Monograph:

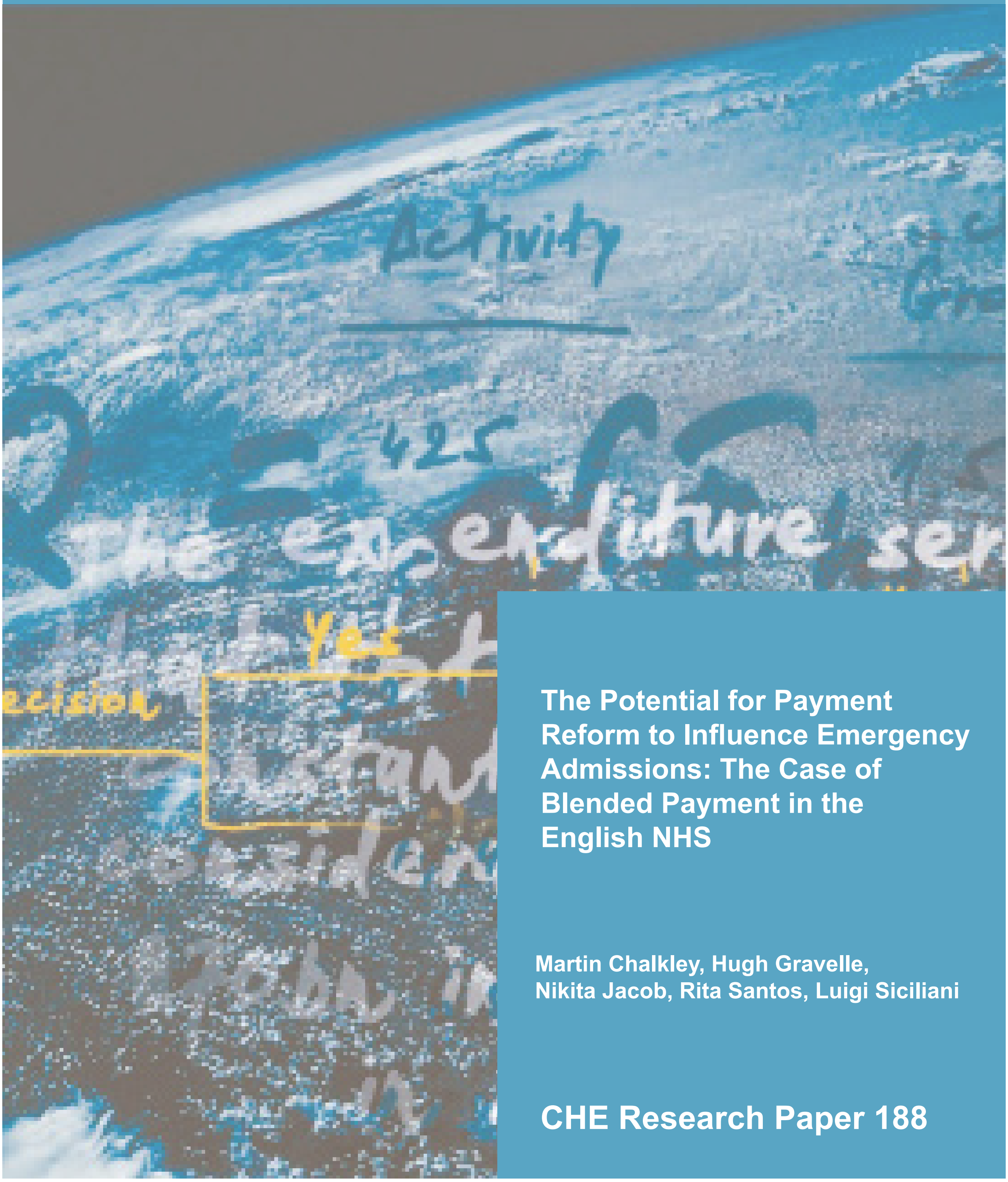
Chalkley, Martin John orcid.org/0000-0002-1091-8259, Gravelle, Hugh Stanley Emrys orcid.org/0000-0002-7753-4233, Jacob, Nikita orcid.org/0000-0001-5546-4521 et al. (2 more authors) (2022) The potential for payment reform to influence emergency admissions::the case of blended payment in the English NHS. Discussion Paper. CHE Research Paper . Centre for Health Economics, University of York , York, UK.

UNIVERSITY of York

RESEARCH

CHE
Centre For Health Economics

NIHR | Policy Research Unit in Economics of Health Systems and Interface with Social Care



The Potential for Payment Reform to Influence Emergency Admissions: The Case of Blended Payment in the English NHS

Martin Chalkley, Hugh Gravelle,
Nikita Jacob, Rita Santos, Luigi Siciliani

CHE Research Paper 188

The potential for payment reform to influence emergency admissions: the case of blended payment in the English NHS

[a]Martin Chalkley
[a]Hugh Gravelle
[a]Nikita Jacob
[a]Rita Santos
[b]Luigi Siciliani

[a]Centre for Health Economics, University of York, UK
[b]Department of Economics and Related Studies, University of York, UK

September 2022

Background to series

CHE Discussion Papers (DPs) began publication in 1983 as a means of making current research material more widely available to health economists and other potential users. So as to speed up the dissemination process, papers were originally published by CHE and distributed by post to a worldwide readership.

The CHE Research Paper (RP) series takes over that function and provides access to current research output via web-based publication, although hard copy will continue to be available (but subject to charge). Results and ideas reported in RPs do not necessarily represent the final position. Work reported in some RPs should be seen as work in progress and may not have been subject to peer review at the time of publication.

Acknowledgements

This research is funded by the National Institute for Health and Care Research (NIHR) Policy Research Programme, conducted through the NIHR Policy Research Unit in Economics of Health Systems and Interface with Social Care (reference PR-PRU-1217-20301). The views expressed are those of the authors and not necessarily those of the NIHR or the Department of Health and Social Care. Hospital Episode Statistics are copyright ©2004/05-2018/19 Health and Social Care Information Centre. Re-used with the permission of NHS Digital. All rights reserved. This project was undertaken on the Data Safe Heaven, which is an ISO 27001-certified environment for handling sensitive data and is provided by the University of York. We are grateful for the support from the York Data Safe Heaven team and the Research Computing team.

No ethical approval was needed.

Further copies

Only the latest electronic copy of our reports should be cited. Copies of this paper are freely available to download from the CHE website www.york.ac.uk/che/publications/. Access to downloaded material is provided on the understanding that it is intended for personal use. Copies of downloaded papers may be distributed to third parties subject to the proviso that the CHE publication source is properly acknowledged and that such distribution is not subject to any payment.

Printed copies are available on request at a charge of £5.00 per copy. Please contact the CHE Publications Office, email che-pub@york.ac.uk for further details.

Centre for Health Economics
Alcuin College
University of York
York,
YO10 5DD, UK
www.york.ac.uk/che

Abstract:

This paper constitutes the second output of the ESHCRU2 project 3.1 Analysis of purchaser-provider contracts: modelling risk sharing and incentive implications. In this project, we have focused on the implications of payment reform of blended payment for emergency care. Building on the new theoretical model (Chalkley et al 2022) this paper is an empirical investigation of hospitals' propensities to admit patients who attend their Accident and Emergency Departments. It provides a basis for considering the potential impact of the blended payment reform on emergency admissions.

1. Introduction

The essence of many hospital payment systems is to pay a specific amount for each patient a hospital treats according to the particular medical condition or diagnosis grouping that patient falls under. Such systems are commonly referred to as Diagnosis Related Groups (DRG) based on following the terminology adopted by Medicare in the US (Guterman and Dobson, 1986). This approach has underpinned the English NHS payment mechanism for hospital services as set out in the National Tariff Payment System (NTPS).[1] For elective care this mandates prices (termed tariffs) that are calibrated to average costs. Emergency hospital care funding was reformed from 2019 and is now funded through a mixture of a national tariff, with adjustments to the price for treatments above an indicative volume, and some element of a fixed budget agreed between commissioners and hospitals[2,3] who also have discretion in adjusting the national tariff to local circumstances. This approach, which is referred to as blended payment, allows local discretion in terms of setting a price for each unit of activity and establishes a two-part tariff in which the prices of activity are reduced below the previously mandated national price and the hospital is compensated for that by a fixed budget. This policy change has brought into focus the potential incentive and risk-sharing properties of different payment mechanisms for the emergency care system.

This payment reform encapsulates a more general desire in the English NHS to move away from pure activity-based payment and in particular towards an approach where many providers of healthcare receive a lump-sum transfer possibly conditional on other performance targets (NHS England and NHS Improvement, 2019).

From an economics perspective, prices act as important signals of the relative merits of different activities. Hence, the move towards blended payment can be seen as a means of reducing the importance of treatment within hospitals and may be accompanied through the conditionality of payment on other performance measures with an increased emphasis on other kinds of healthcare intervention. As part of a broader project we have developed a model of the impact of those new arrangements on emergency care, with one particular focus on the *propensity to admit* patients subsequent to them attending an Accident and Emergency Department (AED). That model highlights the role of hospital-specific variables - such as the implicit weights they place on the value of the treatments given and their own costs of delivering treatment - both within an emergency department and once patients are admitted. The model therefore predicts that the response of hospitals to a reduction in the activity-based price component of their blended contract will depend on a number of factors that are inherently difficult to observe.

The starting point for this paper is the recognition that the choices that hospitals make about emergency admissions under the pre-existing NTPS system may be informative of the attitudes and constraints they face and thus can serve as a guide as to how they will respond to the changing financing arrangements.

We model variations in hospital admissions following an A&E attendance accounting for other factors that are outside of the control of the hospital that also affect the chances of a patient being admitted, particularly the severity of a patient's condition. We then use variation in hospital emergency admissions to draw inferences about how responsive hospitals may be to the

[1] NTPS is summarised here https://www.england.nhs.uk/pay-syst/national-tariff/#:~:text=The%20national%20tariff%20is%20a,cost%20effective%20care%20to%20patients.

[2] Throughout we use the term hospital. In the English NHS the more general term provider captures the idea that a single organisation may supply a great variety of healthcare services, not only those delivered in a hospital. In the setting, we study however the term hospital seems more descriptive and appropriate.

[3] See https://www.england.nhs.uk/wp-content/uploads/2021/02/20-21_National-Tariff-Payment-System.pdf

introduction or a change of a blended payment system. Hence, this paper provides an examination and interpretation through the lens of an economic model of variation in hospitals' propensities to admit patients that attend their A&E department. It relates this variation to an underlying model and draws inferences regarding the extent of variation in the underlying parametric differences between hospitals. Those inferences then provide a guide as to how much impact payment reform can be expected to have.

A key element of our approach is to combine theory with evidence to understand how a yet to be fully observed payment system may impact on health care delivery. It explicitly accounts for heterogeneity across hospitals in making that assessment and it addresses a specific and important payment reform in the NHS in England.

The structure of this paper is as follows. We start with a theoretical framework that establishes the relationship between a hospital's propensity to admit patients and the benefits and costs it perceives from admitting, including the payment it receives. This model provides the basis for understanding how a hospital's propensity to admit may vary. We then adopt an empirical strategy of modelling the probability that an individual patient will be admitted controlling for as many patient and attendance specific factors as possible. We present estimates of a linear probability model, where hospital fixed effects are interpreted as a hospital's propensity to admit, other things equal. We interpret the variation in fixed effects as reflecting the relative importance of benefit and cost parameters affecting the hospital's decision to admit the patient. This adjusted variation in hospital admission propensities gives an insight into the potential for payment reform to influence admissions across the full population of hospitals. Last, we calibrate the theoretical model to reflect the variation in hospital admission propensities, and use this calibration to draw some preliminary inferences regarding the likely impact of reform related to blended payments across different hospitals.

Our overall approach fits with the empirical literature on the impact of fixed price payment systems on hospital activity. In this literature, papers have sought to establish how either the introduction of activity-based payment or changes in the prices paid for treatment influence activity, which in our setting is admission to hospital. Examples of this approach are seen in Januleviciute et al. (2016), O'Reilly et al. (2012), Socha (2014) and Verzulli et al. (2017). The overall assessment of the impact of DRG-based payment on a variety of performance indicators is the subject of a systematic review by Barouni et al. (2021).

Within this area of study there has been discussion of the impact of mixed (fixed price and block payment) systems where these have been adopted in Denmark and other Scandinavian countries (Hansen et al., 2013). However, empirical evidence in respect of these studies is either descriptive in nature or focused on system level performance. In contrast, our study seeks to explain decisions made at the level of individual patients. More fundamentally our approach considers a specific setting and seeks to link empirical observation to a bespoke theoretical framework that has been designed to capture the specific setting of emergency care. We further link the theory model to the data in order to interpret behavioural responses and thereby draw implications for the design of policy. This calibration of theory to data is uncommon. A recent example of the approach can be found in Siciliani et al., (2021). Our focus here is in the context of Chalkley and Malcomson, (2002) in seeking to interpret how performance under one payment system can provide insight into the gains or losses of adopting a different payment system.

The recent empirical literature on emergency care systems mostly focuses on examining differences in mortality between admissions from Accident and Emergency Departments[4] (AEDs) at weekends compared to weekdays. For example, Meacock et al. (2017) found that there was no evidence that mortality rates for emergency patients admitted at weekends were higher than for those with similar characteristics admitted on weekdays. Anselmi et al. (2017) used the mode of arrival to AED to control for severity of illness in patients admitted to hospital in an emergency and found no substantial increase in risk of mortality following emergency admission to hospitals at nights and at weekends. Han et al. (2018) found that, over a 10 year period, there was a higher all-cause mortality risk for emergency weekend and night time admissions, but the increases were small and not statistically significant in individual hospitals in every year.

Our study takes a different approach: we seek to understand how hospitals make decisions on the admissions for patients who have attended AEDs and to measure the extent of variation between hospitals in these decisions, in order to examine how they may respond to a blended payment.

[4] There is a variety of terminology used to describe the hospital facilities that receive and treat individuals who arrive or are delivered in an unplanned way and who require emergency medical care. Throughout this paper we adopt the term Accident and Emergency Department and use the acronym AED. In other jurisdictions Emergency Department (ED) or Emergency Room (ER) are often used.

2. Background and institutional setting

The setting for our study is the treatment of individuals who become suddenly and seriously ill. In the English National Health System (NHS) these individuals may seek attention either from their personal doctor (GP), from a variety of other resources (calling an ambulance, contacting dedicated help phone lines, walk in centres, urgent care centre) or by attending an Accident and Emergency Department (AED) at a hospital. Depending on the seriousness of their condition they may also be directed to AED or transported there by other healthcare organisations. We are concerned with this specific part of the care pathway - AED attendance - and what happens subsequent to that.

AED attendance may result in the patient being treated in the AED setting, being discharged back into the care of the GP or being admitted to the hospital for further treatment. It is this latter event that is the focus of our analysis. We are concerned with understanding the determinants of emergency admissions from AEDs and how the propensity to admit patients varies from hospital to hospital. There has been a longstanding concern with ensuring the appropriate use of hospital resources which, relative to other mechanisms of care, tend to be resource intensive and hence costly (Steventon et al., 2018). For example, the NHS pays approximately ten times as much for an admitted patient than for one who is discharged from AED[5].

The background for NHS payment for hospital services is the National Tariff Payment System (NTPS) (NHS England and NHS Improvement, 2019), previously known as Payment by Results (PbR). NTPS is focused on making payment directly proportionate to the amount of activity that a hospital supplies. For the 2018/19 financial year for which we have data, this system was applied to both AED attendances and any subsequent admissions. In brief, a hospital was paid a price for each AED attendance and another (substantially higher) price if a patient is admitted. Both prices vary according to Healthcare Resource Groups (HRG) categories[6]. The price for admitted emergency patients varies with the reason for admission and the treatment they receive. In the AED, HRGs vary with intensity of the investigations and treatments received.

For the financial year 2019/20 the system was reformed and hospitals were funded through a mixture of the national tariff, with adjustments to the price for treatments above an indicative volume which could result in a much lower marginal price for admissions, and an element of a fixed budget agreed between commissioners and hospitals. This *blended* payment approach establishes a two-part tariff which places a lower price on marginal activity but compensates the hospital via a fixed budget. It is towards understanding and predicting the implications of this change that our research is directed. We set out a theoretical framework in Chalkley et al. (2022) and in this paper we estimate an empirical model that can be interpreted with the aid of that theory to indicate the extent to which the move to blended payment will have an impact on emergency admission rates for different hospitals.

[5] See https://www.england.nhs.uk/publication/2018-19-national-cost-collection-data-publication/

[6] Healthcare Resource Groups are functionally equivalent to Diagnosis Related Groups which originated in the US Medicare system in the 1980s and that are now commonly used to fund hospital services across a large number of countries (Mihailovic et al., 2016).

3. Theoretical framework

Our model follows the framework set out in Chalkley et al.(2022) in which hospitals receive attendances at their AEDs, determined by the level of provision of out-of-hospital services and the characteristics of the catchment area population, and then make decisions on whether to admit patients or to discharge them having treated them in the AED.

The hospital decision problem

Henceforth we consider the position of a particular hospital j. The number of patients that appear at the hospital's emergency department over a given time period is denoted by N_j which is assumed to be a random variable with density $f_j(N)$ and mean μ_j and variance $\sigma_j{}^2$. The hospital determines what proportion α_j of these patients will be admitted for inpatient care. We refer to this proportion as the propensity to admit.

We view hospital $j's$ choice of α_j as maximising the surplus of benefits over costs, and assume that benefits take the form

$$B_j(\alpha_j, \mathrm{N}) = b_{1j}(1-\alpha_j)\mathrm{N_j} + b_{2j}\alpha_j\mathrm{N_j}, \qquad (1)$$

where $b_{2j} > b_{1j} > 0$ are constants that represent the hospital's monetary equivalent assessment of the value of treating a patient exclusively in the AED (b_{1j}) of which there will be $(1-\alpha_j)\mathrm{N_j}$ patients, or as an admitted patient (b_{2j}) of which there will be $\alpha_j\mathrm{N_j}$ patients.

We assume that costs are a convex function of the number treated and for simplicity write the cost function as

$$C_j(\alpha_j, \mathrm{N_j}) = F_j + (\mathrm{N_j} - \alpha_j\,\mathrm{N_j})^2 c_{1j} + (\alpha_j\mathrm{N_j})^2 c_{2j}, \qquad (2)$$

where F_j, c_{1j} and c_{2j} are constants and, reflecting the fact that inpatient care is more intensive, $c_{2j} > c_{1j}$.

The payment the hospital receives depends on the price p_1 per patient treated exclusively in the emergency department, the price p_2 per patient treated as an admission, and a fixed financial transfer of T. So, the total revenue of the hospital is

$$\mathrm{R}(\alpha_j,\, \mathrm{N}) = \mathrm{T} + p_1\,(1-\alpha_j)\mathrm{N_j} + p_2\,\alpha_j\mathrm{N_j} \qquad (3)$$

This encompasses both the previous purely activity-based payment system in the NHS (with $T = 0$) and the newly adopted blended payment contract in which $T > 0$ is set conditional on a target number of treatments and possibly other performance measures. The data that we examine is derived from a system which exclusively relied on the prices $p_1$and p_2.

Hospital choice of admissions

For a given specification of the hospital's revenue function it is now possible (given the remaining assumptions) to solve. The hospital's optimal choice $\alpha^*{}_j$. From the simple linear revenue and quadratic cost functions, we can derive a closed form solution for the hospital's optimal choice $\alpha_j{}^*$. The hospital's net benefit, denoted $v_j(\alpha_j, N)$, is quadratic in both of its arguments. Hence, when taking expectations over N only linear and squared terms appear. Using the fact that $\mathrm{E}[N_j^2] = \mu_j{}^2 + \sigma_j{}^2$ for any density function $\mathrm{f_j(N)}$, the hospital's objective function can be written as

$$\int v_j(\alpha_j, N) f_j(N) dN \; = \; b_{1j}(1-\alpha_j)\,\mu_j + b_{2j}\alpha_j\,\mu_j - \big[F_j + \; (1 + \; {\alpha_j}^2(\,{\mu_j}^2 + \sigma_j^2) - 2\alpha_j\,\mu_j)c_1 + {\alpha_j}^2({\mu_j}^2 + \sigma_j^2)c_{2j}\big] + p_1\,(1-\alpha_j)\,\mu_j \; + \; p_2\alpha_j\,\mu_j + T \qquad (4)$$

Differentiating (7) with respect to α_j and equating to zero gives the first order condition satisfied by ${\alpha_j}^*$as

$$-\, b_{1j}\,\mu_j + b_{2j}\,\mu_j - 2c_{2j}\,\alpha_j^*(\,\mu_j^2 + \sigma_j^2) + 2c_{1j}(1-\alpha_j^*)(\,\mu_j^2 + \sigma_j^2) + (p_2 - p_1)\mu_j = 0. \qquad (5)$$

Equation (5) can be solved to give,

$${\alpha_j}^* = \frac{(p_2 - p_1 + b_{2j} - b_{1j})\mu_j + \,2c_{1j}\big(\mu_j^2 + \sigma_j^2\big)}{2(c_{1j} + c_{2j})\big(\mu_j^2 + \sigma_j^2\big)} \qquad (6)$$

Equation (6) indicates that the hospital's optimal choice of its propensity to admit depends upon its valuation of inpatient and emergency treatments, the costs of these treatments, the magnitude and variability of the demand for its services (the number of patients who attend its AED) and the payment it receives.

The analysis thus far is framed in terms of hospital $j's$ admission propensity assuming a given type of patient. We have data on the admission of individual patients each of whom has particular health conditions, severity of illness and needs. To accommodate this we assume that patients arrive with different severities of conditions with each severity corresponding the patient's *type* $i \in \{1,2,\ldots, I-1, I\}$ with lower types having less severe illness and therefore benefitting less from admission relative to treatment in the AED. For each type i we assume the hospital's objective function is adjusted by replacing α_j with $\alpha_j + a(i)$ where $a(1) < 0$ and $a(.)$ is increasing in i. This results in expression (6) being augmented on the right-hand-side by the term $a(i)$ and subtracting this term from both sides implies that the hospital's admission policy is separable in respect of its characteristics (indicated by parameters with subscript) and patient specific factors captured by $a(i)$. To empirically implement this, given observations on whether a patient of type i is admitted by hospital j we estimate

$$P_{ij} = {\alpha_j}^* + \; A\boldsymbol{z_i} \qquad (7)$$

where z_i is a vector of the characteristics of patient i and A is a vector of coefficients which is assumed to be common across all hospitals. For less severely ill patients, or those without comorbidities, elements of A will take negative values and vice versa.

This empirical model establishes how P_{ij} can be related to patient, attendance and primary care characteristics and the hospital that they attend, with the latter captured by a hospital fixed effect. By including factors that correlate with hospital attendance numbers (μ_j and σ_j) as well as an extensive set of variables to capture z_i the estimated hospital fixed effect will capture the hospital specific unobserved parameters b_{1j}, b_{2j}, c_{1j}or c_{2j}. The model therefore provides guidance for interpreting these fixed effects. From inspection of (6) a hospital that is observed to have a large positive fixed effect (a high α^*) other things equal has either a high net benefit from admissions ($b_{2j}$is much larger than b_{ij}) or a small net cost from admissions (c_{2j} is similar in value to c_{1j}) or both of these.

This gives further insight as to whether changing the price of admissions, as a part of a blended payment reform, is likely to have a large or small impact on a hospital's admission policy. If it is possible to identify hospitals with a high α^*, then these hospitals can be inferred to have a smaller denominator in expression (6) with implications for their responsiveness to a price reduction. Specifically differentiating (7) we see that

$$\frac{d\alpha_j{}^*}{dp_2} = \frac{\mu_j}{2(c_{1j}+c_{2j})\left(\mu_j^2+\sigma_j^2\right)} \qquad (8)$$

where equation (8) indicates that the responsiveness of a hospital's admissions policy to a change in the price for an admitted patient depends on its cost parameters, expected attendances and the variance of attendances.

4. Empirical model of admissions

Data

We conducted a retrospective cohort study of 13,912,890 at AEDs in 127 NHS Hospital Trusts using routinely collected data for 2018/19. Our main sources of data are the Accident and Emergency and the Admitted Patient Care (APC) Hospital Episode Statistics (HES) datasets. HES Accident and Emergency collects data on all attendances to National Health Service (NHS) AEDs and includes basic information such as diagnosis, investigation, treatment, age, sex, area of residence and time and method of arrival and departure[7]. Most AEDs in England can be broadly characterised as either 'minor' or 'major' types. Major AEDs are consultant-led 24-hour service with full resuscitation facilities, while minor ones are designed to treat less serious cases. Other AEDs units are either consultant-led mono specialty AED service, minor injury services or NHS walk-in centres.

We identified emergency admissions to the same NHS Trust by linking HES AED attendances to HES APC 'Finished Consultant Episodes' (FCEs) using the pseudonymised patient identifier.

HES APC collects data on all admissions to NHS hospitals in England which provides detailed clinical, demographic and organisational information for each FCE, including data on diagnoses and procedures, on date and method of admission (e.g. emergency or planned), operations and discharge, care provider and socioeconomic variables mapped from a patient's postcode.

We analyse all 2018/19 AED attendances to 'major' English NHS Trusts AEDs[8] from patients residing in England for which the clinical commissioner was one of 191 Clinical Commission Groups (CCGs). We considered a patient was admitted after attending AED if the patient was discharged from AED with an emergency admission and it had a FCE in HES APC in the same Hospital Trust. We do not include direct admissions[9], i.e., admissions to hospital from GPs, bed bureau or specialists (HES admission codes 22, 23 and 24), or emergency admissions without an AED attendance record.

From these data our key outcome is whether a patient is admitted after an AED attendance to the same NHS Hospital Trust. We identify a number of attendance characteristics including the patient characteristics, their area of residence and GP practice. These are:

- Patient demographic characteristics including gender, age band (under 6 years, 6 to 10, 11 to 15, 16 to 20, 21 to 25, 26 to 30, 31 to 35, 36 to 40, 41 to 45, 46 to 50, 51 to 55, 56 to 60, 61 to 65, 66 to 70, 71 to 75, 76 to 80, 81 to 85, 86 to 90, 91 to 95, over 96 years) and ethnic group (White; mixed; Asian, Black, other ethnic group or unknown ethnicity)[10]. We also control for patient's area characteristics such as their socio-economic status, using the income score of the Index of Multiple Deprivation (IMD)[11], and urbanicity using the patient's recorded Lower Super Output Area (LSOA) of residence.

[7] See https://www.nuffieldtrust.org.uk/research/focus-on-a-e-attendances

[8] The provision of 'minor' AED services varies across the country and these services cater to a patient population that is typically not at risk of emergency admission to inpatient care.

[9] Direct admissions are for either known patients or where the presenting medical problem is clearly diagnosed at point of contact - e.g. an identified case of sepsis at home will be admitted directly to either a hospital ward or to critical care. We omit these because they are not subject to the hospital's admission policy as we have defined it. These admissions, as reported in Meacock et al 2017, are approximately one tenth of the volume of AED attendances. See Appendix 2 for more details on these admissions.

[10] sSe https://www.datadictionary.nhs.uk/data_elements/ethnic_category.html for more information on how NHS digital records ethnicity on HES.

[11] The IMD is the official measure of relative deprivation in England following an established framework that encompasses seven areas of deprivation, including income, employment, and health and disability.

- The severity of the patient's illness on attendance at the AED as proxied by the Healthcare Resource Groups (HRGs) and an indicator for non-urgent AED attendance[12]. HRGs are standard groupings of clinically similar treatments and investigations which use comparable levels of healthcare resources. There are twelve AED HRGs which vary in the number and complexity of AED investigations and treatments. Non-urgent attendances at a major AED are avoidable attendances in the sense that a patient could have been treated in a different healthcare setting. We used the NHS Digital definition but have excluded the requirement for the patient not to be admitted following the attendance. Otherwise, by definition, this variable would be perfectly predictive of whether the attendance resulted in an admission. This type of attendance can be affected by practice opening hours and patient beliefs about the quality and accessibility of their practice. We describe below how we control those.
- The patient's arrival mode at the AED, whether by ambulance or not, is included as a further indicator of the severity of the patient's illness.

To control for the extent and quality of treatment the patient may have received at their GP practice we collected information on the patient's GP practice clinical quality from the Quality Outcome Framework. Almost all practices take part in the QOF which rewards practices for achievement on a large number of quality indicators. We use the percentage of clinical points which the practice achieved as a measure of clinical quality. We also derived practice quality and accessibility indicators from the General Practice Patient Survey. Practice accessibility is proxied by the proportion of patients that were aware that their practice had extended hours during the week (morning or afternoon) or during Saturdays and the ability to see a GP the next day or the same day. The proportion of patients that are satisfied with the practice is a further possible proxy for practice quality that we include. Given that practice accessibility is conditional on the practice workforce, we also include the practice workforce as the number of full-time equivalent (FTE) GPs, nurses and other direct staff per 1000 patients. Practice list morbidity is measured by the average life expectancy at birth for practices (attributed proportionally from MSOAs where the practice patient list lives) and the practice prevalence rates of 16 major conditions which were covered by the QOF over period 2018-19 (asthma, atrial fibrillation, cancer, cardiovascular disease, chronic kidney disease, COPD, dementia, diabetes, epilepsy, heart failure, hypertension, mental health, peripheral arterial disease, rheumatoid arthritis, secondary prevention of coronary heart disease, stroke and transient ischaemic attack). Since not all GP practices offered extended hours access - which are pre-bookable appointments in early morning (6:30am to 8am), evenings (6pm to 8pm) and weekends - in 2018/19, we take account of whether the practice was open when the patient attended the AED, including these extended hours access.

- Accessibility indicators that serve both as possible proxies for patient severity and as proxies for varying demand included week of the year, time and day (week-day/end) of arrival and if the patient's GP practice was open (extended hours, core hours, out of all hours), with arrival in core hours as the reference category. As a measure of geographical access, we control for distance from patient's LSOA to the AED of attendance in bands (less than 10 kms, 10-20 kms, over 20 kms), as well as distance from patient's LSOA to their GP practice in distance bands (less than 1 km, 1-2 kms and over 2 kms).[13]

[12] See https://digital.nhs.uk/data-and-information/data-tools-and-services/data-services/innovative-uses-of-data/demand-on-healthcare/unnecessary-a-and-e-attendances#definitions

[13] Distances are measured as the straight line distance between the LSOA geographical centroid and the nearest AED site of attendance and patient's GP practice surgery.

- The provision of 'minor' AED services can affect the number of patients attending 'major' AED services. Therefore we measure the availability of other emergency care services nearby the patient residence by including which type of AED is nearest (nearest AED to patient's residence is type 1, type 2, type 3, type 4 or not known) and which AED services the patients can access within 10km of their residence (patient's residence is within a 10km radius of a type 1, type 2, type 3 ,type 4 or unknown).

Modelling Strategy

Our resulting empirical analogue of equation (7) is the linear probability model outlined in the following equation:

$$Y_{ijga} = \beta_0 + X_i\beta_X + D_{ija}\,\beta_D + S_{ig}\beta_S + \nu_j + \varepsilon_{ijga}, \qquad (9)$$

where Y_{ijga} is a binary indicator that takes value 1 if there is an admission following AED attendance *a*, at hospital *j*, by patient *i* who is registered with practice *g* and 0 otherwise. X, D and S are characteristics of the patient, the attendance (e.g. time and day of attendance) and the GP practice. The coefficients β_X β_D and β_S measure the impact of those variables on the probability of admission of the AED attendance *a* of patient *i*, who is registered at practice *g*, at hospital *j*. Central to our analysis is the hospital *j* fixed effect, ν_j , whilst ε_{jiga} is the usual idiosyncratic error term. We estimate the model using Stata 17 with the package *xtreg, fe* and with robust standard errors clustered on hospitals.

The hospital fixed effects pick up unobserved hospital specific factors. Given the rich set of observed explanatories in *X, D*, and *S*, we assume that variations in the fixed effects across hospitals is determined by differences in their decisions on their admission propensities α_j. This formulation seeks to explain as much of the variation in admission following an AED attendance as possible such that the remaining variation can then be attributed to the hospital specific idiosyncratic factors such as preferences and costs, thereby providing a basis for understanding how changes in payment contracts may impact their behaviour.

We also estimate two variants of (9) as a robustness check. First, we also include fixed effects for the patient's CCG along with the attendance, patient and GP practice characteristics in addition to the hospital fixed effects:

$$Y_{ijga} = \beta_0 + X_i\beta_X + D_{ija}\,\beta_D + S_{ig}\beta_S + \nu_j + \eta_c + \varepsilon_{ijga}, \qquad (9`)$$

where η_c is the CCG fixed effect. The CCG fixed effects may capture some other unobserved variation in patient access to emergency care not otherwise captured or may reflect otherwise unobserved elements of the severity of a patient's illness which would otherwise be omitted variables. In the second check, we estimate the main model (9) but omit the general practice explanatories as a check to ensure the results are not sensitive to these since general practice characteristics should not affect the hospital's propensity to admit but reflect the supply and quality of a complementary health service.

Relationship to the theoretical model

The linear probability models set out in (9) and (9`) provide a means to relate the estimated hospital effects ε_j to the theoretical hospital's optimal admission policy $\alpha^*{}_j(Z_j)$, where $Z = (b_{1j}, b_{2j}, c_{1j}, c_{2j}, p_1, p_2, \mu_j, \sigma_j)$ is a vector of hospital level factors affecting the admission policy. The first-order Taylor-series approximation to $\alpha^*{}_j$ about given values of $b_{1j}b_{2j}c_{1j}c_{2j}p_1p_2$ is given by;

$$\alpha^*{}_j(Z + \Delta Z) \approx \alpha^*{}_j(Z) + \sum_{k=1}^{8} \frac{\partial \alpha^*{}_j}{\partial Z_i}(Z_{ki} + \Delta Z_{ki}) \qquad (10)$$

where k indicates the index of the variables in Z. Since the empirical models (9) and (9`) include variables to capture μ_j and σ_j then (10) can be rewritten as

$$\alpha^*{}_j(Z + \Delta Z) - \frac{\partial \alpha^*{}_j}{\partial \mu}(\mu + \Delta\mu) - \frac{\partial \alpha^*{}_j}{\partial \sigma}(\sigma + \Delta\sigma) \approx \alpha^*{}_j(Z) + \sum_{k=1}^{6} \quad \frac{\partial \alpha^*{}_j}{\partial Z_{ki}}(Z_{ki} + \Delta Z_{ki}) \qquad (10`)$$

The left-hand side of (10`) corresponds to the estimated hospital fixed effect ε_j and considering small ΔZ implies that this estimated coefficient is the hospital's admission policy $\alpha^*{}_j$ net of the marginal effects changing μ and σ. Inspection of (6) indicates that these marginal effects are negative. On the assumption that these effects are small, we can conclude that

$$\alpha^*{}_j \quad \lessapprox \quad \varepsilon_j. \qquad (11)$$

Hence, in interpreting our regression results we can regard the estimated hospital fixed effects as an approximation of their admission policy and thus a consequence of their idiosyncratic benefits and costs, according to the formula in (6).

5. Results

Table 1 shows how we selected[14] the 13,912,890 AED attendances to type 1 NHS AED Trusts Departments in 2018/19. As discussed above, we restrict our analysis to AED attendances to major consultant-led, open 24 hours per day that have full resuscitation facilities (Type 1).[15]

Table 1 Sample selection 2018 AED attendances

Selection criteria	*Observations*
All AED attendances	22,367,847
Drop duplicates	22,289,194
Keep only Type 1 AED attendances	16,015,063
Drop those died in the department (154 NHS Trusts)	16,001,011
AED attendances merged with non-HES data (GP patient list and workforce, GPPS, QOF, the distance between LSOAs and AED of attendance and GP practice, rurality, GP extended access, QOF dimensions, Deprivation indices, ethnicity data from other HES attendances)	15,995,619
Excluding attendances from patients cared for by CCG's or GP's outside England	15,469,684
Excluding attendances at Specialist Trusts (women/children care Trusts)	15,189,516
Excluding attendances from patients which GP practice have 0 FTE GPs	15,084,005
Excluding the three NHS Trusts with high volume of direct admissions	14,776,250
Number of AED attendances from patients which GP practice characteristics was non-missing	13,912,890
Non-missing regression sample of AED attendances	13,888,084
Number of AED attendances with an APC admission	2,997,462
Clinical Commissioning Groups	191
Number of Hospital Trusts	127

We drop all AED attendances from patients that died in the department (where AED disposal code was death) and those that were admitted via non-AED admission method, i.e. direct admissions, as this is not the population of interest for our analysis. We further excluded attendances at the former primary care trusts, trusts with associated treatment centres, NHS trust treatment centres listed separately to NHS trusts, independent hospitals and other independent sector healthcare providers. We also exclude from the analysis the attendances from patients for which treatment commissioning was one of the 30 commissioning hubs since they are responsible for leading the commissioning of specialised services that care for women and children. We do not include AED attendances by people from other parts of the UK, or attendances of English patients outside England and attendances to AED units run by independent hospitals because these attendances would be covered by separate contracts with CCGs. Finally, we dropped three trusts that had extremely high rates of direct admissions.

The final sample consists of 13,912,890 AED attendances at 127 trusts, of which 2,997,462 were converted into admissions. We dropped 24,806 AED attendances for which we did not have

[14] Further notes on these selections are in Appendix 3.

[15] The other types of AED are type 2 AEDs, which are for single specialities such as ophthalmology or dentistry and Type 3 and 4 AEDs, such as minor injury units or NHS walk in centres, treat minor illnesses and conditions and may have limited opening hours and type 99 is attendance to an unknown type of AED unit.

complete information on the patient characteristics or their GP practice. Therefore, our results are reported using a 13,888,084 AED attendance sample.

Descriptive statistics

The descriptive statistics for the 13,888,084 AED attendances to an NHS Trust type 1 AED in 2018/19 are reported in Table 2.

Table 2. Descriptive Statistics for 2018 A&E attendances

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Attendance characteristics				
Attendance results in emergency admission (dependent variable)	0.20	0.40	0	1
Ambulance	0.30	0.46	0	1
Weekday	0.72	0.45	0	1
Male	0.49	0.50	0	1
Weekday Core hours: 8 am<6:30 pm (GP open)	0.44	0.50	0	1
Week day AM extended hours: 6:30<8 am (GP open)	0.00	0.02	0	1
Week day AM extended hours: 6:30<8 am (GP closed)	0.00	0.05	0	1
Week day PM extended hours: 18:30<20:00 (GP open)	0.01	0.07	0	1
Week day PM extended hours: 18:30<20:00 (GP closed)	0.01	0.09	0	1
Weekend extended hours: 9:00<13:00 (GP open)	0.00	0.05	0	1
Weekend extended hours: 9:00<13:00 (GP closed)	0.03	0.17	0	1
Out of all hours: Weekday (20:00<6:30), Weekend (13:00<9:00)	0.41	0.49	0	1
Patients demographics				
Age 0-4	0.10	0.30	0	1
Age 5-17	0.12	0.33	0	1
Age 18-65	0.53	0.50	0	1
Age 65+	0.25	0.43	0	1
Patients residence characteristics:				
Urban	0.87	0.34	0	1
IMD quartile 1(<25th percentile)- Least deprived	0.26	0.44	0	1
IMD quartile 2 (25th-50th percentile)	0.25	0.44	0	1
IMD quartile 3 (50th-75th percentile)	0.25	0.43	0	1
IMD quartile 4 (>75th percentile)- Most deprived	0.24	0.43	0	1
Patients GP practice characteristics:				
Percentage of patients aware that their GP practice has early morning extended hours	10.57	9.47	0	63.85
Percentage of patients aware that their GP practice has late afternoon extended hours	12.77	8.59	0	61.78
Percentage of patients aware that their GP practice has Saturday extended hours	9.61	10.04	0	72.30
Percentage of patients aware that they were able to see their preferred GP always or a lot	45.39	16.87	0	99.05
Percentage of patients aware that they were able to see their GP the same day	32.86	13.51	1.56	87.32

Percentage of patients aware that they were able to see their GP the next day	10.99	5.66	0	59.01
Percentage of patients that were very or fairly satisfied with the practice overall care	83.08	9.57	37.26	100
FTE GPs per 1000 patients	0.55	0.23	0	5.47
FTE nurses per 1000 patients	0.26	0.14	0	2.23
FTE other direct staff per 1000 patients	0.18	0.18	0	2.32
Average life expectancy	81.16	2.00	73.74	89.19
Clinical QOF points 2018	96.61	5.56	36.84	100
Sample size: 13,888,084 patients.				

More than two thirds (72%) of AED attendances are during weekdays rather than on weekends and weekday attendances have a higher propensity to admit. Out of all AED attendances, 44% (6,126,480) are during weekday core hours while 41% (5,690,036) are outside of core hours – the remainder occur during what are termed extended hours. Nearly half (48%) of the AED attendances are from male patients, 87% are from urban areas, 26% are from patients in the lowest income deprivation quartile and 24% of patients are from the most income deprived quartile. Approximately one third (30%) of attendances arrive at the AED unit using the ambulance. In terms of age, 10% of attendances are from patients in the age group 0-4 years, roughly 12% between ages 5-17, 53% in ages 18-65, 25% are from patients aged 65 and above, respectively.

Patients are generally satisfied with the GP practices overall care (83%) and ability to see their preferred GP (45%) but are unlikely to know about the practice’s arrangement for extended hours services (only 11%, 13% and 10% were aware of the morning, afternoon and Saturday extended hours arrangements, respectively).

Figure 1 shows the distribution of these admission propensities across English NHS Trusts. The average propensity is 0.2 so that 20% of AED attendances get converted to admissions.

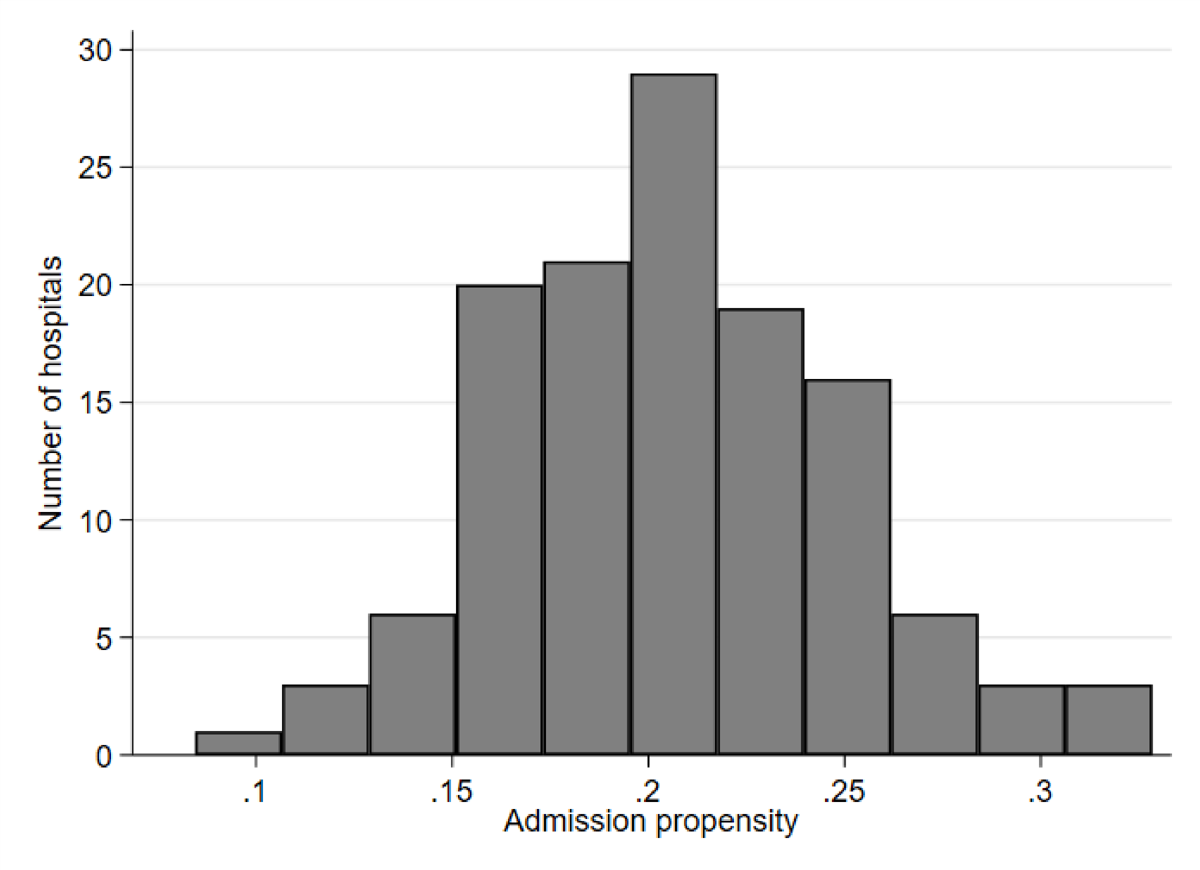


Figure 1: Distribution of admission propensities across hospitals

Model results

Table 3 shows the results for the linear models with hospital fixed effects for the probability of an emergency admission following an AED attendance. The reported estimates have been multiplied by 100 for ease of presentation. Hence, for example, the coefficient of -0.479 against "Male" in column (1) implies that a male attendee has a 0.00479 lower probability of being admitted than their female counterpart. Column (1) reports results where we control for patients, patient's residence - LSOA-, AED attendance, GP practice characteristics and hospital fixed effects.In Column (2) we introduce CCG fixed effects and in column (3) we exclude GP practice indicators from our list of control variables. Estimated coefficients are similar across all three models. (Full results for these models are in Appendix Table A.4.).

Table 3 – Linear probability models with hospital fixed effects (Coefficients and standard errors multiplied by 100)

Variables	Baseline (1)	With CCG fixed effects (2)	Without GP practice characteristics (3)
Patient characteristics			
Male	-0.479***	-0.486***	-0.486***
	(0.020)	(0.020)	(0.020)
Patient's LSOA characteristics			
Living in third most deprived quartile of LSOAs (Ref: least deprived)	-0.091***	-0.099***	-0.121***
	(0.029)	(0.029)	(0.028)

Living in second most deprived quartile of LSOAs (Ref: least deprived)	-0.312***	-0.319***	-0.390***
	(0.032)	(0.032)	(0.029)
Living in most deprived quartile of LSOAs (Ref: least deprived)	-0.689***	-0.691***	-0.815***
	(0.036)	(0.037)	(0.032)
Distance to GP practice between 1 and 2km (Ref: less than 1km)	0.069***	0.011	0.083***
	(0.024)	(0.024)	(0.024)
Distance to GP practice of more than 2km (Ref: less than 1km)	-0.114***	-0.160***	-0.150***
	(0.026)	(0.026)	(0.025)
Patient lives in urban area	-0.205***	-0.228***	-0.443***
	(0.037)	(0.038)	(0.034)
Attendance characteristics			
Arriving by ambulance	10.821***	10.765***	10.812***
	(0.025)	(0.025)	(0.025)
Nearest AED provider to patient's LSOA is a type1 (Ref: nearest AED provider to patient's LSOA is a type 4)	-0.606***	-0.407***	-0.571***
	(0.052)	(0.055)	(0.051)
Nearest AED provider to patient's LSOA is a type2 (Ref: type 4)	-0.581***	-0.430***	-0.606***
	(0.066)	(0.068)	(0.064)
Nearest AED provider to patient's LSOA is a type3 (Ref: type 4)	-0.235***	-0.177***	-0.195***
	(0.054)	(0.056)	(0.052)
Nearest AED provider to patient's LSOA is a type99 (Ref: type 4)	-0.165	0.109	-0.150
	(0.145)	(0.147)	(0.138)
Avoidable admission (using modified NHS digital admission)	-2.889***	-2.841***	-2.847***
	(0.043)	(0.043)	(0.042)
GP practice characteristics			
% clinical QOF points in 2018	-0.002	0.008***	
	(0.002)	(0.002)	
Weighted Average Life expectancy at birth for GP practice	-0.074***	0.014	
	(0.010)	(0.011)	
CCG Fixed effects	*No*	*Yes*	*No*
Provider Fixed effects	*Yes*	*Yes*	*Yes*
Observations	13,888,084	13,888,084	14,452,415
Number of Trusts	127	127	127
Within R2	0.144	0.144	0.144
Between R2	0.175	0.141	0.175
Overall R2	0.143	0.143	0.143

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Full results for these models are in Appendix Table A.4

Overall, we find a large variation in the probability of an admission, i.e. on hospitals fixed effects, following an AED attendance across hospitals after adjusting for patients, attendance, residence and GP characteristics.

Unsurprisingly, given the sample size, all of the patient characteristics are significant. Relative to the reference group of those under the age of 6, patients aged over 60 have a higher probability of admission and those below 60 have a lower probability of admission. Men have a lower probability of admission compared to women. Attendees from mixed, Asian, Black and Other ethnic groups have a higher probability of admission compared to those of White ethnicity. Patients residing in most deprived areas, followed by those in second and third most deprived have the smallest probability of admission, relative to those in the least deprived areas. All of these differences are small, implying a less than 0.01 (1%) difference in the probability of admission.

The probability of admission following an AED attendance is greater for patients living further away from the attended AED. Patients living in urban areas and those residing more than 2 km from their GP practice have a lower probability of admission. The first might be explained by the likely availability of alternative emergency services in urban areas, while the second will include patients in urban and rural areas that live further away from their practice. The distance and urban variables capture different features of the patients' accessibility to emergency services and are mildly correlated (correlation of 0.23).

As expected, patients arriving by ambulance[16] and those arriving during GP weekday morning extended hours when their GP practice was closed have a higher probability of being admitted. Patients arriving during GP weekday evening extended hours, weekend extended hours (GP closed) and out of all GP hours have a lower probability of being admitted.

Attendance HRGs that indicate more intensive investigations or treatments have a significantly higher probability of admission. On the other hand, patients with a non-urgent/avoidable diagnosis, treatment and investigation are less likely to be admitted. Since patients that live in areas with several types of emergency services nearby are likely to attend a type 1 AED only when they feel sicker, the provision of other emergency care services nearby the patient's residence affects admissions. We observed a decrease in the likelihood of admission if the nearest AED to the patient's residence is a type 1 or type 2. Admission probability is higher if the patient's residence is located within a 10 km radius of a type 3 or type 4 AED, suggesting that patients who live near a minor AED will bypass it and go to a type 1 AED when they feel sicker and so are more likely to be admitted. We also controlled for weekdays and the week of attendance to AED (see Appendix Table A.4). Patients are less likely to be admitted at weekends and Monday to Thursday relative to Friday. This apparent conflict with the raw admission rates on weekdays versus weekends is due to the fact that patients attending at weekends have characteristics which make them more likely to be admitted.

When we control for GP characteristics we observed that patient's registered with GP practices with more patients aware that their GP practice provides morning or/and afternoon extended hours are less likely to be admitted. Patients registered with GP practices with a higher proportion of patients satisfied with overall care and with being seen on the same day have a higher probability of admission. Indicators of GP practice size have mixed effects on the likelihood of an admission. While patients registered with practices with a higher proportion of full-time equivalent GPs per thousand

[16] These coefficient on ambulance arrivals is large relative to its standard error and implies a 0.1(10%) increase in the probability of admission. This raises the possibility of predicted probabilities falling outside of the range 0 to 1. However, there is little variation between hospitals (our unit of analysis) in terms of the covariates and our focus is on variation in admission rates rather than the admission rates themselves.

patients significantly increases the likelihood of admission, those registered at practice with the proportion of other direct staff have a smaller probability of admission. In terms of disease prevalence rates of patients' GP practice, the fact that the patient is registered at a practice with a higher prevalence of atrial fibrillation, asthma, COPD, diabetes, obesity, hypertension, learning disability and stroke or transient ischaemic attack increases the probability of being admitted. Higher prevalence rates for chronic kidney disease, dementia, epilepsy, mental health, depression, osteoporosis, rheumatoid arthritis and peripheral arterial disease lead to a decrease in the likelihood of admission.

Including CCG as well as practice fixed effects changes some of the estimated coefficients on practice characteristics suggesting that there are unobserved practice factors affecting admission propensities and that the average level of these factors varies across CCGs. When we included CCG effects, we observed that patients from GP practices with a higher percentage of clinical QOF points have a higher probability of admission. We also find that some of these GP practice characteristics such as the percentage of patients aware their GP have evening extended hours, see their GP same day, full-time GP's, nurses and other direct staff per thousand patients lose their statistical significance when we include CCG fixed effects, but we see higher admissions for those who reported that they could see their GP the next day. Some of the significant negative effects on admission for conditions such as chronic kidney disease, osteoporosis, rheumatoid arthritis are no longer prominent when we add CCG fixed effects, but we also observe a decline in the likelihood of admission for patients registered at practices with higher prevalence rates of depression, cancer and coronary heart disease and an incline in admission for those in practices with a higher prevalence of learning disability. The propensity to admit is smaller for patients registered at practices with higher average life expectancy at birth, however, we lose this effect when we introduce CCG effects.

We also estimated a more parsimonious model, dropping practice characteristics and just controlling for attendance and patient characteristics and hospital fixed effects. The results are very similar to the baseline model.

Our main focus is on variation across hospitals and Figure 2 shows the variation of unadjusted percentages of admissions, i.e. the hospitals propensities to admit without controlling for any characteristics. These are expressed relative to the hospital that has the unadjusted admission propensity closest to the average. Figure 3 shows the first set of results from the model which corresponds to our baseline model estimates. It shows the distribution of the adjusted admission propensities once we include the attendance, patient, GP practice characteristics and hospital fixed effects. The admission propensity goes from a minimum of 0 to a maximum of 1, with a mean 0.20 and standard deviation of 0.40.

Likewise, in the second set of results shown in Figure 4, we adjust for all the case-mix variables, including GP practice characteristics, as done previously, but include CCG fixed effects along with hospital fixed effects.

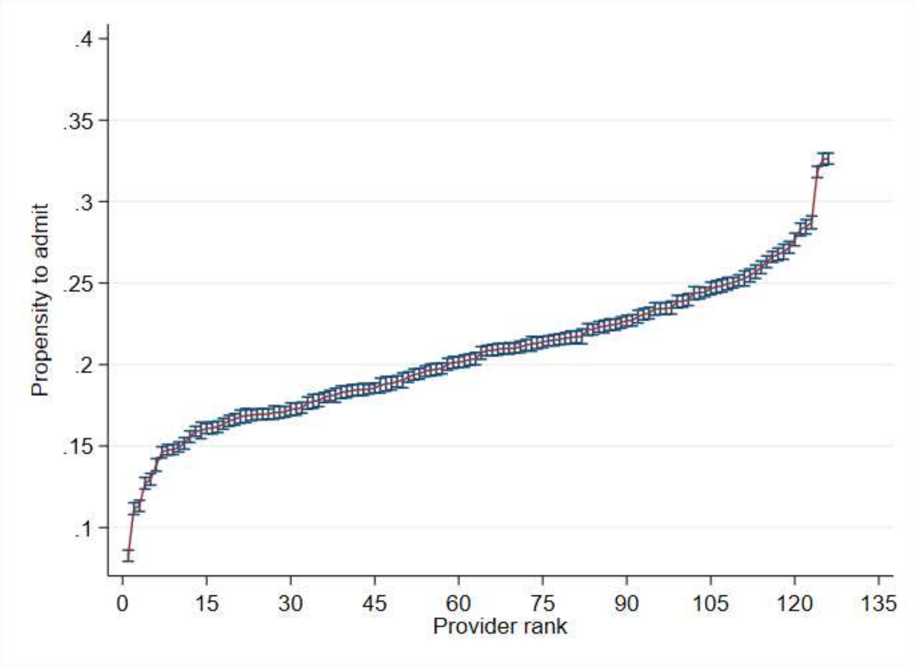


Figure 2 - Hospitals admission propensities without adjusting for case-mix

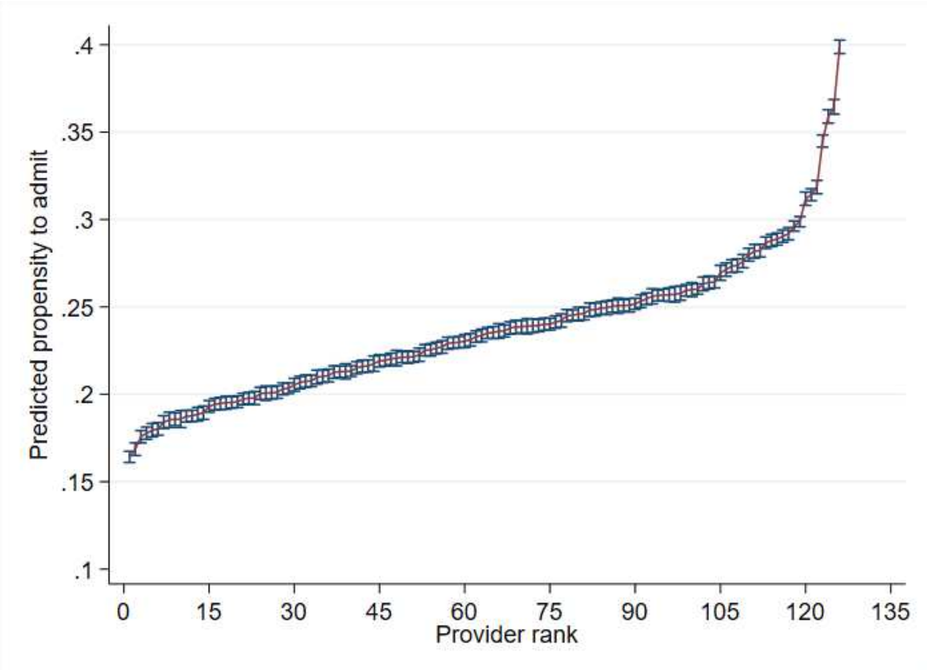


Figure 3: Hospitals admission propensities after adjusting for case-mix and GP characteristics (Baseline model)

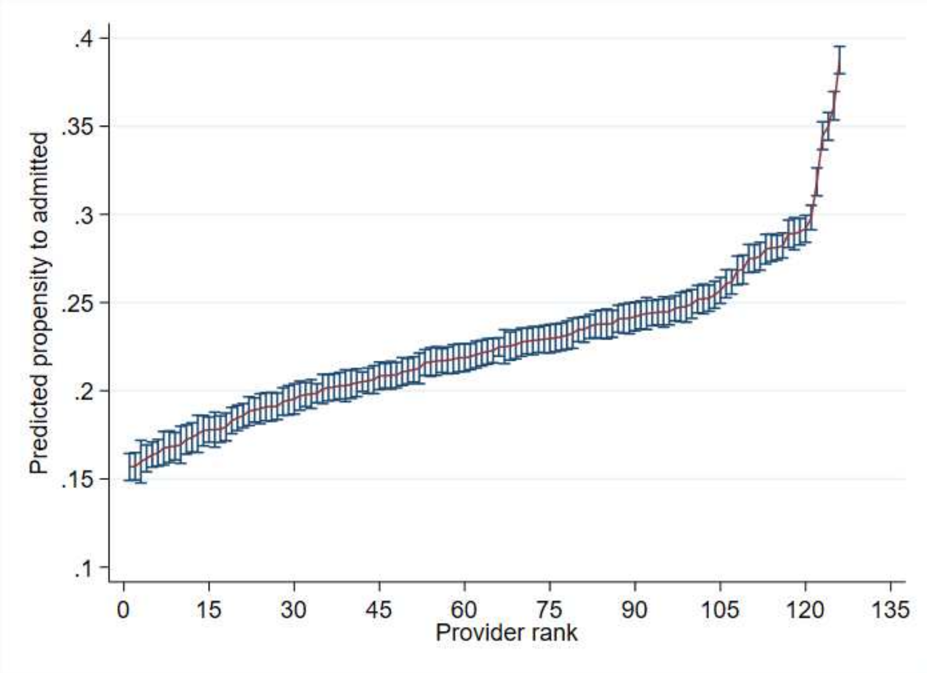


Figure 4: Hospitals admission propensities adjusted for case-mix, GP practice characteristics and CCG fixed effects

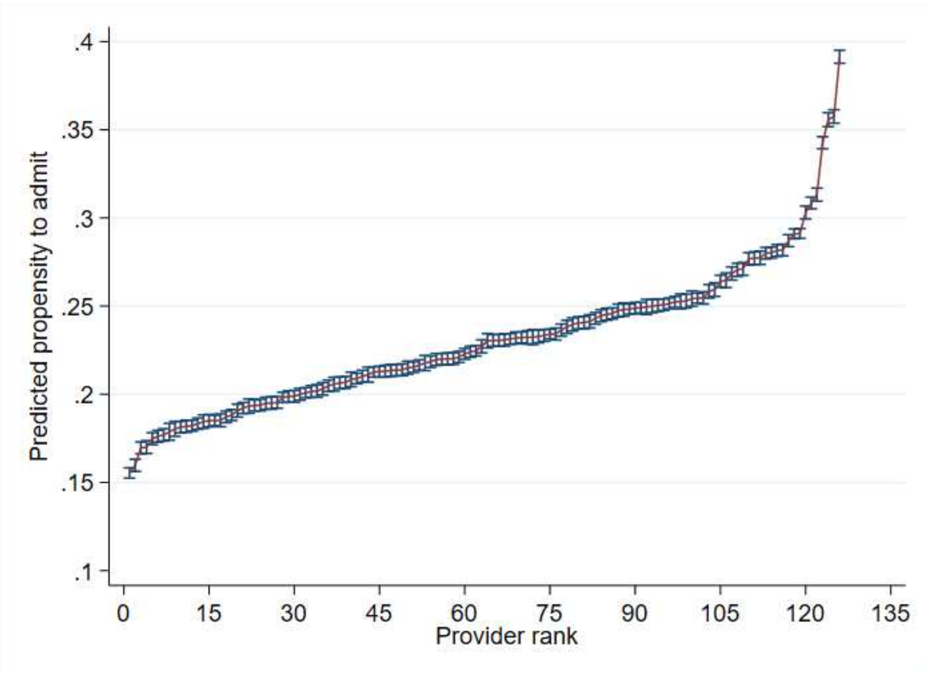


Figure 5: Hospitals admission propensities after adjusting for case-mix (without GP practice characteristics)

The adjusted admission propensities estimated using the parsimonious model, without GP practice characteristics that might be influenced by the CCG, are reported in Figure 5. The results are relatively similar across all three sets of analyses, and therefore the distribution of the estimated adjusted admission propensities, which shows that our results are robust. The correlation across the different specifications is 0.97.

The spatial distribution of admission propensities across hospitals is shown in Figure 6. Darker blue indicates hospitals with higher propensities. Once adjusted for the hospital's case-mix (patient, attendance and GP practice characteristics), the spatial distribution of admission propensities (Figure

7) shows less areas in dark blue. The Liverpool, Bradford, Buckinghamshire and Guildford areas still have the highest admission propensities, while Newcastle, York, Coventry and Norfolk have around average admission propensities after the adjustment.

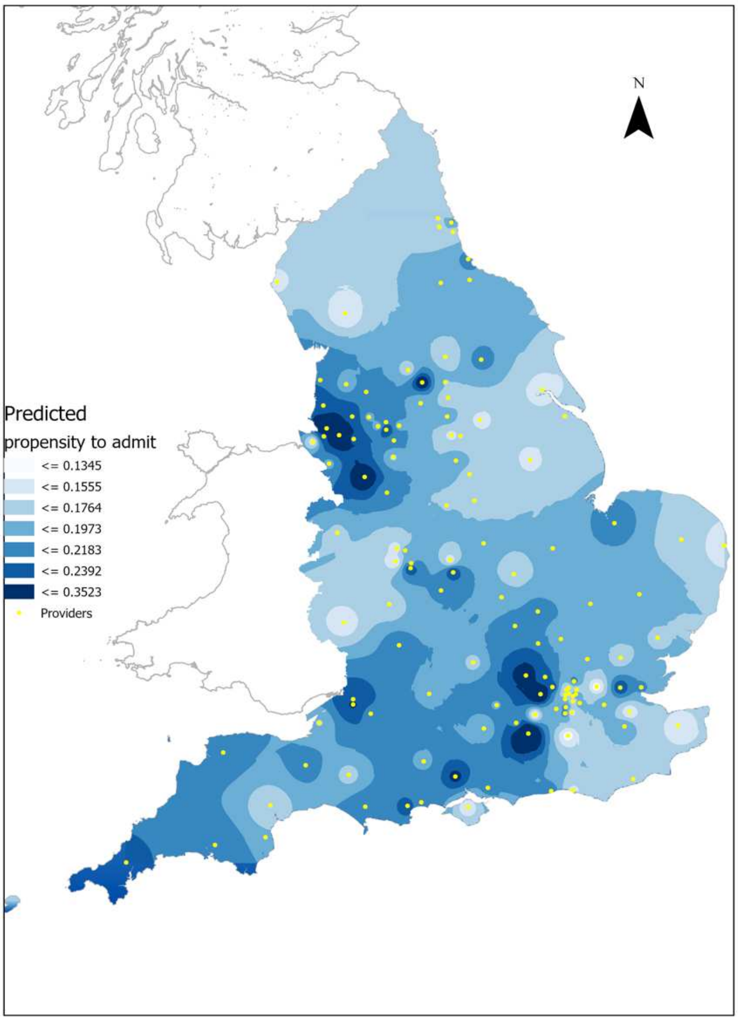


Figure 6: Spatial distribution of hospitals' admission propensities

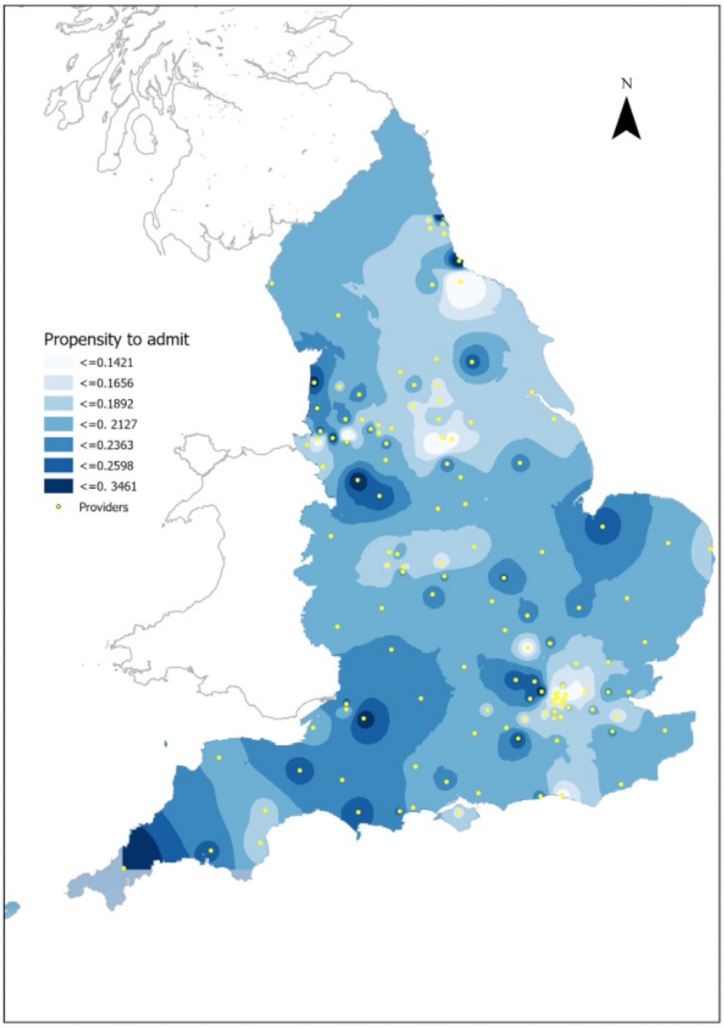


Figure 7: Spatial distribution of hospitals' adjusted admission propensities – (adjusted for the hospital's case-mix - patient, attendance and GP practice characteristics)

6. Interpretation and implications for policy

Our focus in this section is on how the empirical findings detailed above can assist in understanding the *potential* for blended payment - a reduced emphasis on activity-based finance - to affect hospitals' decisions in respect of how many patients to admit. We utilise the theoretical model and our empirical results in combination.

As discussed above, the theoretical model provides a means of interpreting propensities to admit as estimates of hospitals' α_j and as such a reflection of the underlying parameters that determine their admissions choices. Rather than focus on variation in these admission propensities, we consider how responsive hospitals are likely to be to a change in the payment that they face on account of the move to blended payment and therefore a reduction in p_2. That responsiveness is shown in the expression in equation (8) which offers a convenient simplification. Whereas the admission propensities themselves depend on hospital specific benefits, which we are unable to observe and for which we do not have reasonable values, responsiveness of admission propensities depends only on cost parameters for which we can infer reasonable values.

In respect of the expression in equation (8), we have values for the prices (p_1, p_2) derived from the National Tariff – we use the average prices for admitted and non-admitted patients attending AED. We assume these are common across all hospitals[17]. In respect of μ_j and σ_j we utilise hospital level data on the daily average number and variability (standard deviation) of AED attendances. This leaves the cost parameters c_{1j} and c_{2j} to be specified. These parameters are specific to an individual hospital and inherently not observed. To establish credible values for c_{1j} and c_{2j} we make simplifying assumptions that (a) prices are set to approximately cover the average cost of treating patients and (b) hospitals have chosen a cost minimising scale for their AEDs and thus will be operating where average cost is equal to marginal cost. A value for the cost parameter c_{2j} can then be derived from the equality between price and average cost, which on the further assumption of efficient scale also equates to marginal cost. To obtain marginal cost we can differentiate expression (2) and then equating this to p_2 gives

$$p_2 = 2c_{2j}{\alpha_j}^2\mu_j. \qquad (12)$$

Equation (12) can be solved to for c_{2j} to give,

$$c_{2j} = \frac{p_2}{2{\alpha_j}^2\mu_j}. \qquad (13)$$

The same approach applied to attendances yields

$$c_{1j} = \frac{p_1}{2(1-{\alpha_j}^2)\mu_j}. \qquad (14)$$

Expressions (13) and (14) give individual hospital values for cost parameters that are conditional on hospital specific information on attendances and the estimated hospital fixed effect.

Inferring responsiveness to payment reform

Inputting the imputed values for costs, along with the prices and hospital specific attendance distribution parameters into (8) now permits a hospital-by-hospital indication of a responsiveness of shifting to blended payment by reducing the price of admitted patients.

[17] For the purposes of our imputation we ignore adjustments that are made through the Market Forces Factor.

We adopt this method to simulate the impact of a 10% decrease in the price paid for emergency admission for all hospitals in our study. We utilise their estimated α_j and their specific μ_j and σ_j values to impute cost parameters from (13) and (14) and then apply equation (8) to calculate an imputed responsiveness of α_j to p_2. We scale this to represent a 10% decrease in price. The results are shown for each hospital in Figure 8.

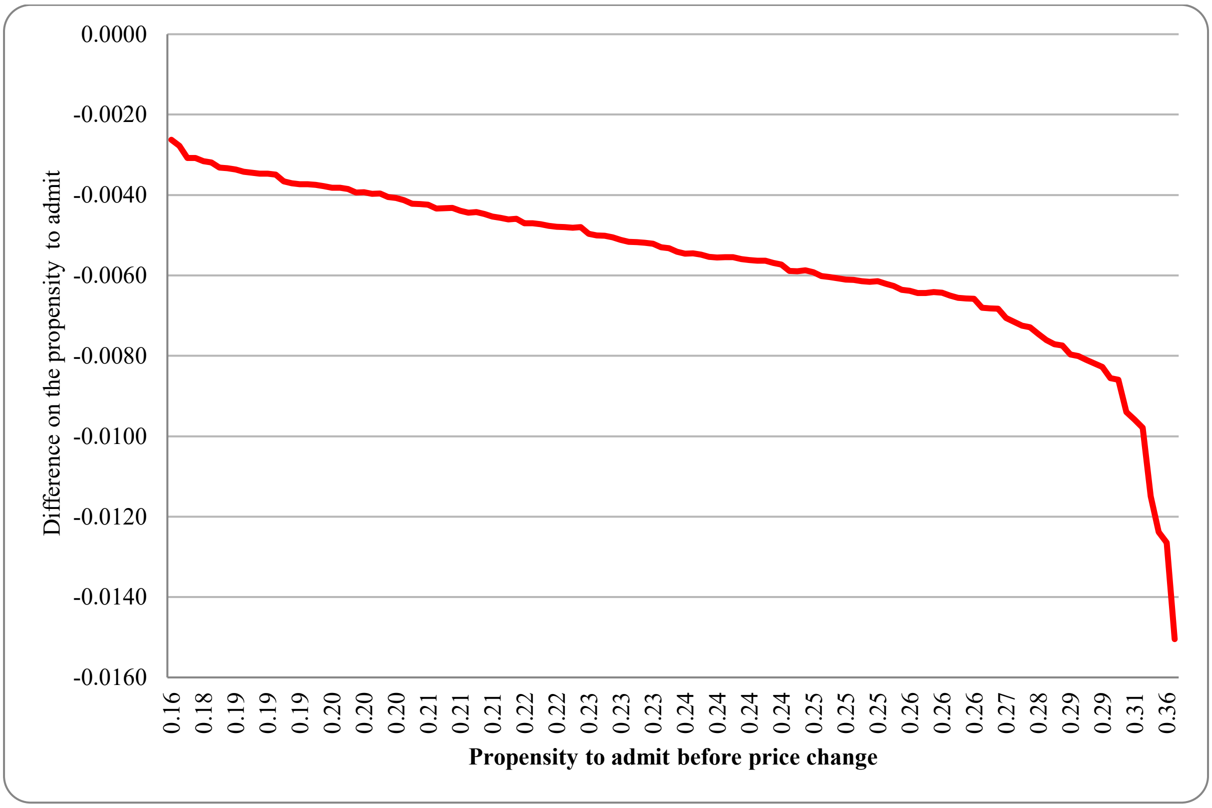


Figure 8: Impact of 10% decrease of emergency admission price on hospitals' propensities to admit – hospitals are ranked according to their existing propensities to admit

A first key observation from the simulation is that the model and subsequent empirical imputation implies that hospitals will respond differently to this simulated policy intervention. The most responsive hospitals (those at the right in the figure) are implied to reduce the probability of admitting a patient by more than five times the reduction in probability for the least responsive. The horizontal scale of the figure relates to the current α for each hospital, so it is those that admit most patients that are predicted to be most responsive to a decrease in the prices for admissions. However, a second key observation is that the imputed responses of all hospitals are of a small magnitude. At most the 10% price reduction is imputed to reduce the admission probability by 2 percentage points so that a hospital that admits, for example, 25% of its attending patients would reduce this to 23% following a 10% price reduction. For the majority of hospitals the imputed effect is much smaller.

7. Conclusion

Hospital resources, relative to other mechanisms of care tend to be resource intensive and costly and this concern has been quite well documented. In this study we focus on the impact of different payment arrangements that have been developed and are being utilised for emergency care. The essence of reform, and a principle that is going to be applied across many health care services in the English NHS, is to place less reliance on activity-based payments and to substitute some element of fixed payment for these. From an economics perspective this is a change in incentives and for hospital hospitals in particular implies a lower return to admitting patients from AED. From a broader perspective of emergency care this policy shift is less clear however. In a previous paper (Chalkley et al., 2022) we have considered the interaction of the incentive for hospitals to admit fewer patients with the incentive of other agencies (such as CCGs) to avoid admissions in the first instance. A conclusion from that analysis is that payment reform needs to be considered across the full range of emergency care interventions and that a reduction in one area, such as the proportion of patients admitted, might be accompanied by an increase elsewhere, as in the number of patients presenting themselves to hospital. The impact of the payment reform might conceivably be the opposite of what is intended if the increase in attendances is large relative to the decline in admission propensity.

This suggests that evidence regarding the quantitative impact of payment reform is vital and the present paper presents the first component of that evidence: we have focused on an empirical examination of the extent to which hospitals vary in their propensity to admit patients, and the implications of that variation for how they may respond to the newly emerging payment system. This is a multi-layered exercise.

We begin with a theoretical framework that is derived from (Chalkley et al., 2022). That is crucial to specifying a relevant empirical approach and for interpreting empirical findings in a way that is relevant to policy. The theoretical model indicates that we should expect hospital specific admission propensities according to a number of observable and unobservable factors, where the latter can be encapsulated in a hospital fixed effect.

We then implement the empirical approach to estimate the hospital specific admission propensities after adjusting for their different case mix, and examine the extent to which these propensities differ across hospitals. Using data from the HES AED for 2018-19, we seek to account for the influences on admission that may be outside of the hospital's control- the mix of patients it receives which includes age, gender, ethnicity, mode of arrival, the extent of alternative provision for emergency care in its area. We also include factors to assess the ease with which patients can attend the hospital and the extent of provision they experience from primary care GPs. Since we do not measure all factors that are outside of the hospital's control, the variation in admission rates can be seen as a lower bound for the amount of variation that is beyond the control of the hospital. Our findings highlight the wide variation of the probability to admit across NHS trust hospitals under the current contract of national tariff payment systems. One key observation here is that the empirical evidence immediately suggests that the impact of payment reform will differ across different hospitals because after controlling for patient case mix they exhibit different admission propensities and hence differences in the underlying parameters than affect choice. This suggests there may be important regional variations in the impact of policy, because we have established that there are substantial regional variations in admission propensities.

The third layer is to combine the theoretical framework with empirical findings to draw implications for how different hospitals can be expected to respond to the new payment regimes. Of necessity this exercise is preliminary and subject to refinement, but there is a tradition in economic modelling of calibrating a model to empirical data and this is a valuable method of providing insight into the order or magnitude of effects that the available evidence suggests will be likely. The most tentative part of our exercise lies in trying to infer cost parameters for hospitals and it will be important in future work to test the sensitivity of the results to different assumptions regarding costs. Nevertheless, our calibration exercise indicates that the impact of payment reform can be expected to vary substantially (responsiveness varies by a factor of five across different hospitals) but in an absolute sense the effects will be either modest or small.

It is too premature to draw robust conclusions regarding the impact of payment reform, we reiterate that this paper concerns only one element of the emergency care system and we will shortly be reporting on the empirical evidence regarding the determination of emergency attendances – our theoretical framework indicates that it is important to consider these elements jointly. Nevertheless this study provides, we believe for the first time, some useful quantification of the potential for payment reform to influence emergency care admissions. The key points to note are that the potential varies across different hospitals and therefore across regions – or what in the new NHS terminology is referred to as *place* – and that our results indicate that payment reform alone is likely to have only a modest impact on hospital admissions, at least in as far as those are the outcome of hospital decisions. The caveat remains, that we have examined only one component of a more complex reality.

8. References

Anselmi, L., Meacock, R., Kristensen, S.R., Doran, T., Sutton, M., 2017. Arrival by ambulance explains variation in mortality by time of admission: retrospective study of admissions to hospital following emergency department attendance in England. *BMJ Qual. Saf*. 26, 613–621. https://doi.org/10.1136/bmjqs-2016-005680

Barouni, M., Ahmadian, L., Anari, H.S., Mohsenbeigi, E., 2021. Investigation of the impact of DRG based reimbursement mechanisms on quality of care, capacity utilization, and efficiency- A systematic review. *Int. J. Healthc. Manag*. 14, 1463–1474. https://doi.org/10.1080/20479700.2020.1782663

Chalkley, M., Gravelle, H., Jacob, N., Santos, R., Siciliani, L., 2022. Payment reform, purchaser and provider decisions and the performance of emergency healthcare systems: the case of blended payment in the English NHS. *CHE Research Paper 187*. University of York.

Chalkley, M., Malcomson, J., 2002. Cost Sharing in Health Service Provision: An Empirical Assessment of Cost Savings. *J. Public Econ*. 84, 219–249.

Guterman, S., Dobson, A., 1986. Impact of the Medicare prospective payment system for hospitals. *Health Care Financ. Rev*. 7, 97–114.

Han, L., Sutton, M., Clough, S., Warner, R., Doran, T., 2018. Impact of out-of-hours admission on patient mortality: longitudinal analysis in a tertiary acute hospital. *BMJ Qual. Saf*. 27, 445–454. https://doi.org/10.1136/bmjqs-2017-006784

Hansen, X.B., Bech, M., Jakobsen, M.L., Lauridsen, J.T., 2013. Does Mixed Reimbursement Schemes Affect Hospital Activity and Productivity? An Analysis of the Case of Denmark. *Health Econ. Pap*.

Januleviciute, J., Askildsen, J.E., Kaarboe, O., Siciliani, L., Sutton, M., 2016. How do hospitals respond to price changes? Evidence from Norway. *Health Econ.* 25, 620–636.

Meacock, R., Anselmi, L., Kristensen, S.R., Doran, T., Sutton, M., 2017. Higher mortality rates amongst emergency patients admitted to hospital at weekends reflect a lower probability of admission. *J. Health Serv. Res. Policy* 22, 12–19. https://doi.org/10.1177/1355819616649630

Mihailovic, N., Kocic, S., Jakovljevic, M., 2016. Review of Diagnosis-Related Group-Based Financing of Hospital Care. *Health Serv. Res. Manag. Epidemiol*. 3, 2333392816647892. https://doi.org/10.1177/2333392816647892

NHS England and NHS Improvement, 2019. 2020/21 National Tariff Payment System – a consultation notice Guidance on blended payments.

O'Reilly, J., Busse, R., Häkkinen, U., Or, Z., Street, A., Wiley, M., 2012. Paying for hospital care: the experience with implementing activity-based funding in five European countries. *Health Econ*. *Policy Law* 7, 73–101. https://doi.org/10.1017/S1744133111000314

Siciliani, L., Gaughan, J.M., Gutacker, N., Gravelle, H., Chalkley, M., 2021. Paying for health gains. *CHE Research Paper 183*. University of York.

Socha, K., 2014. Mixed reimbursement of hospitals: Securing high activity and global expenditures control? COHERE-Cent. *Health Econ. Res. Dep. Bus. Econ*. Discuss. Pap. 3.

Steventon, A., Deeny, S., Friebel, R., Gardner, T., Thorlby, R., 2018. Emergency hospital admissions in England: which may be avoidable and how? (Briefing). Health Foundation.

Verzulli, R., Fiorentini, G., Lippi Bruni, M., Ugolini, C., 2017. Price changes in regulated healthcare markets: do public hospitals respond and how? *Health Econ*. 26, 1429–1446.

9. Appendices

Data Sources

Table A.1. Data sources

Dataset	***Reporting level***	***Period***	***Source***
Accident and Emergency attendances	Patient	2018-19	Hospital Episode Statistics Accidents and Emergency
Emergency admissions	Patient	2018-19	Hospital Episode Statistics Admitted Patient Care
General Practice Patient Survey (GPPS)	Practice	2018-19	https://www.gp-patient.co.uk/
GP practice patient list and workforce characteristics	GP practice	2018-19	Practice Patient List and Workforce: https://digital.nhs.uk/data-and-information/publications/statistical/general-and-personal-medical-services type of contract: https://digital.nhs.uk/data-and-information/publications/statistical/gp-contract-services/2018-19/gpprac1819
Quality Outcomes Framework (QOF points, disease prevalence)	GP practice	2018-19	Quality and Outcomes framework- https://digital.nhs.uk/data-and-information/publications/statistical/quality-and-outcomes-framework-achievement-prevalence-and-exceptions-data
Income deprivation	Patient LSOA	2018-19	Indices of multiple deprivation- https://www.gov.uk/government/collections/english-indices-of-deprivation; NHS digital attribution dataset
Rurality	Patient LSOA	2011	Office of National Statistics; NHS digital attribution dataset
Health Resource Groups	Patient	2017-18	Hospital Episode Statistics; NHS digital HRG grouper
Attribution Data Set	Patient LSOA	2018-19	Numbers of Patients Registered at a GP Practice: LSOA Level
Mortality data	GP practice	2013-17	Public Health England, based on ONS mortality data- https://fingertips.phe.org.uk
GP Extended Opening Hours	GP practice	2018-19	Hospital Episode Statistics Outpatient data
GP extended dataset	GP practice	2018-19	https://www.england.nhs.uk/statistics/statistical-work-areas/extended-access-general-practice/
GP practice location	GP practice	2018-19	NHS Choices
LSOA centroid data	Patient LSOA	2011	https://geoportal.statistics.gov.uk/
AED location data	Hospital Trust	2018-19	NHS Choices

Direct admissions

Direct admissions are usually defined where patients are admitted directly by GPs or consultants in ambulatory clinics, bypassing AED. However, they might include emergency admissions to units and wards for either known patients or where the presenting medical problem is clearly diagnosed at point of contact or in the event of escalation, due to a lack of bed capacity (Reference: Community Hospitals Admissions Transfers & Discharge Policy).

The reported number of ‘direct admissions’ is approximately one tenth of the volume of AED attendances (Meacock et al 2017, Health Foundation 2018).If we account for all hospital admissions to a hospital Trust that do not have an AED attendance record, the proportion of direct admissions ranges between 17.7% and 1.3%. Three hospitals (RC9, RA9, RTR) have more direct admissions than emergency admissions with an AED attendance record.

In this study, we only consider HES admissions code 21 (admitted from the hospital own AED): 15,813,861 AED attendances from which 27% were admissions (3,308,639). We can find 1,367,557 ‘direct’ admissions, i.e., admissions bypassing AED (without an AED record).

If we consider admissions from GP, Bed bureau, Consultant Clinic (codes 22, 23 and 24) we have more 1,111,431 (=867,443 + 58,556 + 185,432) `direct’ admissions (some of them with an AED record).

HRGs for direct admissions do not differ from the other emergency admissions: higher percentage of admissions in DZ, EB, FD and AA HRG chapters (Respiratory System Procedures and Disorders, Cardiac Disorders, Nervous System Procedures and Disorders and Digestive System Disorders). When we use three digit HRG, the codes differ slightly, the main HRGs for ‘direct’ admissions are DZ1, FD0, UZ0, EB1 and EB0, while for emergency admissions with an AED record they are EB1, DZ1, EB0, FD0 and WH0.

Since our analysis focuses on the propensity of the Hospital Trust to admit patients and the Hospital Trust and the AED consultants are not involved in these ‘direct’ admissions decisions, we dropped all the ‘direct’ admissions.

We only consider HES admissions code 21 (admitted from the hospital own AE): 15,813,861 AE attendances from which 27% were admissions (3,308,639). We can find 1,367,557 ‘direct’ admissions, i.e., admissions bypassing AE (no AE record).

If we consider admissions from GP, Bed bureau, Consultant Clinic (codes 22, 23 and 24) we have more 1,111,431 (=867,443 + 58,556 + 185,432) `direct’ admissions (some of them with an AE record).

3 Sample selection notes

We excluded the following-
(i) Type 2, 3, 4 and type 99 AED attendances and only use Type 1 as these are consultant led, open 24 hours per day and have full resuscitation facilities. Type 2 AEDs are for single specialities such as ophthalmology or dentistry and Type 3 and 4 AEDs, such as minor injury units or NHS walk in centres, treat minor illnesses and conditions and may have limited opening hours and type 99 is attendance to an unknown type of AED unit. This was because the provision of ‘minor’ AED services varies across the country and these services cater to a patient population that is typically not at risk of admission to inpatient care, that is, a population that is not the focus of this analysis.
(ii) Those that died in the department and those that were admitted via non-AED admission method as this is not the population of interest for our analysis.
(iii) Trusts with 0, 5 and N. We excluded primary care trusts, trusts with associated treatment centres, NHS trust treatment centres listed separately to NHS trusts, independent hospitals and other independent sector healthcare providers.

(iv) Exclusion of direct admissions. We dropped three hospitals RC9, RA9, RTR that had direct admissions.
(iv) Commissioning hubs and specialist trusts that care for women and children. We exclude the 30 commissioning hubs (NHS Digital) from the analysis since they are responsible for leading the commissioning of specialised services for a wider population.
(v) Patients cared for by CCGs or GPs outside England. We excluded AED attendances by people from other parts of the UK, or attendances of English patients outside England and attendances to AED units run by independent providers because these attendances would be covered by separate contracts with CCGs.
(vi) Using CCG codes from the QOF 2018-19 report, we found that some CCGs had merged (On April 1, 2019 NHS Erewash, Hardwick, North Derbyshire and South Derbyshire CCGs merged to form NHS Derbyshire. NHS North, East, West Devon CCG and NHS South Devon and Torbay merged into NHS Devon). According to the "CCG level exceptions and exclusions report table" there were 191 CCGs in 2018/19.
We found that there were 194 CCGs in October 2018 and in March 2019. However, in March 2020 there were 191 CCGs. So, we report 191 CCGs for the analysis.
(vi) After eliminating observations that fall in one or more of these categories, the final estimation sample consists of 13,912,890 AED attendances with 2,997,462 admissions across 127 trusts and 191 CCGs for the period 2018-19.
(vii) The non-missing data for regression analysis consists of 13,888,084 AED attendances with 2,835,283 admissions.

4 Regression model results

Table A.4. Full results for models with providers fixed effects

Variables	*Coefficients (Standard errors)*		
	Baseline (1)	With CCG fixed effects (2)	Without GP practice characteristics (3)
Patient characteristics			
Age 6-10 (under 6 years as the reference group)	-6.305***	-6.288***	-6.308***
	(0.057)	(0.057)	(0.056)
Age 11-15 (under 6 years as the reference group)	-7.850***	-7.834***	-7.826***
	(0.055)	(0.055)	-0.054
Age 16-20 (under 6 years as the reference group)	-7.808***	-7.834***	-7.839***
	(0.052)	(0.052)	(0.051)
Age 21-25 (under 6 years as the reference group)	-7.441***	-7.455***	-7.498***
	(0.050)	(0.050)	(0.049)
Age 26-30 (under 6 years as the reference group)	-6.660***	-6.666***	-6.707***
	(0.049)	(0.049)	(0.048)
Age 31-35 (under 6 years as the reference group)	-6.013***	-6.021***	-6.067***
	(0.051)	(0.051)	(0.050)
Age 36-40 (under 6 years as the reference group)	-5.450***	-5.463***	-5.494***
	(0.053)	(0.053)	(0.052)
Age 41-45 (under 6 years as the reference group)	-4.900***	-4.916***	-4.970***
	(0.055)	(0.055)	(0.054)

Age 46-50 (under 6 years as the reference group)	-3.848***	-3.861***	-3.871***
	(0.054)	(0.054)	(0.053)
Age 51-55 (under 6 years as the reference group)	-2.837***	-2.848***	-2.851***
	(0.054)	(0.054)	(0.053)
Age 56-60 (under 6 years as the reference group)	-1.235***	-1.248***	-1.234***
	(0.056)	(0.056)	(0.055)
Age 61-65 (under 6 years as the reference group)	0.676***	0.666***	0.720***
	(0.059)	(0.059)	(0.058)
Age 66-70 (under 6 years as the reference group)	2.526***	2.512***	2.582***
	(0.059)	(0.059)	(0.058)
Age 71-75 (under 6 years as the reference group)	4.056***	4.049***	4.106***
	(0.057)	(0.057)	(0.056)
Age 76-80 (under 6 years as the reference group)	5.184***	5.186***	5.240***
	(0.058)	(0.058)	(0.057)
Age 81-85 (under 6 years as the reference group)	6.142***	6.151***	6.188***
	(0.059)	(0.059)	(0.058)
Age 86-90 (under 6 years as the reference group)	6.849***	6.860***	6.903***
	(0.064)	(0.064)	(0.063)
Age 91-95 (under 6 years as the reference group)	8.115***	8.121***	8.214***
	(0.084)	(0.084)	(0.082)
Age 96+ (under 6 years as the reference group)	9.453***	9.470***	9.506***
	(0.148)	(0.147)	(0.145)
Male gender	-0.479***	-0.486***	-0.486***
	(0.020)	(0.020)	(0.020)
Mixed ethnicity groups (Ref: White Ethnicity)	0.570***	0.596***	0.471***
	(0.074)	(0.074)	(0.072)
Asian ethnicity (Ref: White Ethnicity)	1.018***	1.074***	0.894***
	(0.043)	(0.043)	(0.039)
Black ethnicity (Ref: White Ethnicity)	0.730***	0.810***	0.596***
	(0.053)	(0.054)	(0.052)
Other ethnic group (Ref: White Ethnicity)	0.348***	0.409***	0.210***
	(0.061)	(0.061)	(0.059)
Unknown ethnicity (Ref: White Ethnicity)	-0.065	-0.099*	-0.131**
	(0.058)	(0.058)	(0.057)
Patient's LSOA characteristics			
Living in third most deprived quartile of LSOAs (Ref: least deprived LSOA quartile)	-0.091***	-0.099***	-0.121***
	(0.029)	(0.029)	(0.028)
Living in second most deprived quartile of LSOAs (Ref: least deprived LSOA quartile)	-0.312***	-0.319***	-0.390***
	(0.032)	(0.032)	(0.029)
Living in most deprived quartile of LSOAs (Ref: least deprived LSOA quartile)	-0.689***	-0.691***	-0.815***

	(0.036)	(0.037)	(0.032)
Distance to AED of attendance between 10 and 20km (Ref: Distance to AED of attendance of less than 10km)	1.107***	1.056***	1.215***
	(0.039)	(0.041)	(0.038)
Distance to AED of attendance more than 20km (Ref: Distance to AED of attendance less than 10km)	1.210***	1.206***	1.352***
	(0.043)	(0.046)	(0.042)
Distance to GP practice between 1 and 2km (Ref: Distance to GP practice is less than 1km)	0.069***	0.011	0.083***
	(0.024)	(0.024)	(0.024)
Distance to GP practice of more than 2km (Ref: Distance to GP practice is less than 1km)	-0.114***	-0.160***	-0.150***
	(0.026)	(0.026)	(0.025)
Patient lives in urban area	-0.205***	-0.228***	-0.443***
	(0.037)	(0.038)	(0.034)
Attendance characteristics			
Arriving by ambulance	10.821***	10.765***	10.812***
	(0.025)	(0.025)	(0.025)
Arriving during weekday AM extended hours w/ GP open (Ref: Arriving during core GP hours)	0.112	0.094	0.140
	(0.427)	(0.426)	(0.420)
Arriving during weekday AM extended hours w/ GP closed (Ref: Arriving during core GP hours)	0.997***	0.977***	0.991***
	(0.194)	(0.194)	(0.190)
Arriving during weekday PM extended hours w/ GP open (Ref: Arriving during core GP hours)	-1.983***	-2.010***	-1.992***
	(0.149)	(0.149)	(0.147)
Arriving during weekday PM extended hours w/ GP closed (Ref: Arriving during core GP hours)	-1.886***	-1.886***	-1.843***
	(0.121)	(0.121)	(0.118)
Arriving during weekend extended hours w/ GP open (Ref: Arriving during core GP hours)	0.066	0.054	-0.009
	(0.221)	(0.222)	(0.217)
Arriving during weekend extended hours w/ GP closed (Ref: Arriving during core GP hours)	-0.358***	-0.360***	-0.350***
	(0.068)	(0.068)	(0.067)
Arriving out of all GP hours (Ref: Arriving during core GP hours)	-0.993***	-1.009***	-0.983***
	(0.025)	(0.025)	(0.024)
HRG UZ01Z, Invalid grouping (Ref: HRG VB11Z, No Investigation with No Significant Treatment	25.914***	25.981***	25.831***
	(1.518)	(1.518)	(1.482)
HRG VB01Z, Any Investigation with Category 5 Treatment (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	39.444***	39.348***	39.278***
	(1.400)	(1.399)	(1.363)
HRG VB02Z, Category 3 Investigation with Category 4 Treatment (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	39.508***	39.510***	39.425***

	(1.376)	(1.375)	(1.340)
HRG VB03Z, Category 3 Investigation with Category 1-3 Treatment (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	25.624***	25.627***	25.483***
	(1.374)	(1.374)	(1.338)
HRG VB04Z, Category 2 Investigation with Category 4 Treatment (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	34.843***	34.893***	34.720***
	(1.374)	(1.374)	(1.338)
HRG VB05Z, Category 2 Investigation with Category 3 Treatment (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	17.344***	17.392***	17.241***
	(1.376)	(1.375)	(1.340)
HRG VB06Z, Category 1 Investigation with Category 3-4 Treatment (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	11.427***	11.473***	11.362***
	(1.375)	(1.375)	(1.339)
HRG VB07Z, Category 2 Investigation with Category 2 Treatment (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	13.285***	13.342***	13.179***
	(1.374)	(1.374)	(1.338)
HRG VB08Z, Category 2 Investigation with Category 1 Treatment (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	10.961***	11.004***	10.809***
	(1.374)	(1.374)	(1.338)
HRG VB09Z, Category 1 Investigation with Category 1-2 Treatment (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	3.315**	3.370**	3.149**
	(1.374)	(1.373)	(1.338)
HRG VB10Z, Dental Care (Ref: HRG VB11Z, No Investigation with No Significant Treatment)	3.450**	3.485**	3.256**
	(1.374)	(1.373)	(1.338)
Nearest AED provider to patient's LSOA is a type1 (Ref: nearest AED provider to patient's LSOA is a type 4)	-0.606***	-0.407***	-0.571***
	(0.052)	(0.055)	(0.051)
Nearest AED provider to patient's LSOA is a type2 (Ref: nearest AED provider to patient's LSOA is a type 4)	-0.581***	-0.430***	-0.606***
	(0.066)	(0.068)	(0.064)
Nearest AED provider to patient's LSOA is a type3 (Ref: nearest AED provider to patient's LSOA is a type 4)	-0.235***	-0.177***	-0.195***
	(0.054)	(0.056)	(0.052)
Nearest AED provider to patient's LSOA is a type99 (Ref: nearest AED provider to patient's LSOA is a type 4)	-0.165	0.109	-0.150
	(0.145)	(0.147)	(0.138)
Patient's LSOA is within a 10km radius of a type1 AED	-0.897***	-0.929***	-0.950***
	(0.044)	(0.048)	(0.043)
Patient's LSOA is within a 10km radius of a type2 AED	-0.816***	-0.334***	-1.103***
	(0.039)	(0.045)	(0.037)
Patient's LSOA is within a 10km radius of a type3 AED	0.550***	0.554***	0.502***

	(0.032)	(0.036)	(0.032)
Patient's LSOA is within a 10km radius of a type4 AED	0.249***	0.109**	0.356***
	(0.041)	(0.049)	(0.040)
Patient's LSOA is within a 10km radius of a type99 AED	-0.275***	0.384***	-0.366***
	(0.085)	(0.097)	(0.082)
Avoidable admission (using modified NHS digital admission)	-2.889***	-2.841***	-2.847***
	(0.043)	(0.043)	(0.042)
Monday (Ref:Friday)	-0.769***	-0.766***	-0.755***
	(0.038)	(0.038)	(0.037)
Saturday (Ref:Friday)	-1.118***	-1.105***	-1.110***
	(0.041)	(0.041)	(0.040)
Sunday (Ref:Friday)	-1.428***	-1.414***	-1.416***
	(0.045)	(0.045)	(0.044)
Thursday (Ref: Friday)	-0.292***	-0.291***	-0.300***
	(0.039)	(0.039)	(0.038)
Tuesday (Ref: Friday)	-0.615***	-0.614***	-0.611***
	(0.039)	(0.039)	(0.038)
Wednesday (Ref: Friday)	-0.428***	-0.426***	-0.432***
	(0.039)	(0.039)	(0.038)
2018 , week 14 (Ref: 2018, week 13)	-0.803***	-0.801***	-0.773***
	(0.210)	(0.210)	(0.206)
2018 , week 15 (Ref: 2018, week 13)	-0.594***	-0.592***	-0.589***
	(0.210)	(0.210)	(0.206)
2018 , week 16 (Ref: 2018, week 13)	-0.635***	-0.630***	-0.629***
	(0.210)	(0.210)	(0.205)
2018 , week 17 (Ref: 2018, week 13)	-0.305	-0.304	-0.293
	(0.210)	(0.210)	(0.205)
2018 , week 18 (Ref: 2018, week 13)	-0.418**	-0.414**	-0.404**
	(0.209)	(0.209)	(0.205)
2018 , week 19 (Ref: 2018, week 13)	-1.237***	-1.233***	-1.221***
	(0.209)	(0.209)	(0.205)
2018 , week 20 (Ref: 2018, week 13)	-1.104***	-1.097***	-1.093***
	(0.209)	(0.209)	(0.205)
2018 , week 21 (Ref: 2018, week 13)	-0.906***	-0.908***	-0.884***
	(0.209)	(0.209)	(0.205)
2018 , week 22 (Ref: 2018, week 13)	-1.184***	-1.177***	-1.204***
	(0.209)	(0.209)	(0.205)
2018 , week 23 (Ref: 2018, week 13)	-0.956***	-0.954***	-0.925***
	(0.209)	(0.209)	(0.205)
2018 , week 24 (Ref: 2018, week 13)	-1.026***	-1.025***	-1.040***
	(0.209)	(0.209)	(0.205)
2018 , week 25 (Ref: 2018, week 13)	-0.921***	-0.922***	-0.938***

	(0.209)	(0.209)	(0.205)
2018 , week 26 (Ref: 2018, week 13)	-1.335***	-1.328***	-1.337***
	(0.209)	(0.209)	(0.205)
2018 , week 27 (Ref: 2018, week 13)	-1.581***	-1.574***	-1.565***
	(0.209)	(0.209)	(0.204)
2018 , week 28 (Ref: 2018, week 13)	-1.676***	-1.670***	-1.685***
	(0.209)	(0.209)	(0.205)
2018 , week 29 (Ref: 2018, week 13)	-1.441***	-1.436***	-1.443***
	(0.209)	(0.209)	(0.205)
2018 , week 30 (Ref: 2018, week 13)	-1.582***	-1.583***	-1.577***
	(0.210)	(0.210)	(0.205)
2018 , week 31 (Ref: 2018, week 13)	-1.381***	-1.378***	-1.365***
	(0.210)	(0.210)	(0.206)
2018 , week 32 (Ref: 2018, week 13)	-1.345***	-1.342***	-1.324***
	(0.210)	(0.210)	(0.206)
2018 , week 33 (Ref: 2018, week 13)	-1.052***	-1.048***	-1.037***
	(0.210)	(0.210)	(0.206)
2018 , week 34 (Ref: 2018, week 13)	-1.250***	-1.248***	-1.240***
	(0.210)	(0.210)	(0.206)
2018 , week 35 (Ref: 2018, week 13)	-1.319***	-1.312***	-1.293***
	(0.210)	(0.210)	(0.206)
2018 , week 36 (Ref: 2018, week 13)	-1.202***	-1.199***	-1.182***
	(0.210)	(0.210)	(0.206)
2018 , week 37 (Ref: 2018, week 13)	-1.041***	-1.035***	-1.037***
	(0.209)	(0.209)	(0.205)
2018 , week 38 (Ref: 2018, week 13)	-1.035***	-1.031***	-1.031***
	(0.209)	(0.209)	(0.205)
2018 , week 39 (Ref: 2018, week 13)	-1.039***	-1.032***	-1.030***
	(0.209)	(0.209)	(0.205)
2018 , week 40 (Ref: 2018, week 13)	-1.066***	-1.064***	-1.082***
	(0.209)	(0.209)	(0.205)
2018 , week 41 (Ref: 2018, week 13)	-0.888***	-0.888***	-0.879***
	(0.209)	(0.209)	(0.205)
2018 , week 42 (Ref: 2018, week 13)	-0.909***	-0.904***	-0.907***
	(0.209)	(0.209)	(0.205)
2018 , week 43 (Ref: 2018, week 13)	-0.534**	-0.538**	-0.547***
	(0.210)	(0.210)	(0.206)
2018 , week 44 (Ref: 2018, week 13)	-0.757***	-0.758***	-0.728***
	(0.210)	(0.210)	(0.205)
2018 , week 45 (Ref: 2018, week 13)	-0.620***	-0.621***	-0.625***
	(0.209)	(0.209)	(0.205)
2018 , week 46 (Ref: 2018, week 13)	-0.724***	-0.724***	-0.722***

	(0.209)	(0.209)	(0.205)
2018 , week 47 (Ref: 2018, week 13)	-0.356*	-0.355*	-0.384*
	(0.209)	(0.209)	(0.205)
2018 , week 48 (Ref: 2018, week 13)	-0.567***	-0.569***	-0.593***
	(0.209)	(0.209)	(0.205)
2018 , week 49 (Ref: 2018, week 13)	-1.014***	-1.013***	-1.005***
	(0.209)	(0.209)	(0.205)
2018 , week 50 (Ref: 2018, week 13)	-0.685***	-0.683***	-0.679***
	(0.209)	(0.209)	(0.205)
2018 , week 51 (Ref: 2018, week 13)	-0.552***	-0.544***	-0.575***
	(0.209)	(0.209)	(0.205)
2018 , week 52 (Ref: 2018, week 13)	-0.274	-0.272	-0.281
	(0.209)	(0.208)	(0.204)
2019, week 1 (Ref: 2018, week 13)	-1.096***	-1.094***	-1.082***
	(0.209)	(0.209)	(0.205)
2019, week 2 (Ref: 2018, week 13)	-0.905***	-0.904***	-0.897***
	(0.209)	(0.209)	(0.205)
2019, week 3 (Ref: 2018, week 13)	-0.711***	-0.707***	-0.711***
	(0.209)	(0.209)	(0.205)
2019, week 4 (Ref: 2018, week 13)	-0.712***	-0.710***	-0.687***
	(0.209)	(0.209)	(0.205)
2019, week 5 (Ref: 2018, week 13)	-0.894***	-0.892***	-0.897***
	(0.209)	(0.209)	(0.205)
2019, week 6 (Ref: 2018, week 13)	-1.058***	-1.053***	-1.061***
	(0.209)	(0.208)	(0.204)
2019, week 7 (Ref: 2018, week 13)	-1.134***	-1.129***	-1.105***
	(0.209)	(0.209)	(0.205)
2019, week 8 (Ref: 2018, week 13)	-0.854***	-0.850***	-0.862***
	(0.209)	(0.209)	(0.205)
2019, week 9 (Ref: 2018, week 13)	-0.732***	-0.730***	-0.728***
	(0.209)	(0.209)	(0.205)
2019, week 10 (Ref: 2018, week 13)	-0.559***	-0.556***	-0.579***
	(0.209)	(0.209)	(0.205)
2019, week 11 (Ref: 2018, week 13)	-0.638***	-0.635***	-0.619***
	(0.209)	(0.209)	(0.205)
2019, week 12 (Ref: 2018, week 13)	-1.277***	-1.272***	-1.283***
	(0.209)	(0.209)	(0.205)
2019, week 13 (Ref: 2018, week 13)	-6.552***	-6.547***	-6.516***
	(0.211)	(0.211)	(0.207)
GP practice characteristics			
% clinical QOF points in 2018	-0.002	0.008***	
	(0.002)	(0.002)	

% patients aware that GP has AM extended hrs	-0.007***	-0.003***	
	(0.001)	(0.001)	
% patients aware that GP has PM extended hrs	-0.002*	-0.001	
	(0.001)	(0.001)	
% patients aware that GP has Sat extended hrs	-0.001	-0.000	
	(0.001)	(0.001)	
% patients able to see pref GP (always or a lot)	0.001*	0.001	
	(0.001)	(0.001)	
% patients able to see GP the same day	0.003***	0.000	
	(0.001)	(0.001)	
% patients able to see GP the next day	0.002	0.004**	
	(0.002)	(0.002)	
% patients very or fairly satisfied with GP care	0.003**	0.004***	
	(0.002)	(0.002)	
FTE GPs per 1,000 patients	0.099**	0.051	
	(0.049)	(0.051)	
FTE nurses per 1,000 patients	0.044	0.052	
	(0.087)	(0.090)	
FTE other direct staff per 1,000 patients	-0.218***	-0.115	
	(0.069)	(0.072)	
GP practice disease register - Atrial Fibrillation (in %)	0.349***	0.336***	
	(0.046)	(0.048)	
GP practice disease register - Asthma (in %)	0.072***	0.030**	
	(0.013)	(0.014)	
GP practice disease register - Cancer (in %)	-0.016	-0.058**	
	(0.027)	(0.028)	
GP practice disease register - Coronary heart disease (in %)	0.039	-0.117***	
	(0.033)	(0.036)	
GP practice disease register - Chronic kidney disease (18+) (in %)	-0.025***	-0.001	
	(0.009)	(0.009)	
GP practice disease register - Chronic obstructive pulmonary disease (in %)	0.064***	0.143***	
	(0.024)	(0.026)	
GP practice disease register - Cardiovascular disease - primary prevention (30-74) (in %)	-0.015	0.017	
	(0.022)	(0.022)	
GP practice disease register - Dementia (in %)	-0.118***	-0.187***	
	(0.040)	(0.041)	
GP practice disease register - Depression (in %)	0.002	-0.009**	
	(0.004)	(0.004)	
GP practice disease register - Diabetes mellitus (17+) (in %)	0.024**	0.054***	
	(0.010)	(0.011)	

GP practice disease register - Epilepsy (18+) (in %)	-0.128*	-0.388***	
	(0.073)	(0.075)	
GP practice disease register - Heart failure (in %)	0.054	0.015	
	(0.043)	(0.046)	
GP practice disease register - Hypertension (in %)	0.034***	0.014*	
	(0.008)	(0.008)	
GP practice disease register - Learning disability (in %)	0.049	0.085	
	(0.054)	(0.056)	
GP practice disease register - Mental health (in %)	-0.756***	-0.488***	
	(0.033)	(0.034)	
GP practice disease register - Obesity (in %)	0.029***	0.014***	
	(0.004)	(0.004)	
GP practice disease register - Osteoporosis (in %)	-0.055***	-0.027	
	(0.018)	(0.019)	
GP practice disease register - Peripheral arterial disease (in %)	-0.673***	-0.199***	
	(0.070)	(0.073)	
GP practice disease register - Palliative care (in %)	0.061*	0.051	
	(0.034)	(0.036)	
GP practice disease register - Rheumatoid arthritis (16+) (in %)	-0.229***	-0.062	
	(0.067)	(0.070)	
GP practice disease register - Stroke and transient ischaemic attack (in %)	0.192***	0.205***	
	(0.051)	(0.053)	
Weighted Average Life expectancy at birth for GP practice	-0.074***	0.014	
	(0.010)	(0.011)	
CCG Fixed effects	*No*	*Yes*	*No*
Provider Fixed effects	*Yes*	*Yes*	*Yes*
Constant	15.719***	5.072***	11.369***
	(1.639)	(1.714)	(1.354)
Observations	13,888,084	13,888,084	14,452,415
Number of Trusts	127	127	127
Within R2	0.144	0.144	0.144
Between R2	0.175	0.141	0.175
Overall R2	0.143	0.143	0.143

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1