which we would expect to be associated with better targeting of resources to higher needs.

This synopsis should be referenced as follows:
Barr B, Anselmi L, Urwin S, Mentzakis E, Sutton M, Wang S, *et al*. Accounting for unmet need in equitable healthcare resource allocation: Synopsis. *Health Soc Care Deliv Res* 2026;**14**(17): 1–38. https://doi.org/10.3310/GJBB1722

Third, the longitudinal adjustment provides a new method for improving the way the utilisation formula accounts for supply-induced variation in utilisation, using longitudinal data on people as they move between geographical areas. This analysis suggested that there is high supply-induced utilisation in the North West and lower supply-induced utilisation in the South East, indicating that this should be taken into account in allocating funding in proportion to need. However, estimates using the data that were available were sensitive to assumptions about people who do not use health care and the inclusion of information on area-based characteristics. In particular, this had a large effect on estimates of supply-induced utilisation in London. We, therefore, propose that this is implemented following replication and checking the stability of estimates using data linked to primary care registrations.

Fourth, the primary care diagnosis adjustment involved using linked data on primary care diagnosis to predict secondary care utilisation, filling data gaps in the current general and acute formulae. This did enhance predictions of secondary care needs, tending to change the distribution of need estimates in relation to age and deprivation. Data on primary care diagnosis are currently not available nationally, and, therefore, this approach cannot currently be implemented. Progress needs to be made in linking national primary care data and making it available for resource allocation purpose. When this is available, including this in the general and acute formula as we have outlined will improve the estimation of need.

Estimating the probability of not being diagnosed, when people have clinical disease, continues to present major difficulties. The new dynamic state approach that we outline here presents some promise and should be developed to be used alongside other survey-based methods. Limitations relate to the accuracy of death certification, the size of data available and lack of data on disease progression in clinical records. Some of these are likely to be addressed soon, for example, as data over larger populations become available and improvements in death registration come into practice. The difficulty in validating the approach and the lack coherence between alternative measures of underdiagnosis means that there remains a great deal of uncertainty in the estimates.

To understand the likely effects on mortality of each of these adjustments, and how this differs by level of deprivation, we use instrumental variable methods with small area measures of mortality. We find that the mortality effect of a marginal change in secondary care expenditure follows an inverted U shape with deprivation – larger in the middle deprivation groups, and smaller in the high and low deprivation groups. Using these estimates, we explore the potential distributional effects of applying our adjustments for unmet needs, assuming the overall budget did not change. As some adjustments indicate higher unmet need in more affluent populations (e.g. underdiagnosis and longitudinal adjustment), our estimates indicate that implementing these would increase the mortality gap between the least and most deprived places.

There is no evidence from our research that levels of unmet need are associated with patterns of avoidable mortality, the current measure used to adjust for unmet need in the NHS formulae. Unmet need is conceptually a separate issue from health inequalities and should be addressed through separate refinements to the formula. Some of these may lead to increases in health inequalities. To maintain a focus on health inequalities, it will be necessary to maintain a health inequalities adjustment, based on avoidable mortality, which our analysis shows will reduce health inequalities.

Additional information

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Patient data statement

This work uses data provided by patients and collected by the NHS as part of their care and support. Using patient data is vital to improve health and care for everyone. There is huge potential to make better use of information from people's patient records, to understand more about disease, develop new treatments, monitor safety, and plan NHS services. Patient data should be kept safe and secure, to protect everyone's privacy, and it is important that there are safeguards to make sure that they are stored and used responsibly. Everyone should be able to find out about how patient data are used. #datasaveslives You can find out more about the background to this citation here: https://understandingpatientdata.org.uk/data-citation.

Data-sharing statement

The study did not use any personal data. The data used were either held by NHS England as the data owner and data processor and analysis carried out by analysts seconded to NHS England's resource allocation team, or were accessed through an end-user licence with CPRD. The data controller and processor for NHS data was the NHS, and for CPRD data was CPRD. All data requests should be made to https://digital.nhs.uk/services/data-access-request-service-dars and www.cprd.com/data-access.

Ethics statement

The research used anonymised secondary data and did not involve any primary data collection or use of personal data. Ethics approval was, therefore, not needed based on the advice of the University of Liverpool Research Ethics Committee.

Information governance statement

Access to CPRD data was based on the approval of the Independent Scientific Advisory Panel (protocol 20_000096). The data used were either held by NHS England as the data owner and data processor and analysis carried out by analysts seconded to NHS England's resource allocation team, or were accessed through an end-user licence with CPRD. The data controller and processor for NHS data was the NHS and for CPRD data was CPRD. All data requests should be made to https://digital.nhs.uk/services/data-access-request-service-dars and www.cprd.com/data-access

Disclosure of interests

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Brendan Collins has worked as Head of Health Economics, Advanced Analytics and Policy Modelling for Welsh Government, and currently works a consultant for UNICEF, is a Trustee for the Health Equalities Group, and between 2020–2023 sat on a NIHR HSDR committee, and ACMD Prevention standing committee.

Richard Cookson has received grants/contracts from Wellcome Trust, UKRI, Danish Centre for Healthy Life and Wellbeing, University of Bergen, and consulting fees from Genentech, Roche, and Bristol Myers Squibb.

We endeavour to obtain ICMJE disclosure of interests forms for all named authors. In this case we have been unable to obtain these forms for every author. Please contact the corresponding author if you have any queries.

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This synopsis was published based on current knowledge at the time and date of publication. NIHR is committed to being inclusive and will continually monitor best practice and guidance in relation to terminology and language to ensure that we remain relevant to our stakeholders.

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List of supplementary material

Report Supplementary Material 1
Unmet need in healthcare resource allocation literature review

Supplementary material can be found on the NIHR Journals Library report page (https://doi.org/10.3310/GJBB1722).

Supplementary material has been provided by the authors to support the report and any files provided at submission will have been seen by peer reviewers, but not extensively reviewed. Any supplementary material provided at a later stage in the process may not have been peer reviewed.

The supplementary materials (which include but are not limited to related publications, patient information leaflets and questionnaires) are provided to support and contextualise the publication. Every effort has been made to obtain the necessary permissions for reproduction, to credit original sources appropriately, and to respect copyright requirements. However, despite our diligence, we acknowledge the possibility of unintentional omissions or errors and we welcome notifications of any concerns regarding copyright or permissions.

List of abbreviations

ACRA	Advisory Committee on Resource Allocation
CCG	Clinical Commissioning Group
CFR	case fatality rate
CHD	coronary heart disease
COPD	chronic obstructive pulmonary disease
CPRD	Clinical Practice Research Datalink
DFT	Distance From Target
G&A	general and acute
GP	general practice
HES	Hospital Episode Statistics
HSE	Health Survey for England
ICB	integrated care board
ICS	integrated care system
IMD	Index of Multiple Deprivation
LSOA	Lower Support Output Areas
NHAIS	National Health Application and Infrastructure System
TAG	Technical Advisory Group
US	understanding society
WP	work package

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