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The unavoidable costs of being a small and remote hospital: technical report

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Contents

1. Overview

1.1 Introduction

The Advisory Committee for Resource Allocation (ACRA) plays a key part in setting resource allocations for integrated care boards (ICBs).

ACRA is an independent, expert, technical committee made up of academics, GPs, NHS managers and public health experts. ACRA's role is to develop evidence based recommendations on how to estimate the relative need for healthcare resources across different populations, using data on people's characteristics and how their characteristics are associated with future healthcare needs. More detail is outlined in ACRA's terms of reference.

These relative needs are designed to guide resource allocation of in a way that supports equal opportunity of access for equal need and contributes to reducing health inequalities that are amenable to healthcare. These aims are confirmed when NHS England commissions ACRA in each allocation round.

Following the 2023/24 allocations round, ACRA were commissioned to recommend any updates to the need estimates for 2025/26 onwards.

As part of the development programme for resource allocations, an update to the remoteness adjustment was prioritised for development. The adjustment is part of the ICB core allocations model and reflects the additional cost of providing services in small and remote providers, where their remoteness makes their sub-optimal scale unavoidable.

Since 2016/17, an adjustment has been made to target allocations to account for the unavoidable costs of being small and remote for 8 hospital sites. The purpose of this adjustment is to target funding at ICBs to meet the unavoidably higher costs of small and remote hospital sites, where the costs are higher because the level of activity is too low for the hospital to operate at full efficiency. Sites receiving the adjustment were selected on the following criteria:

- acute sites with a type 1 A&E department
- serve a population of under 200,000 within a 1-hour travel time

- the next nearest site (with type 1 A&E services) is 1 hour or more away by normal road travel times (including ferry times where relevant), for at least 10% of the population served

Further information about site selection can be found on the NHS England allocations website.

The adjustment was reviewed and an updated model was developed in 2021. This model considered unavoidable costs for small remote hospitals at provider, site and department level, and the evidence for economies of scale using 18/19 cost data from the Patient Level Information Costing System (PLICS) and Hospital Episode Statistics admitted patient care (HES APC) data.

The key finding from the model developed in 2021 was that the most important factor in determining economies of scale was not the size of the site or provider but the size of the department. As smaller hospitals tend to have fewer departments that are larger relative to their size, focusing only on the overall size of a small hospital would give an incomplete picture. Since the 2022/23 allocation round, this updated model was implemented only for 1 hospital site where the updated model indicated a higher adjustment than original modelling.

However, there may be factors other than size that impact on the cost of providing services in small hospitals in remote locations and ACRA recommended that this be investigated further. This paper sets out the results of a 2024 update to the 2021 model. It updates the previous dataset to include 3 years of PLICS and HES data and makes a number of improvements to the model and its application. It also expands the modelling to include the impact of remoteness on cost alongside the consideration of economies of scale.

In line with previous modelling, economies of scale were found to be mostly present at the department level, with more limited evidence at the site and provider levels. An association was also found between remoteness, as measured by distance to the next nearest Type 1 A&E and increased cost per episode.

The findings of the model are being used to calculate adjustments to resource allocations for 2025/26, replacing the previous methodology. The list of hospitals subject to the remoteness adjustment have not been changed as part of this work.

The paper details the process by which the model is applied to calculate these adjustments. This paper is structured as follows:

- background to allocations and current ”remoteness” adjustment
- introduction and background to the model, including a short summary of the literature
- approach, outlining the theoretical framework, assumptions, and hypotheses from engagement with sites
- information on data sources and the statistical model
- limitations of the model
- model results
- application and impact of model

1.2 Background to allocations

The principle at the heart of the approach to setting allocations is ensuring equal opportunity of access for equal need.

The approach to allocations is also informed by NHS England’s duty to have regard to the need to reduce inequalities between patients with respect to their ability to access services and with respect to the outcomes they achieve.

These 2 aims are reflected in the allocations target formula, which produces a target allocation or “fair share” for each area, based on a complex assessment of factors such as demography, morbidity, deprivation, and the unavoidable cost of providing services in different areas.

1.2.1 Target allocations methodology

The formulae for target allocations estimate the relative need and relative unavoidable costs between ICBs for healthcare services. There are separate formulae for ICBs’ core responsibilities, specialised services and primary medical care. For each of these, the relative need is calculated for each GP practice, which is then aggregated to the ICB level. It does not seek to calculate an absolute level of need for each area, but to assess relative need (and relative unavoidable costs).

The relative need for each practice is based on:

- the age and sex distribution of the population (all else being equal, areas with older populations typically have a higher need per head) and additional need over and above that due to age (all else being equal, areas with poorer health have a higher need per head)
- unmet need and health inequalities
- the unavoidably higher costs of delivering health care due to location alone, known as the Market Forces Factor (this reflects that unit staff, land and building input costs are higher in some parts of the country, for example, in London)
- the higher costs of providing emergency ambulance services in sparsely populated areas, and the higher costs of unavoidably small hospitals with 24-hour accident and emergency services in remote areas

Each component of the allocation formula is based on statistical modelling that examines the association between the use of health services on the one hand, and the characteristics of individual patients and the areas where they live on the other. These models are used to decide which factors to include in the formula to predict future need per head and the relative weight on each of the factors.

The models include adjustments for unavoidable costs, reflecting cost pressures on ICBs that are unavoidable. These include the Market Forces Factor, an adjustment for PFI finance costs and the adjustment for scale and remoteness which is discussed in this publication.

1.2.2 Previous adjustments for small, remote sites

The first adjustment for small, remote sites was made to CCGs in 2016/17. A cost curve was estimated for all hospitals, which gave the estimated cost of sites by activity levels. The estimated relative costs were adjusted to remove the impact of differences in case mix and in costs that are already compensated through the market forces factor (that is, unavoidable differences in unit input costs across the country).

Estimated costs for predicted activity for a hospital serving a population of 250,000 people, around the national average, were used as the reference point for estimating the scale of higher costs at remote sites.

The adjustment reflected the expected higher costs based on the cost-curve, rather than the actual costs of the hospital, which may be affected by other factors unrelated to its scale. Predicted activity for a given population catchment area was used for the remote hospitals instead of actual activity, as the latter may be affected by other factors, such as patient choice. This option was limited by the use of reference costs to provide average costs for each type of activity at each provider, rather than at site level.

The adjustments were partially updated in 2022/23 using a new approach developed during 2021 exploiting the newly available Patient Level Information and Costing (PLICS) data. The PLICS data support a better understanding of costs by providing costing of activity at an individual level, allowing for variation in costing between patients.

The key finding from the new statistical modelling was that the most important factor in determining economies of scale is not the size of the site but the size of the department. As smaller hospitals tend to have fewer departments that are larger relative to their size, the model indicates that focusing on the overall size of the site alone would lead to an overestimation of the costs of being a small hospital. However, this was questioned by ACRA who suggested that there may be factors other than size that impact on the costs of providing services in small hospitals in remote locations. Since 2022/23, the adjustment applied for each hospital has been the higher value from either the pre-existing 2016/17 adjustment or the updated adjustment.

2. The updated model

2.1 Background to the model

The model draws on a theoretical framework to understand how scale might be driving costs, with a hypothesis based on the economic theory of the firm. It also draws on engagement with systems that include a small remote provider, who suggested that earlier work underestimated the scale of unavoidable cost pressures faced by these sites (see section 2.5). As a result of this, the scope of the modelling includes remoteness and associated non-scale cost effects as potentially reimbursable variables of interest.

A statistical model was used to examine the relationship between costs per episode for admitted patients and the scale and remoteness of healthcare services and other unavoidable cost drivers reimbursed elsewhere, while controlling for provider and patient-level characteristics. The analysis covers sites of non-specialist acute providers in England that submitted NCC PLICS data for 2018/19, 2019/20, and 2021/22 at the episode level for admitted patients. Data from 2020/21 were excluded so that our analysis was not biased by atypical activity patterns during the COVID-19 pandemic.

2.2 Summary of literature

A rapid evidence review in 2020, when the early version of this model was developed, highlighted international literature suggesting economies of scale exist in healthcare settings, there is, however, limited England-based research on the topic. The few studies focussing on England confirm the same outcomes, for example, Freeman et al. (2019) find that economies of scale exist in both elective and non-elective care specialties.

Most studies have investigated economies of scale at the hospital level or among grouped activities, meaning results are only applicable at a hospital level rather than understanding the effect of economies of scale at a more disaggregated level such as a department within a hospital. Additionally, these studies have used aggregated cost measures, such as reference costs (Freeman et al., 2019) or annual variable costs (Scott & Parkin, 1995), which was also a limitation of the original model used in this adjustment. With the development of the PLICS dataset, which provides patient and episode level costs, it is possible to achieve greater granularity. Using this, it is possible to test for the existence of economies of scale at the specialty, site and provider level. This allows for a more detailed and specific application of the results of the model.

2.3 Theoretical framework

A theoretical framework was developed to understand how scale and remoteness might be driving costs, making the hypothesis based on economic theory of the firm.

The impact of remoteness on cost was hypothesised to materialise through 3 different channels. First, via scale at the site level, as sites with sparse populations might face insufficient demand and be unable to exploit economies of scale. Second, via increased temporary staff at the site, as sites based in remote and rural areas might be unable to attract substantive staff. Third, via complex healthcare needs of their patient populations. Figure 1 shows the framework with more detail of the variables that capture each mechanism.

Figure 1 - Theoretical framework conceptual map

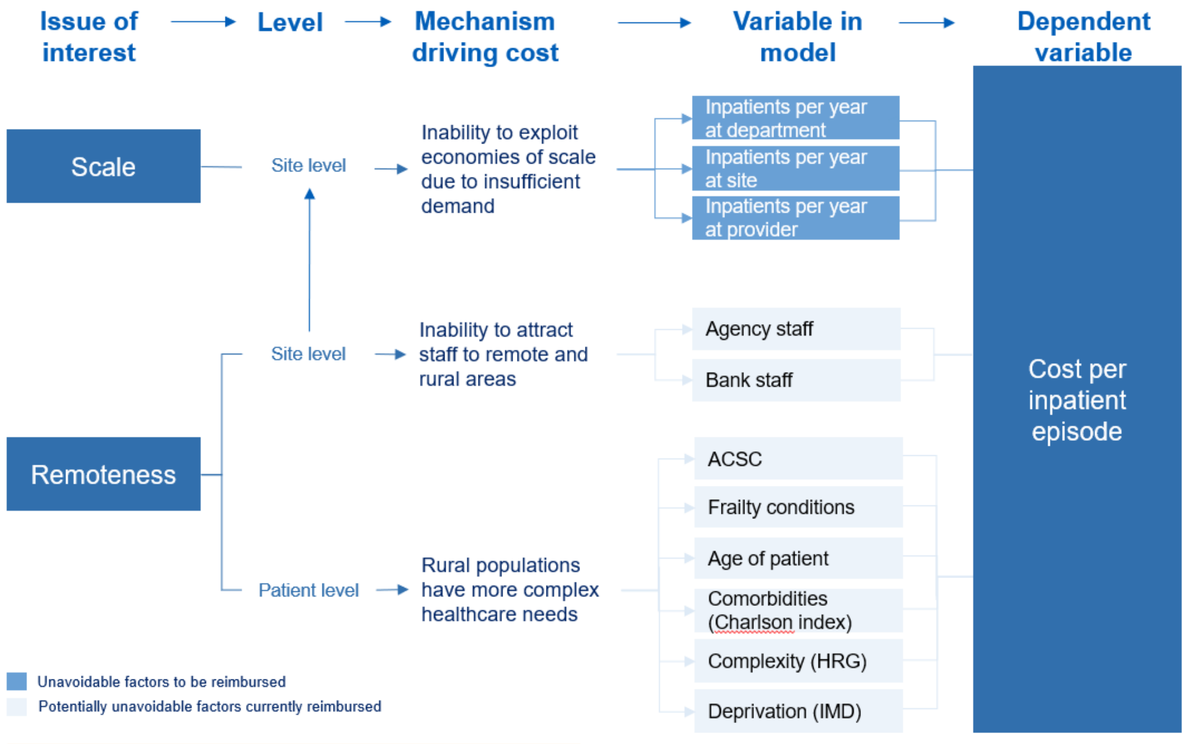

Figure 1 was developed by for the 2020 project and expanded during the engagement work (see Section 2.5).

2.4 Economies of scale

The model first tested whether there was evidence for economies of scale at the site and specialty level.

Scale was measured at 3 different levels:

- department size as a count of yearly total admitted patient episodes per treatment function at a site
- site size as a count of yearly total admitted patient episodes at a provider site
- provider size as a count of yearly total admitted patient episodes at a provider

Economies of scale refer to the relationship between the size of a firm and costs. As a firm grows, it may be able to reduce average unit cost by increasing scale and spreading the cost of production over more units of output.

The regression model quantifies the magnitude of department, site, and provider-level economies of scale by regressing scale measures on reported cost. To ensure that the effect of scale in cost is a net effect, the regression was run on patient-level cost, controlling for HRG code and other patient-level characteristics, as well as provider-level factors that are associated with cost.

The modelling assumes a linear relationship between each of the scale variables and the log of cost per episode. It is plausible that the underlying relationship between scale and log cost is not linear. Non-linear options for the scale variables were also tested, but it was concluded that the linear variable structure performed sufficiently well and was most straightforward to apply.

2.5 Engagement and expansion to the framework

In late 2022 and early 2023, the project team engaged with representatives from the providers and ICBs that currently receive an adjustment to their revenue allocation, to assess the above framework and test other drivers of unavoidable cost proposed by people familiar with the sites.

As a result of the engagement, a more detailed list of potential cost drivers was developed relating to economies of scale and scope, remoteness from other sites and urban centres, causing recruitment and retention difficulties, and the demographics of the population. The most frequently mentioned significant cost drivers are summarised in **Error! Reference source not found.**

Figure 2 - 4 key challenges that small, remote hospitals reported most frequently as significant cost drivers

	Challenge	Detail
1	24-hour services	Every trust noted that it was difficult to supply and staff 24 hour services, particularly A&E and maternity units. They noted a combination of minimum staffing levels, low attendance and required ancillary services (such as diagnostics) which could mean services run at a deficit.
2	Workforce	All but 1 site noted that workforce was a significant challenge to them. This included the difficulty of recruiting to remote areas, having an ageing workforce close to retirement and significant incentives needing to be offered. They in turn said they spend a high amount on agency to fill gaps.
3	Demographics	All but 1 site highlighted that they had an ageing population. This can result in patients with expensive to treat comorbidities and the need to maintain a wide

		range of services. Sites also raised population fluctuation as further challenges. These demographics could also interact other challenges of being remote.
4	Travel challenges	All sites noted how difficult travel was in the local area, with travel to the next equivalent site ranging from 40 to 90 minutes. This impacts the movement of both patients and staff and could exacerbate other challenges.

Each driver was reviewed for plausibility and impact, and whether cost differences are already accounted for elsewhere in allocations. For example, variation in demographics and health are included as part of the main general and acute need index and so were not considered as part of this adjustment. Challenges 1, 2 and 4 in **Error! Reference source not found.** were, however, all considered potentially in scope of the adjustment.

There were several challenges in adding variables to the model to quantify non-scale drivers such as workforce. These included:

- the lack of detailed national data on key factors
- variation in approaches taken by sites to manage challenges so that no 1 cost indicator represents the range of responses (for example agency versus rostering staff from other sites)
- challenges in disentangling the effect of workforce and other costs that are specifically caused by being small or remote, as providers may also rely on solutions such as temporary staffing unrelated to remoteness

While there are several challenges in measuring the proposed non-scale drivers, we believe that they are all linked, at least in part, to remoteness. So, rather than developing multiple indicators for each non-scale driver, a site “remoteness” measure was estimated that would allow us to quantify the additional unavoidable cost pressure associated with being remote, when controlling for all other appropriate factors. This was tested alongside the impact of scale.

Several options for remoteness variables were considered (see Annex A). The following were developed in more detail:

a) travel times to alternative emergency provision, representing the need for surge capacity and the difficulties of diversion to alternative provision

b) cultural remoteness to quantify difficulties in recruitment

The variable chosen to represent (a) was travel time to the next nearest Type 1 A&E. This measure considers remoteness from a care-provision point of view, based on the hypothesis that diversion in an emergency is less practical in remote providers, leading to higher costs due to the need for surge capacity. It may also capture cost pressures associated with the inability to share resources with neighbouring care providers. Additionally, it aligns with the rationale for our target sites being unavoidably small and remote; they serve a remote population which would not have access to adequate and timely urgent care provision if services were configured differently.

For each site the quickest route to the nearest Type 1 A&E was calculated based on average daytime road travel times (9am-4pm) using the Rootfinder add-in to Mapinfo. We tested the variable as a categorical variable with 15-minute intervals, using splines to allow variation within categories. We also tested a continuous variable, using a minimum value reflecting our assumption that at short distances there would be little cost sensitivity. However, without clear justification for the choice of categories or time floors, a simple variable measuring the log of the time in minutes to A&E was used.

It was more difficult to conceptualise and measure cultural remoteness and the factors that led to difficulty in recruiting staff. We tested a measure of time to nearest urban centre. However, there was a moderate to strong correlation between this measure and the travel time measure so we use only the time to A&E variable. Due to the correlation, it is likely that the selected measure will also pick up many of the workforce issues faced by sites that are far from urban centres.

2.6 Primary data sources

The data source for the dependent variable was the National Cost Collection Patient Level Information and Costing Data (PLICS) for 3 financial years (2018/19, 2019/20 and 2021/22, which includes all cost activity and resource categories (that is, the total patient-level cost). PLICS data capture the variation in the cost of providing healthcare at the episode level, meaning that this level of detail allows us to understand the drivers of costs per episode.

The dataset was limited to general acute (non-specialist) sites with inpatient provision. This reflects a change in method from the previous work, which included specialist, community, short-term non-acute and long-stay sites where they were part of an acute non-specialist provider. This is because they are not comparable alternatives to general acute sites. Episode-level data were used for admitted patients. Admitted patients PLICS were chosen due to these data being the most complete (see Annex E for a robustness check testing A&E data). A small number of records with a mental health treatment function code (710, 711, 713, 715) were excluded.

After cleaning, the dataset included 45.6 million episodes across the 3 years. Negative costs were excluded, but cost outliers were not excluded, in a departure from previous model versions, as many outliers are likely to reflect genuine variation in costs and there are few reliable methods to automatically filter out unwarranted outliers (see Annex E for robustness checks on outliers).

The cleaned dataset for 21/22 includes 115 providers, 211 sites and 154 treatment specialties.

Other data included:

- activity data and patient data from linked Hospital Episode Statistics
- capital and provider and site data from Estates Return Information Collection (ERIC)
- bed data from weekly NHS England sitreps
- workforce data from the NHS Electronic Staff Record (ESR)
- IT spend from NHS Trust accounts consolidation
- Clinical Negligence Scheme for Trusts (CNST) information from NHS Resolution
- C difficile data from government public health statistics
- PFI information from HM Treasury

2.7 Statistical model

Using these data, statistical modelling was used to identify the relationship between the scale of healthcare services, remoteness of sites, and the costs per episode for admitted patients. We use a pooled ordinary least-squares (OLS) model with 3 broad categories of independent variables:

- scale – the main variable of interest, measured at the department, site and provider level
- remoteness – an additional variable of interest, measured based on time to nearest Type 1 A&E
- control variables – covering both avoidable and potentially unavoidable costs which are already reimbursed elsewhere, and provider and site characteristics

We also use Healthcare Resource Group (HRG) fixed effects. A more detailed description of the model and a full list of variables can be found at Annex B. This model builds on the preferred version identified by the previous modelling team, with key changes discussed in this paper.

Several variables from previous work were excluded in the model presented here. This was usually because these factors:

- potentially lie on the causal pathway between scale or remoteness and increased cost
- are collinear with another variable of interest
- are obsolete due to other modelling changes

A list of these and the rationale for exclusion is below.

- Patient density – patient episode per metre squared of internal gross floor area. This is correlated with scale / remoteness and may form part of, or dilute, the causal relationship with cost.
- Proximity to other providers – drive time distance from a provider's main site to the next closest provider's main site. This is now obsolete due to the inclusion of the new preferred remoteness variable.
- Proportion of agency and bank staff spend of total staff costs. Spend on staffing due to difficulties in substantive recruitment is 1 of the key hypotheses about how remoteness may increase costs. Temporary staff spend was therefore excluded to avoid controlling out the potential additional cost pressure identified for remote sites.
- Provider with a single site – dummy variable controlling for providers with a single site only. No longer needed due to other modelling changes.

- Dedicated small sites – dummy variable controlling for sites with fewer than 5 specialties that are part of the largest 30% of providers. No longer needed due to changes to site inclusion criteria.

2.8 Robustness checks

Several robustness checks were carried out to arrive at this preferred specification. These are described at Annex E.

3. Limitations

3.1 PLICS data quality and age of data

Acute PLICS data were classified as experimental statistics during the years collected and should therefore be used with caution. Experimental statistics are new official statistics undergoing evaluation. They are published to involve users and stakeholders in their development and to build in quality at an early stage.

The concerns from experimental statistics are around measurement errors and adherence to national audit standards of different providers, which may introduce bias on estimated coefficients.

This has been mitigated by including data from multiple years. The final model is now pooled OLS run over 3 years' data. However, the earliest observations come from 2018/19, and the most recent PLICS data (22/23) were not available in time to be included in the analysis. As with other components of the allocation formula, we will revisit the formula in due course and exploit improved data.

3.2 Defining and measuring departments

3.2.1 Specialties

A combination of site and treatment specialty (the specialty in which the consultant was working during the period of care) were used as a proxy for department. There are limitations to this approach, as in some cases a specialty will not represent an independent department. However, it was not possible to identify true "departments" in existing data, and so specialty is used as a reasonable proxy. Main specialty was also considered (the specialty under which the consultant is contracted) was also considered instead of treatment specialty, but not pursued as treatment specialty is assumed to better reflect actual patterns of care delivery than the specialty in their contract. Removal of specialties that are unlikely to reflect valid acute inpatient departments was tested as well as the removal of some other small "departments". This did not change the results. However, further sensitivity analysis on the definition of a department could be carried out in future.

3.2.2 Scale effects by department

This model quantifies the scale effect associated with being a large or small department in absolute terms. However, it is plausible that the scale effect may be more important in some departments than others. Future work could be done to explore the impact of each department's size relative to the mean size for that department across all sites, or to identify departments that are expected to have the greatest scale challenges.

3.3 Defining sites

Some key variables are measured at site level, so it was important to identify sites that should be present in the data and their associated activity particularly when working with multiple years' data. However, there is no "official" list of acute NHS sites. A list was developed using a combination of sources including ERIC, the Organisational Data Service and A&E sitrep data to identify sites for inclusion in the dataset.

3.4 Episode weighting

The dataset is episode-level, with each episode receiving the same weight in estimating the model. As larger departments, sites and providers inherently carry out a greater proportion of all activity, this means that a greater proportion of observations in the data come from these larger providers. As this analysis is primarily concerned with smaller sites, future work might consider adjusting for this (for example, with a weighted regression).

3.5 Specialised activity in acute providers

The model consists of acute providers only. However, many acute providers undertake specialised activity. These will largely be excluded from our dataset automatically as:

a) admissions for specialised care such as cystic fibrosis, chemotherapy, radiotherapy or renal dialysis are not collected under regular day or night admissions in HES.

b) Acute PLICS at a patient level for the years used did not include critical care, chemotherapy, rehabilitation, directly accessed pathology services, renal dialysis, radiotherapy, directly accessed diagnostic services, cancer multi-disciplinary team meetings, specialist palliative care, cystic fibrosis and cystic fibrosis-network care providers.

However, there might still be some specialised-type activity that is included in PLICS and is not explicitly controlled for in this model.

3.6 Scope vs scale

Being able to exploit economies of scope, that is, the advantages that result from offering a range of services together, was raised as an issue by some sites in engagement. However, the relationship between scope and scale is not clear-cut, meaning that it is not possible to infer whether economies or diseconomies are due to scale or scope, see for example Preyra and Pink 2006, Carey et al. 2015, Freeman et al. 2019.

It is difficult to observe whether services at the specialty level are split or shared across sites within a multisite provider. Because of the difficulties disentangling scale and scope the model does not focus explicitly on scope. Instead it is assumed that issues of scope will be picked up by scale and remote variables.

3.7 Missing data

The Estates Returns Information Collection (ERIC) dataset, which is used to derive variables on backlog maintenance and the teaching trust flag, has a large number of missing values at site level. However, robustness testing showed that missing values had minimal effect on model estimates.

4. Model results

4.1 Descriptive statistics

A summary of key descriptive statistics and a correlation matrix between variables can be found in Annex C - Descriptive statistics of variables of interest and Annex D - Correlation matrix of variables.

4.2 Results of statistical model

The model explains around 32% of the variation in episode costs at episode level in the pooled model. This means that about two-thirds of the variation is not explained by the model, which is not uncommon for this type of regression, and is higher than for the allocation need models when estimated at person level. We would expect the explained variation to be higher at a site level, but this is more difficult to estimate. Some of the unexplained difference might be due to factors that are not easily identified and measured but that affect episode costs. One common example from the literature is leadership quality and governance – while this is controlled for using CQC Well Led scores, these are an imperfect measure.

Table 1 summarises the output of the model, presented using normal standard errors. The model was also run with standard errors clustered at provider level (the most conservative approach) as in the analysis the treatment variables of interest (scale and remoteness) are either at department, site or provider level (see Annex F). The rationale is that when treatment is assigned by 'clusters', error terms within those clusters may be correlated. For example in this analysis, all episodes at a site in a particular year take the same value for the site-level scale variable.

Even when taking this most conservative approach, the department-level scale effect is still highly statistically significant but the final selected remoteness variable (log of the distance to nearest A&E) is no longer statistically significant. However, provider-level standard errors are the most conservative option considered, and throughout the development of this model large and significant effects have been found on remoteness across several alternative model specifications and means of constructing this variable. Additionally, the magnitude of the effect is consistent with evidence from engagement and other analysis. It is therefore considered highly unlikely that the result on remoteness is due to chance variation, despite the decrease in statistical significance when using provider-level clustered standard errors.

Table 1 - Results of linear regression of cost per episode

Variable*	Coefficient
Department size (number of episodes at department)	-0.0000178***
	[-0.0000179,-0.0000178]
Site size (number of episodes at site)	3.91e-08***
	[2.87e-08,4.95e-08]
Provider size (number of episodes at provider)	6.16e-08***
	[5.59e-08,6.74e-08]
Log of time to nearest A&E	0.0396***
	[0.0388,0.0405]

Non-elective admission	-0.114***
	[-0.115,-0.112]
Day case admission	-0.629***
	[-0.630,-0.627]
Ambulatory Care Sensitive Conditions – chronic	-0.173***
	[-0.175,-0.171]
CQC quality of care	
Missing	0.0965***
	[0.0940,0.0990]
1 = Inadequate	-0.0370***
	[-0.0440,-0.0300]
2 = Requires improvement	0
	[0,0]
3 = Good	0.0222***
	[0.0212,0.0232]
4 = Outstanding	-0.150***
	[-0.152,-0.148]
CQC well-led	
Missing	-0.0863***
	[-0.0893,-0.0833]
1 = Inadequate	0
	[0,0]
2 = Requires improvement	-0.000493
	[-0.00246,0.00147]
3 = Good	-0.0321***
	[-0.0342,-0.0299]
4 = Outstanding	0.0190***
	[0.0166,0.0215]
Log of A&E type 1 performance	0.0635***
	[0.0617,0.0654]
Log of Clostridium Difficile infection rate (hospital acquired)	0.0191***
	[0.0182,0.0200]
Log of total backlog maintenance % NBV buildings	0.0284***
	[0.0281,0.0287]
Year of PFI	
PFI post-2006	0
	[0,0]
PFI pre-2006	0.0259***
	[0.0248,0.0269]
No PFI	-0.0944***
	[-0.0961,-0.0926]
Age profile of estate	
Missing age	-0.148***

	[-0.151,-0.145]
2005-2024	0.171***
	[0.170,0.173]
1995-2004	0
	[0,0]
1985-1994	-0.0396***
	[-0.0409,-0.0383]
1975-1984	0.0692***
	[0.0681,0.0704]
1965-1974	0.0708***
	[0.0696,0.0719]
1955-1964	0.0542***
	[0.0506,0.0578]
pre-1955	0.157***
	[0.155,0.158]
Log of total trust CNST spend % NBV	-0.0267***
	[-0.0279,-0.0255]
Log of site hot index	-0.0246***
	[-0.0249,-0.0243]
Teaching trust	0.0184***
	[0.0175,0.0194]
Log of consultants share of medical staff	0.195***
	[0.191,0.199]
Log of clerical staff share of total staff	0.186***
	[0.183,0.190]
Log of daily bed occupancy	0.386***
	[0.380,0.391]
Log of long stay share of occupied beds	-0.0736***
	[-0.0750,-0.0722]
Log of additional IT spend % of NBV	0.00534***
	[0.00504,0.00564]
Observations	43844535
R^2	0.318

95% confidence intervals in brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*There are additional variables included in the model as controls but not reported here: month of episode, age of patient, Charlson index, frailty indicator, living in the most deprived areas and PFI as % of NBV. The model has HRG fixed effects.

4.3 Effect of scale

In the model, larger department size is associated with lower costs per episode, indicating economies of scale at the department level. These seem continuous, as a minimum efficient scale point was not identified at the department level. At the site and provider levels, relatively small diseconomies of scale or scope were identified. These results are robust in different model specifications (see Annex E for more details).

On average, having 1,000 additional episodes per year in a department is associated with around 1.8% lower costs per episode, holding other variables constant.

On average, having 1,000 additional episodes per year in a site is associated with around 0.004% higher costs per episode, holding other variables constant.

On average, having 1,000 additional episodes per year at a provider would lead to around 0.006% higher costs per episode, holding other variables constant.

The findings suggest that economies of scale may operate at certain levels (for example, only at department level) but not at other levels. They could also be explained by diseconomies of scope, where more episodes in different departments lead to higher costs than more episodes in the same department due to added complexity and the management and back-office levels. The relationship between scale and scope is not clear-cut in healthcare (see section 3.6).

4.4 Effect of remoteness

The log of the cost per episode increases with time to nearest type 1 A&E (log of time to A&E, coefficient = 0.0396). The time to next nearest A&E shows an increase of approximately 0.04% in cost for every additional 1% increase in travel time to the next nearest hospital. For example, being 45 minutes from a Type 1 A&E is associated with an approximate 8% increase in cost compared to being 15 minutes away.

5. Impact of the model

To turn the estimates in the modelling into a financial adjustment, the cost of each episode at eligible small sites in the pooled dataset across all included years was predicted and compared to the predicted cost of that same episode if it had taken place in a “comparison hospital” that wasn’t small or remote. To develop the comparison hospital, department, site and provider averages were calculated using all episodes from hospitals with a Type 1 A&E, a catchment population of more than 200,000, and more than 90% of the catchment population within an hour’s travel of another site.

All other characteristics of that episode are assumed to be the same. Where there is excess cost, that is, the episode costs more in the small, remote site, these excess costs are added together to make a total excess cost. This is then scaled to also apply to A&E and outpatient care. To account for inflation the excess costs for each year are calculated separately and relevant cost uplift factors are applied using published tariff factors and a weighted average produced. A step by step process can be found in Annex G.

The adjustments calculated for each site can be seen in Table 2. The new adjustments led to a large increase compared to the previous approach, with a minimum 55% increase, with some increases over 3 times the previous adjustment. The 2 adjustments are not directly comparable due to the different methodologies. However, the increases are likely to be due to a) the inclusion of the remote variable, b) the new approach to estimating and applying scale at department and site level and c) a cost uplift factor applied to account for inflation.

Table 2 - Calculated adjustments for each remote site (uplifted using cost uplift factors for 2023/24 and 2024/25)).

	Adjustment	
Site	£k	Estimated percentage
St Mary's Hospital, Isle of Wight	19,383	8.6%
North Devon District Hospital	14,044	6.1%
Scarborough General Hospital	10,379	5.8%
Hereford County Hospital	13,798	5.6%
Cumberland Infirmary	13,587	4.7%
West Cumberland Hospital	11,062	7.4%
Furness General Hospital	11,123	6.0%
Pilgrim Hospital	12,450	4.8%

The process above relied on full linked PLICS and HES records to predict the cost per episode. While all sites in receipt of the adjustment submitted data to both PLICS and HES, for 1 of the remote sites the linkage between the 2 was not valid, meaning it wasn’t possible to link the data and include data from this site in the regression model.

To produce an estimate for this site, patient level variables were extracted from HES directly to use alongside site and provider level variables. The coefficients from the model were used to predict the cost for this site. This provider also provides mental health inpatient care at the site, so records with a mental health treatment function code (710, 711, 713, 715) were excluded as they were not included in the PLICS acute collection and were out of scope of the adjustment.

It should be noted that the number of episodes recorded in HES were higher than those in PLICS for all sites, although the difference varied for each site. It is possible therefore that in future iterations of the model when data quality improves that the adjustment for this site may be reduced.

6. References

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Annex A – Remote variable options

Table of possible remote indicators that may act as proxies for the issues raised that relate to remoteness.

Variables will be tested for their relationship with cost and the specific hypotheses where possible. Some of the indicators may be highly correlated. If that is the case, we will only include the most relevant in the model. The variables below are in addition to costs related to operating sub-scale already included in the model.

Level	Remoteness specific hypotheses to be tested	Location 1	Location 2	How currently accounted for in allocations	Possible indicator
Site	It is difficult to attract staff to remote hospitals due to their distance from urban centres and the impact that has on lifestyle and family, such as lack of access to cultural activities and schools. This leads to a range of additional staff costs to manage this (such as agency, pay band). **May be exacerbated for small hospitals with less scope for training and development.**	Hospital site	Urban centres/cultural hub		Distance and travel time from site to nearest urban centre.
Site	Cost of transfer for the most urgent cases which cannot be managed on site (helicopter or ambulance)	Hospital site (with A&E)	Nearest type 1 A&E	Some already picked up via EACA	Travel time between postcode of 2 A&E sites

Level	Remoteness specific hypotheses to be tested	Location 1	Location 2	How currently accounted for in allocations	Possible indicator
Site	Long distances to the next site that can deliver services means that diversion isn't possible. Therefore, there may be a minimum staffing need to manage surges.	Hospital site (with type 1 A&E)	Nearest type 1 A&E		Travel time between postcode of 2 A&E sites
Site	Being remote may lead to additional cost of unproductive time, travel and accommodation where sourcing staff from other **sites** to deliver services	Hospital site	Next nearest hospital site delivering relevant service		Travel time between 2 sites with relevant specialty
Trust/site	Being remote may lead to additional cost of unproductive time, travel and accommodation where sourcing staff from other **trusts** to deliver services.	Hospital site	Next nearest trust		Travel time between site and neighbouring trust
Site	Being a long distance from universities with medical or nursing schools means that junior staff are less likely to do placements at remote sites and may limit the number of more junior staff joining.	Hospital site or provider?	Nearest university with medical or nursing school		Distance from site to nearest university with medical or nursing school (not prioritised as likely to be similar to travel time to nearest urban centre)

Level	Remoteness specific hypotheses to be tested	Location 1	Location 2	How currently accounted for in allocations	Possible indicator
Local area	Distance from urban centres also has an impact on recruitment for the wider system infrastructure- availability and quality of primary, community and mental health care leads to more treatment in acute settings	Hospital site as proxy?	Urban centres/cultural hub	May be picked up to some extent in ICB funding for other services	Distance/travel time from site to nearest urban centre (same as possible indicator for recruitment issues)
Local area	Distance from urban centres also has an impact on recruitment for the wider system infrastructure- Delayed discharge of medically fit patients (due to social care and housing availability) leads to higher costs per spell	Hospital site as proxy?	Urban centres/cultural hub	Difficult to pinpoint effect of remoteness	
Patient	Long distances to the next nearest hospital are the primary justification for keeping a small hospital with a type 1 A&E open despite operating **sub scale**.	Patient home	Next nearest relevant hospital	Scale variable already included	N/A – cost effects should be picked up via scale variable
Patient	It takes more time to get patients to hospital and may be fewer public transport options leading to increased patient transport and ambulance costs	Patient home	Nearest relevant hospital	EACA adjustment	N/A – already included elsewhere and patient transport costs not likely to be material
Patient	Populations less willing to travel out of area due to distances, putting pressure on local hospitals	Patient home	Next nearest relevant hospital	Should be reimbursed via national payment system for elective care or agreement with commissioner for urgent care	N/A – not clear that this affected all hospitals. Already included elsewhere

Level	Remoteness specific hypotheses to be tested	Location 1	Location 2	How currently accounted for in allocations	Possible indicator
Patient	Long travel distances may lead to delayed health seeking in **primary and secondary care** leading to more complex health care need which costs more to deliver	Patient home	Nearest GP/hospital	Should already be included as part of need index but further analysis could be undertaken	N/A – already covered by General and Acute need index

Annex B – Model structure and variables included

The regression can be summarised using the following equation

$$Y_{it} = \beta_1 X_{1it} + \beta_2\, X_{2it} + \beta_3\, X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \varphi_h + \varepsilon_{it}$$

Where Y_{it} is the log of total cost net of MFF for patient episode, i in year t $X_{1\mathrm{it}}$ is the size of the department, X_{2it} is the size of the site, and X_{3it} is the size of the provider where patient episode i occurred in year t.

X_{4it} is the remoteness of the site where the episode occurred, X_{5it} is a vector of unavoidable cost variables that are not currently reimbursed, X_{6it} is a vector of potentially unavoidable cost variables relating to patient characteristics that are reimbursed elsewhere, and X_{7it} is a vector of provider and site control variables. Finally, φ_h is a vector of Healthcare Resource Group (HRG) fixed effects and ε_{it} is the error term.

Dependent variable:

- Total cost (net of MFF) – cost per patient episode / MFF current payment index

Key variables of interest – scale of services and site remoteness:

- department size – count of the annual episodes at a specialty within a site Specialty are defined by treatment function code
- site size – count of the annual episodes at a site within a provider
- provider size – count of the annual episodes at a provider
- distance to A&E: a variable measuring average road travel time in minutes to the next nearest site with a Type 1 A&E

Potentially unavoidable variables that are reimbursed elsewhere via existing ICB allocations:

- patient age – age group of patient
- patient frailty – categories for frailty conditions (Soong et al. 2015)
- patient co-morbidities – the Charlson index
- episode complexity – Health Resource Group
- patient deprivation – dummy variable to account for patients in the most deprived 10% of the Index of Multiple Deprivation

- teaching hospital (training tariffs) – dummy variable differentiating between a teaching and non-teaching trust
- non-elective admission – dummy variable differentiating between patients admitted through a non-elective or elective point of delivery
- day case – dummy variable controlling for day case episodes
- early PFI – dummy variable to control for Private Financing Initiatives from before 2006
- CNST as % of Net Book Value – sum of historic Clinical Negligence trust spend / ([closing net book value + opening net book value] / 2)
- backlog maintenance as % of Net Book Value – value of critical infrastructure risk / ([closing net book value + opening net book value] / 2)
- PFI as % of Net Book Value (NBV) – capital value of trust PFI / ([closing net book value + opening net book value] / 2) where NBV is the total value of the trust's assets

Provider/site characteristics:

- Site hot index – the additional emergency activity at site relative to national average * relative size of the hot site
- CQC quality rating – site average rating of Safe, Caring, Effective and Responsive CQC domains. CQC go from 1 to 4, where a rating of 1 means the trust is inadequate, 2 means it requires improvement, 3 means it is good and 4 means it is outstanding
- CQC well-led rating – site well-led rating. Well-led scores are scored in the same way as CQC quality ratings, that is, 1 to 4 (see above)
- Clostridium Difficile infection rate (hospital acquired) – (new hospital acquired C-diff cases reported by trust / (average daily occupancy * n days in period)) * 100,000
- A&E performance – percentage of patients seen within the 4-hour target
- Beds occupied by long stay patients – beds occupied for more than 21 days / total beds occupied
- Bed occupancy (general and acute) – total beds occupied / total beds open
- Investment in IT (hardware and systems) - additional spend on IT 2018/19 / ([closing net book value + opening net book value] / 2)
- Clerical staff share of total staff – administrative and clerical FTE / total staff FTE
- Consultant staff share of total staff – consultant FTE / total medical and dental FTE

- ACSC episodes – dummy variable controlling for patient episodes presenting with chronic ambulatory care sensitive conditions
- Age profile of estate – categorical variable indicating the decade in which the majority share of a site's estate was built

The model also controls for the month in which the patient episode occurred.

Annex C - Descriptive statistics of variables of interest

Variable	Mean	Standard Deviation	Min	Max
Total cost (net of MFF)	1,637.26	3631.71	1.00	5,122,812.00
Department size (number of episodes at department)	1,952.97	3,981.78	1.00	63,068.00
Site size (number of episodes at site)	74,649.85	45,154.50	12.00	229,132.00
Provider size (number of episodes at provider)	142,033.33	69,978.44	39,219.00	455,566.00
Remoteness (time to nearest A&E)	25.56	12.86	3.16	85.20

Annex D - Correlation matrix of variables

	Department size	Site size	Provider size	Log of time to next nearest A&E
Department size	1.00			
Site size	0.20	1.00		
Provider Size	0.13	0.32	1.00	
Log of time to next nearest A&E site	-0.01	0.10	-0.29	1.00
Charlson Index	0.07	0.02	0.01	0.03
Comorbidity flag: Anxiety	0.06	0.01	-0.01	0.00
Comorbidity flag: Delirium	0.05	0.02	0.00	0.01
Comorbidity flag: Dementia	0.09	0.01	0.00	0.02
Comorbidity flag: Functional dependence	0.01	0.00	0.00	0.01
Comorbidity flag: Falls	0.03	0.01	-0.01	0.02
Comorbidity flag: Incontinence	0.04	0.00	0.00	-0.01
Comorbidity flag: Mobility Problems	0.09	0.00	-0.01	-0.01
Comorbidity flag: Pressure ulcers	0.05	0.00	0.00	0.01
Comorbidity flag: Senility	0.05	0.00	-0.03	0.02
Month	0.06	-0.08	-0.02	0.00
HRG Code	-0.08	0.00	-0.01	-0.02
ACSC flag	0.12	0.00	-0.01	0.02
CQC well-led rating	0.02	0.04	-0.11	-0.10
CQC quality rating	0.04	0.06	-0.12	0.00
Age profile of Estate	0.00	-0.14	-0.11	0.10
PFI dating earlier than 2006	-0.08	-0.26	-0.40	0.14
Age category	0.10	-0.04	-0.03	0.07
Most deprived 10% flag	0.05	0.02	0.10	-0.11
Teaching hospital flag	0.01	0.26	0.48	-0.29
Non-elective admission flag	0.27	0.10	-0.01	0.07
Day case flag	-0.21	-0.10	-0.01	-0.04
Log of consultant staff share of total staff	-0.03	0.23	0.17	-0.05
Log of A&E performance	-0.05	-0.08	-0.13	-0.04
Log of backlog maintenance as % of Net Book Value	0.02	-0.18	0.01	0.04
Log of PFI as % of Net Book Value (NBV)	0.05	0.24	0.35	-0.16
Log of bed occupancy rate	-0.01	0.05	-0.01	0.00
Log of the percentage of beds occupied by long stay patients	-0.05	0.07	0.20	-0.31
Log of C.Diff infection rate	0.02	0.06	0.18	-0.02
Log of clerical staff share of total staff	-0.03	-0.08	-0.07	-0.04
Log of IT investment	0.01	-0.11	-0.09	-0.04
Log of site hot index	0.17	0.08	-0.01	0.20
Log of CNST as % of Net Book Value	-0.04	-0.19	-0.22	0.22

Annex E - Robustness checks

A number of robustness checks were carried out after the initial model was developed in 2020. These can be found in at the end of this section. Further checks carried out in this new iteration are found below.

Multicollinearity checks

A Variance Inflation Factor (VIF) test for multicollinearity was run and found no severe issues: all the variables in the model had a VIF of <5. The VIF is a direct measure of how much the variance of the coefficient, (that is, its standard error) is being inflated due to multicollinearity.

Outliers

The 2020 modelling excluded all negative costs as well as the top and bottom 1% of the logged cost per episode. In the updated model, the exclusion of negative values was continued, however further tests were done on very high and low values.

To check the impact, the 2021/22 model was run excluding the top and bottom 1%. This led to a loss of 136,466 complete episodes with low costs and 133,346 with high costs from the regression.

This analysis showed that removing the outliers had a small reduction in the scale effect at department level and a larger impact on the remoteness variable although overall trends remained the same. Investigation of the cost distribution for the top 1% found a very small number of extreme outliers. Therefore, removing the top 1% in line with the original modelling would exclude many relatively expensive but plausible costs. This was consistent with advice from TAG, confirming a high degree of genuine variation in episode costs that makes it difficult to automatically exclude unwarranted outliers. Outliers were not therefore automatically excluded.

Following TAG's advice, the few extreme outliers in the top 1%, defined as any record with a total cost (adjusted for MFF) of more than £1m, were investigated. There were 3 extreme outliers in 2018/19, 1 in 2019/20 and 30 in 2021/22. After examining all the extreme outliers and comparing the total costs to local and national costs for similar records with the same POD and HRG, these costs appeared unlikely to be accurate. However, as a robustness check, a version of the model removing the extreme outliers was carried out and compared against the original model. There was negligible difference between the results, and therefore high-cost outliers were not excluded from the model. If the modelling is updated in future years, these checks should be repeated to avoid potential instability due to the presence of one-off extreme outliers.

A&E model

In engagement work some sites suggested that the economies of scale may be larger for A&E services than those already found using APC data. This could therefore mean the model including only APC data may underestimate the unavoidable cost for small sites with Type 1 A&Es.

To investigate this a model was developed to understand the drivers of A&E costs. This model included cost and attendance data for type 1 A&E sites for the year 2019/20 as well as a number of control variables used in this model and the APC model.

Findings from this model did not appear to support the hypothesis that the excess cost of running a small A&E is higher than the equivalent additional cost in small departments providing admitted patient care. This implies that using only APC data in the existing model is unlikely to be a major contributor to the hypothesised underestimate of excess unavoidable costs for small remote providers in previous results.

It was discussed with TAG and decided not to proceed with this model as the effect was small and therefore continued with modifications to the APC model, applying the findings to the whole cost base.

Alternative modelling specifications and approaches

As additional robustness checks, in the original model development in 2021, different model specifications were tested. These included

- non-linear specifications of scale variables (decile, quadratic, cubic and linear)
- limiting the model to sites with a type 1 A&E
- removing control variables
- removing all independent variables with missing data to allow all episodes to be included in the model

It was found that in each case the size and the direction of the scale variables were broadly comparable, so the original specification was retained.

In addition, alternative approaches to pooled OLS, including the Mundlak approach were considered and tested. However, due to the complexity of the Mundlak approach and difficulties with its application to the full dataset due to the computing power required the pooled OLS model was used.

Interaction of scale and remoteness

Based on findings from engagement a hypothesis was tested that there might be an interaction between scale and remoteness effects. The suggested reason for this was that the effect of scale might vary between remote and non-remote sites. For instance, recruitment difficulties due to far away from cultural centres could amplify the cost effect of being small and thus not giving opportunities for staff development.

A statistically significant interaction effect was found between size and remoteness at department and site levels. The interaction at department level showed a stronger effect of scale in the least remote sites, potentially reflecting greater opportunities to generate efficiencies from scale in non-remote, likely urban areas. However, there was little difference between the scale effect in any of the other categories. It was more challenging to interpret the interaction effect in the site size model. Following advice from TAG, it was concluded that as the impact on the overall fit of including interactions is small, they should not be included due to the increased complexity of the model. Interaction terms have not therefore been included in the final model.

Accounting for heteroskedasticity in the application of the model

Heteroskedasticity is the situation where the variance in error term, or the difference between the modelled and observed values, varies. Where the dependent variable is in log form this can cause bias when transforming the variable back to non-log form. This has the potential to bias the predictions in the application stage due to the inherent non-linearity of the log transformation. A modified Wald statistic for groupwise heteroskedasticity, and visual examination of a plot of the residuals, suggests heteroskedasticity is present in the pooled OLS model.

To manage this, a Duan smearing estimator can be used to provide a bias-adjusted prediction for each episode, and the comparison episode. The Duan smearing technique does not require the errors to be normally distributed, but does require the residuals to be homoscedastic.

The Duan factor S is calculated as

$$S = \frac{1}{n}\sum_{i=1}^{n} \exp\left(e_i\right)$$

Where e_i are the residuals from the regression of log (Y).

The Duan factor is then multiplied by the exponent of the predicted value to get an adjusted prediction.

In addition to a better function fit for the data, another advantage of models with logged dependent variable is that they are less sensitive to outliers. For example, before logging, if the mean were 1,000 then an outlier of £1million would be 1000x larger, but after taking logs is only 2x larger. Outliers were not removed, as detailed previously, as they didn't affect the results of the log-transformed model. However, this can create problems when calculating the fitted values because when the data are skewed, the exponent of the mean of the log values is not the same as the mean of the original data. For example, in the dataset the mean of the exponentiated values is around £955 while the mean of the original data is around £1637.

One way to deal with this is to apply a smearing factor, as described above. However, as the difference is mainly due to outliers it was not deemed necessary. This is evidenced by comparing the exponent of the median of the logged values and the original median, which are identical to the second decimal place. It was therefore decided not to apply a smearing factor.

Annex F – Model output with standard errors clustered at provider level

Variable*	Coefficient
Department size (number of episodes at department)	-0.0000178***
	[-0.0000214,-0.0000142]
Site size (number of episodes at site)	3.91e-08
	[-0.00000102,0.00000110]
Provider size (number of episodes at provider)	6.16e-08
	[-0.000000402,0.000000526]
Log of time to nearest A&E	0.0396
	[-0.0544,0.134]
Non-elective admission	-0.114*
	[-0.214,-0.0126]
Day case admission	-0.629***
	[-0.742,-0.515]
Ambulatory Care Sensitive Conditions - chronic	-0.173***
	[-0.211,-0.135]
CQC quality of care	
Missing	0.0965
	[-0.0405,0.233]
1 = Inadequate	-0.0370
	[-0.208,0.134]
2 = Requires improvement	0
	[0,0]
3 = Good	0.0222
	[-0.0448,0.0892]
4 = Outstanding	-0.150
	[-0.319,0.0185]
CQC well-led	
Missing	-0.0863
	[-0.268,0.0956]
1 = Inadequate	0
	[0,0]
2 = Requires improvement	-0.000493
	[-0.147,0.146]
3 = Good	-0.0321
	[-0.198,0.134]
4 = Outstanding	0.0190
	[-0.176,0.214]
Log of A&E type 1 performance	0.0635
	[-0.0640,0.191]
Log of Clostridium Difficile infection rate (hospital acquired)	0.0191
	[-0.0516,0.0898]
Log of total backlog maintenance % NBV buildings	0.0284*
	[0.00280,0.0540]

Year of PFI	
PFI post-2006	0
	[0,0]
PFI pre-2006	0.0259
	[-0.0793,0.131]
No PFI	-0.0944
	[-0.265,0.0766]
Age profile of estate	
Missing age	-0.148*
	[-0.287,-0.00838]
2005-2024	0.171**
	[0.0610,0.282]
1995-2004	0
	[0,0]
1985-1994	-0.0396
	[-0.168,0.0884]
1975-1984	0.0692
	[-0.0495,0.188]
1965-1974	0.0708
	[-0.0399,0.181]
1955-1964	0.0542
	[-0.0783,0.187]
pre-1955	0.157*
	[0.0312,0.282]
Log of total trust CNST spend % NBV	-0.0267
	[-0.121,0.0677]
Log of site hot index	-0.0246*
	[-0.0467,-0.00248]
Teaching trust	0.0184
	[-0.0717,0.109]
Log of consultants share of medical staff	0.195
	[-0.210,0.600]
Log of clerical staff share of total staff	0.186
	[-0.162,0.535]
Log of daily bed occupancy	0.386
	[-0.0243,0.796]
Log of long stay share of occupied beds	-0.0736
	[-0.184,0.0365]
Log of additional IT spend % of NBV	0.00534
	[-0.0187,0.0294]
Observations	43844535
R^2	0.318

95% confidence intervals in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*There are additional variables included in the model as controls but not reported here: month of episode, age of patient, Charlson index, frailty indicator, living in the most deprived areas and PFI as % of NBV (see Robustness checks for detail on PFI). The model has HRG fixed effects.

Annex G – Steps used to calculate site adjustments from model outputs

The steps to calculate adjustments for each small, remote site are as follows:

a. Run final model with the 3 scale variables (department, site and provider), remoteness variable and all other agreed control variables
b. Predict costs for each episode at department, site and provider level.

$$\text{Log}(total\ cost\ adj.MFF) = \beta_0 + \beta_1 Dept\ size + \beta_2 Site\ size + \beta_3 Prov\ size + \beta_3\ Remoteness + \beta n\ Controls \ldots$$

c. Calculate a weighted average number of episodes for each department type and site and provider level for sites that are not small or remote. This uses all episodes from sites with a catchment population of more than 200,000, with a Type 1 A&E and more than 90% of the catchment population within an hour's travel of another site, i.e. not remote.
d. Predict costs for each episode if the department, site and provider operated at the weighted average number of episodes.

$$\log(total\ cost\ adj.MFF) = \beta_0 + \beta_1 \boldsymbol{mean}\ dept\ size + \beta_2\ \boldsymbol{mean}\ Site\ size + \beta_3 \boldsymbol{mean}\ Prov\ size + \beta_3\ \boldsymbol{mean}\ Remoteness + \beta n\ Controls \ldots$$

e. Sum the differences between the exponents of each calculation.
f. Additional cost effects only were aggregated and then scaled to reflect all acute site costs for the 8 sites that are eligible for the adjustment. These criteria have been taken as given as part of this project.
g. To account for inflation the excess costs for each year are calculated separately and relevant cost uplift factors are applied using published tariff factors and a weighted average produced.

