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# Relationship between emergency department and inpatient occupancy and the likelihood of an emergency admission: a retrospective hospital database study

Steven Wyatt <sup>1</sup>, Ruchi Joshi,<sup>2</sup> Janet M Mortimore,<sup>3,4</sup> Mohammed A Mohammed<sup>1,5</sup>

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<sup>1</sup>Strategy Unit, NHS Midlands and Lancashire Commissioning Support Unit, West Bromwich, UK

<sup>2</sup>Emergency Department, Walsall Healthcare NHS Trust, Walsall, UK

<sup>3</sup>Faculty of Education, Health and Wellbeing, University of Wolverhampton, Wolverhampton, UK

<sup>4</sup>Performance and Information Team, Walsall Healthcare NHS Trust, Walsall, UK

<sup>5</sup>Faculty of Health Studies, University of Bradford, Bradford, UK

## Correspondence to

Steven Wyatt, Strategy Unit, NHS Midlands and Lancashire Commissioning Support Unit, West Bromwich B70 9LD, UK; [swyatt@nhs.net](mailto:swyatt@nhs.net)

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## ABSTRACT

**Background** We investigate whether admission from a consultant-led ED is associated with ED occupancy or crowding and inpatient (bed) occupancy.

**Methods** We used general additive logistic regression to explore the relationship between the probability of an ED patient being admitted, ED crowding and inpatient occupancy levels. We adjust for patient, temporal and attendance characteristics using data from 13 English NHS Hospital Trusts in 2019. We define quintiles of occupancy in ED and for four types of inpatients: emergency, overnight elective, day case and maternity.

**Results** Compared with periods of average occupancy in ED, a patient attending during a period of very high (upper quintile) occupancy was 3.3% less likely (relative risk (RR) 0.967, 95% CI 0.958 to 0.977) to be admitted, whereas a patient arriving at a time of low ED occupancy was 3.9% more likely (RR 1.039 95% CI 1.028 to 1.050) to be admitted. When the number of overnight elective, day-case and maternity inpatients reaches the upper quintile then the probability of admission from ED rises by 1.1% (RR 1.011 95% CI 1.001 to 1.021), 3.8% (RR 1.038 95% CI 1.025 to 1.051) and 1.0% (RR 1.010 95% CI 1.001 to 1.020), respectively. Compared with periods of average emergency inpatient occupancy, a patient attending during a period of very high emergency inpatient occupancy was 1.0% less likely (RR 0.990 95% CI 0.980 to 0.999) to be admitted and a patient arriving at a time of very low emergency inpatient occupancy was 0.8% less likely (RR 0.992 95% CI 0.958 to 0.977) to be admitted.

**Conclusions** Admission thresholds are modestly associated with ED and inpatient occupancy when these reach extreme levels. Admission thresholds are higher when the number of emergency inpatients is particularly high. This may indicate that riskier discharge decisions are taken when beds are full. Admission thresholds are also high when pressures within the hospital are particularly low, suggesting the potential to safely reduce avoidable admissions.

## INTRODUCTION

In the NHS, the main route to a hospital bed in an emergency is via an ED.<sup>1</sup> A recent paper highlighted that case-mix-adjusted admission thresholds via ED increased considerably in recent years such that patients with similar risk profiles are now less likely to be admitted than a few years ago.<sup>2</sup> It

## Key messages

### What is already known on this subject

- The likelihood of a patient being admitted via the ED is known to vary with patient case-mix factors and other factors such as arrival mode (eg, ambulance vs walk-in).
- Less is known about the extent to which the decision to admit is influenced by how busy the ED or the hospital is.
- Understanding this relationship might suggest opportunities to improve patient safety and enhance hospital efficiency.

### What this study adds

- This study uses patient-level data and mixed-effects general additive logistic regression to assess the extent to which ED crowding and inpatient (bed) occupancy levels influence admission thresholds via ED in 13 English NHS Hospital Trusts in 2019.
- The probability of emergency admission from ED corresponds modestly to crowding and occupancy, reducing as ED gets busier and increasing when the number of elective and maternity inpatients is high or when the number of emergency inpatients is particularly high or low.
- Further work is required to uncover the underlying mechanisms, understand the implications for patient safety, hospital efficiency and generalisability of these findings.

could be argued that increases in admission thresholds via ED indicate that policy and service interventions to reduce avoidable admissions may be taking effect. The NHS in England, like many other health systems, has for some time sought to reduce avoidable admissions. But others have suggested increases in admission thresholds may be driven by a lack of hospital beds. This might undermine patient safety if patients are discharged when their clinical condition warrants admission.<sup>3</sup> The bed availability argument is supported by data showing increases in bed occupancy in the NHS in England over recent years.<sup>4</sup> The issue of ED crowding, which is often attributed to lack of inpatient beds, continues to receive considerable attention. Studies

have demonstrated that crowding in the ED leads to delays in care and poor outcomes.<sup>5</sup>

The probability that a patient in an ED is admitted to a ward or assessment unit is known to vary according to several patient and attendance characteristics (eg, diagnosis, arrival mode, age). However, less is known about the relationship between the probability of admission via ED and the busyness of the hospital at that time. If, having adjusted for case-mix, admission thresholds vary according to ED crowding levels or inpatient occupancy, then this might indicate the circumstances when more risky discharge decisions are taken or when EDs are more able to safely avoid unnecessary admissions.

In this paper, we explore the extent to which ED crowding and inpatient (bed) occupancy levels are associated with admission thresholds via ED in 13 English NHS Hospital Trusts in 2019.

## METHODS

### Study design, setting and population

We conducted a retrospective cross-sectional analysis of 1 314 942 attendances at consultant-led EDs in 13 NHS Hospital Trusts (providers) located in England. The providers are located throughout England and have a combined catchment population of 4.8 million people.<sup>6</sup> Some of the 13 providers deliver care from more than one site.

The attendances took place between 1 January 2019 and 31 December 2019. Follow-up attendances were excluded along with attendances for patients who were dead on arrival, who died in the department or who left the department having refused treatment or before being treated (n=80 850, 5.6%). Records without a valid age, gender, resident lower super output area were also excluded from the analysis (n=36 908, 2.6%).

### Variables and data sources

Our analysis was based on three datasets held in the National Commissioning Data Repository. These datasets are commonly pseudonymised such that variables which serve to identify the patient (eg, name, addresses, NHS number, etc) are replaced with a coded pseudonym, with a consistent pseudonym used for a given patient in all three datasets. Dataset 1 contained information about attendances at EDs. Dataset 2 contained information about admitted patient care and dataset 3 contained supplementary information about the dates and times that patients were admitted to, discharged from and moved between inpatient units and wards within a hospital. The structure and content of these tables are described in the National Commissioning Data Repository Reference Library.<sup>7</sup>

Because the datasets were commonly pseudonymised, we were able to identify whether the patient had recently attended the ED or indeed any other consultant-led ED and the outcome of this attendance.

Our outcome variable was admission from ED (yes/no). The outcome variable was defined by linking a patient's ED attendance record in dataset 1, with inpatient records in dataset 2 to search for an emergency admission for the patient occurring on the same day as the discharge from ED.

Potential explanatory variables were identified with reference to previous studies and included patient characteristics (age, gender, ethnicity, deprivation, primary diagnosis, acuity, prior ED attendances and admissions), arrival mode, by ambulance or other means, and the month of year, day of week and time of day of arrival which were available in dataset 1.

Patient ethnicity was assembled into six groups: white, Asian/Asian British, black/black British, mixed parentage, other ethnic groups and not known/not stated. Socioeconomic status was measured using the 2015 Index of Multiple Deprivation (IMD) rank assigned to the lower super output area in which the patient lived.<sup>8</sup> IMD ranks were grouped into quintiles. A patient's prior ED activity was assigned to three levels: none, attended ED at least once but not admitted via ED, and attended and admitted at least once. Prior ED activity levels were assigned for two time periods: the 28 days before attendance and between 29 and 365 days before attendance (dataset 1 contained information about attendances in the 12 months prior to our study period). Thirty-nine two-digit primary ED diagnosis classification codes were used to define the patient's diagnosis in ED. Arrival month, arrival weekday and arrival hour were derived from the arrival date and time fields. Direct observations of patient acuity were not consistently available over the study period.

Dataset 1 was also used to calculate the number of patients in each trust's ED at 15-minute intervals over the course of the study period. This was achieved by counting patients who had arrived in the department before the end of each 15-minute period and left after the start of the period. Similarly, datasets 2 and 3 were used to calculate the number of patients in inpatient beds at 15-minute intervals, by admission method (overnight elective, day case, emergency, maternity). These measures of ED and inpatient occupancy, our variables of interest, were assigned to each attendance based on the start time of treatment in ED or the arrival time in ED if treatment start time was not available.

### Statistical methods

Mixed-effects general additive logistic regression was used to explore the shape of the relationship between ED and inpatient occupancy and the probability of admission having adjusted for a range of patients and attendance characteristics.<sup>9</sup>

All candidate predictor variables were identified from prior literature<sup>2</sup> and were included in a preliminary model on the basis of adequately strong univariate association with the outcome variable or because inclusion improved the fit of the multi-variable model. The relationship between age and admission appeared non-linear and so was centred and entered into the model as a smoothed (thin plate spline) term. Several variables (ethnicity, deprivation, prior activity in the previous 28 and 29–365 days, diagnosis, arrival month, arrival weekday, arrival hour, provider trust) were recoded as design (dummy) variables. We tested the impact of including a small number of plausible variable interactions.

Our preliminary model included the following variables: age, sex, deprivation quintile, ethnicity, presenting diagnosis, arrival mode, arrival weekday, arrival hour, arrival month, prior attendances and admissions in the last 28 and 29–365 days, numbers of patients in ED, and the number of emergency, maternity, overnight elective and elective day-case inpatients. Provider trust was included in the model as a random effect. The preliminary model also included two interaction terms: age–gender and arrival mode–diagnosis.

Once we had constructed a well-fitting preliminary model using the patient and attendance variables, we sought to introduce our novel predictors of interest, measures of ED and inpatient occupancy. These variables were first centred and scaled within each provider trust and tested as linear covariates and as general additive (or smoothed) terms. These took the form of thin plate splines.

Decisions about which variables to include in the final model were taken with reference to the significance of the model coefficients, the Wald test, the log-likelihood value, the Bayesian information criterion and the unbiased risk estimator. The final model fit was measured using the C-statistic (area under the receiver operating characteristic curve), calibration plots and the Hosmer-Lemeshow goodness-of-fit test.

While general additive models are flexible and can illustrate the (non-linear) shape of the relationship between an independent and dependent variable, the strength of the relationship between smoothed independent and dependent variables can be difficult to interpret. To overcome this issue, we built a second model, transforming the ED and inpatient occupancy variables into quintiles to represent five levels of busyness in ED and on inpatient wards by type of admission (elective, day case, emergency and maternity). We devised five occupancy quintiles (very high occupancy, above average occupancy, average occupancy, below average occupancy, very low occupancy) for ED crowding and inpatient occupancy. These design variables replaced the smoothed occupancy terms of the primary model. The model coefficients for these design variables were used to illustrate the significance and strength of the impact of high and low occupancy levels on the probability of admission.

The model covariates for time of day, day of week and month of year were used to adjust for the usual temporal patterns of busyness in as much as they influence whether a patient is admitted or not. The occupancy terms therefore estimate the effects of busyness over and above these usual patterns.

Effects sizes were converted to average relative risks using the approach described by Grant.<sup>10</sup>

To illustrate the materiality of our findings, we use this model to predict the number of patients in ED that would be admitted under occupancy conditions (quintiles) that are most conducive to admission and discharge.

Data processing was conducted in Microsoft SQL Server Management Studio V.17.5 and analysis in R V.3.5.1<sup>11</sup> and several R packages: tidyverse, broom, lmtree, PredictABEL, ResourceSelection and mgcv.

## RESULTS

### Description of ED attendances

Over the 12-month study period, there were 1 314 942 eligible ED attendances at the study sites, 33.2% of which were admitted (table 1). The distribution of attendances by age and sex was broadly similar to those for the country as a whole, but attendances of people from black and minority ethnic groups, more deprived areas and from the north east and north west were marginally under-represented (see online supplemental file 1).

A higher proportion of female attendances were admitted (34.1% vs 32.4%). The proportion of patients who were admitted increased with age. A total of 30.5% of patients arrived by ambulance and more than half (58.6%) of these patients were admitted. Patients attending with illness presentations (eg, cardiac, respiratory, gastrointestinal conditions) were considerably more likely to be admitted than patients with injury presentations.

The average (mean) number of patients in ED over the study period was 647 (SD 198). Mean ED occupancy varied across the 13 providers from 19 to 79 patients. There were on average 11 065 emergency inpatients over the study period (provider range 509–1285), 894 overnight elective inpatients (provide range 23–204), 282 elective day-case inpatients (provider range

**Table 1** Description of ED attendances

All attendances	–	1 314 942	(100.0%)	33.2%
Sex	Female	676 281	(51.4)	34.1
	Male	638 661	(48.6)	32.4
Age group	0–14 years	284 479	(21.6)	18.7
	15–34 years	303 026	(23.0)	21.7
	35–54 years	255 491	(19.4)	28.3
	55–74 years	241 292	(18.4)	42.9
	75+ years	230 654	(17.5)	61.8
Arrival mode	Ambulance	400 411	(30.5)	58.6
	Walk-in	914 531	(69.5)	22.2
Diagnosis	Cardiac conditions	69 152	(5.3)	60.0
	Contusion/abrasion	80 584	(6.1)	6.6
	Dislocation/fracture/joint injury/amputation	91 706	(7.0)	21.4
	Gastrointestinal conditions	100 024	(7.6)	45.2
	Respiratory conditions	117 785	(9.0)	42.9
	Soft tissue inflammation	26 458	(2.0)	22.1
	Urological conditions	60 055	(4.6)	48.0
	Other/not known	769 178	(58.5)	31.2
Provider	Provider 1	146 530	(11.1)	27.
	Provider 2	104 195	(7.9)	33.9
	Provider 3	86 816	(6.6)	31.2
	Provider 4	109 529	(8.3)	46.5
	Provider 5	102 475	(7.8)	35.7
	Provider 6	133 043	(10.1)	30.0
	Provider 7	47 689	(3.6)	33.3
	Provider 8	76 986	(5.9)	32.2
	Provider 9	105 800	(8.0)	29.3
	Provider 10	43 348	(3.3)	43.2
	Provider 11	136 909	(10.4)	35.0
	Provider 12	109 969	(8.4)	33.1
	Provider 13	111 653	(8.5)	29.6

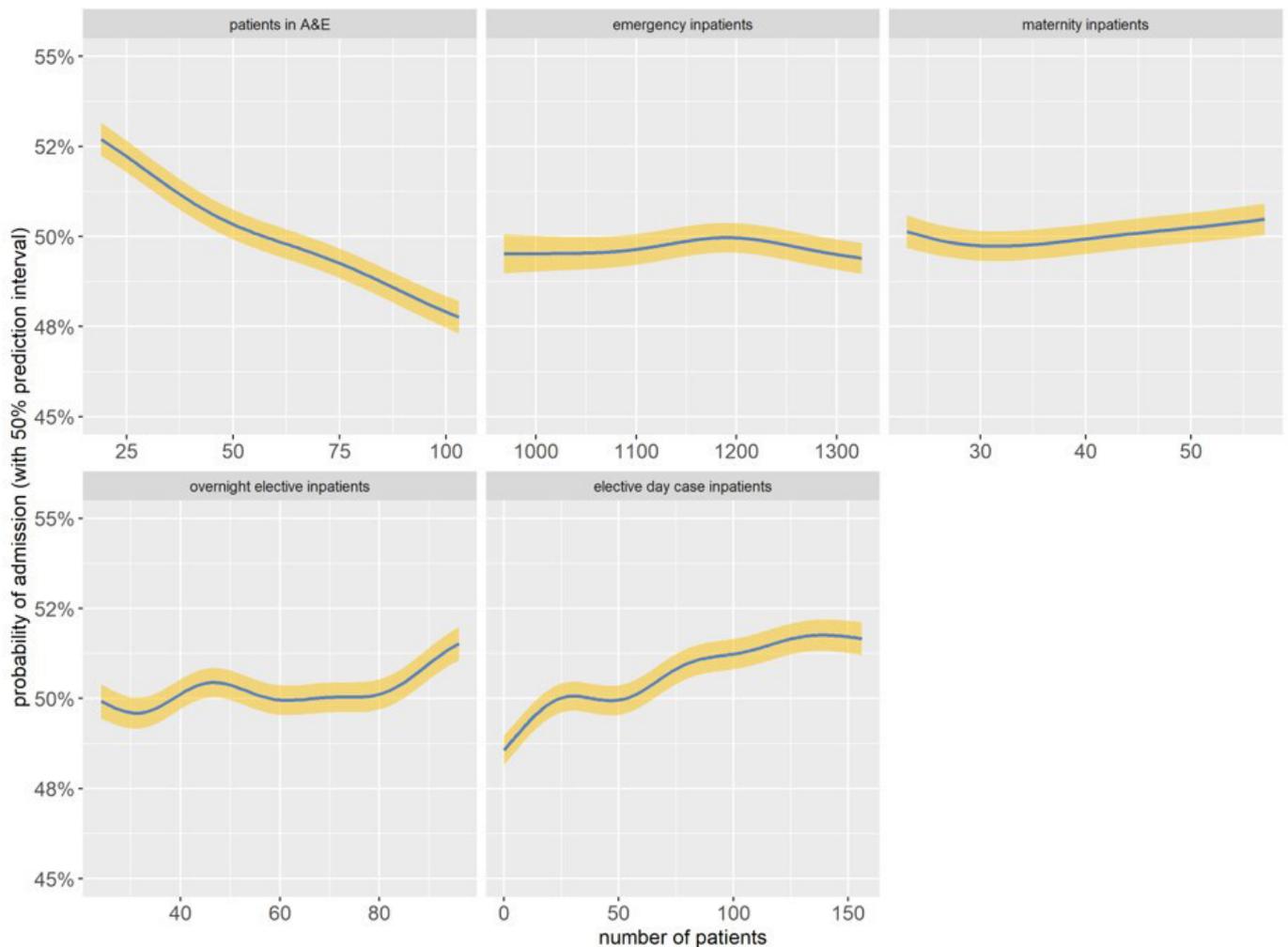
10–35) and 454 maternity inpatients (provider range 11–58) (see table B of online supplemental file 2).

Counts of patients in ED and the number of inpatients varied systematically by time of day, day of week and month of year (see figure 3 of online supplemental file 2). There was nonetheless considerable residual variation over and above these temporal patterns.

### Model fit

Our final model estimated the probability of a patient being admitted using the following variables: patient's age, gender, ethnicity, deprivation, primary diagnosis, prior ED attendances and admissions, arrival mode, month of year, day of week and time of day of arrival, the numbers of patients in ED, and the number of emergency, maternity and elective and day-case inpatients at the start of treatment.

The C-statistic for the model was 0.831. A full set of the model covariates and coefficients are included as online supplemental file 3. A calibration plot and the receiver operating characteristic curve are shown in online supplemental file 4.



**Figure 1** The relationship between ED and inpatient occupancy and the probability of admission; shaded area indicates 50% prediction interval.

### The relationship between ED crowding and inpatient occupancy on admission thresholds

We illustrate the relationship between ED and emergency inpatient occupancy and the probability of admission, with respect to an exemplar patient; a 65-year-old white man who lives in a deprived area (IMD 2015 quintile 1), who presents via walk-in at provider 12 with a cardiac condition at 16:00 on a Monday in October, with no previous attendance in the last year. This case is selected because under average ED and emergency inpatient occupancy conditions given the time of day, day of week and month of year, the modelled probability of admission for such a patient is 50%.

Figure 1 illustrates how this probability of admission varies under alternative ED and inpatient occupancy conditions. The adjusted probability of admission via ED falls in a broadly linear fashion as the number of patients in ED rises. The adjusted probability of admission peaks around 1200 emergency inpatients but falls marginally in a non-linear fashion on either side of this. The adjusted probability of admission rises marginally with the number of maternity inpatients. The adjusted probability of admission rises as the number of overnight elective patients exceeds 80 patients and in a broadly linear fashion with the number of day-case patients.

To illustrate the relationship between ED and inpatient occupancy and the probability of admission in more general terms, we developed a second model in which the five smoothed patient

occupancy variables (ED patients, emergency inpatients, maternity inpatients, overnight elective inpatients and elective day-case inpatients) were each divided into five quintiles of busyness (very high occupancy, above average occupancy, average occupancy, below average occupancy, very low occupancy). Table 2 and figure 2 contains the model covariates for each of the occupancy levels, having adjusted for all other terms in the model. The adjusted ORs range from 0.95 to 1.06 indicating modest effects.

## DISCUSSION

### Key findings

Our study explored the relationship between ED and inpatient occupancy and admission thresholds. We found that admission thresholds are not fixed, but rather appear to correspond modestly to levels of ED and inpatient occupancy levels. These effects are limited to times when occupancy and crowding reach extreme levels. Under normal circumstances, clinical judgements do not appear to be affected by the context within which the decision is taken. But there is evidence that admission decisions are modified somewhat when EDs and hospitals become unusually busy or quiet.

After adjusting for patient and attendance characteristics including time of day and day of week, the 'same' patient is more likely to be admitted when ED occupancy is low and when

**Table 2** Adjusted OR and average relative risks of admission by ED and inpatient occupancy quintiles

Term	Quintile	Adjusted OR	95% CI	Adjusted average relative risks	95% CI
ED occupancy quintiles	1—very low occupancy	1.060	1.042 to 1.077	1.039	1.028 to 1.050
	2—below average occupancy	1.013	0.999 to 1.027	1.009	0.999 to 1.018
	3—average occupancy (ref)	1.000		1.000	
	4—above average occupancy	0.983	0.969 to 0.997	0.988	0.979 to 0.998
	5—very high occupancy	0.952	0.938 to 0.966	0.967	0.958 to 0.977
Emergency inpatient occupancy quintiles	1—very low occupancy	0.988	0.974 to 1.002	0.992	0.982 to 1.001
	2—below average occupancy	1.008	0.994 to 1.022	1.005	0.996 to 1.014
	3—average occupancy (ref)	1.000		1.000	
	4—above average occupancy	0.996	0.983 to 1.010	0.998	0.988 to 1.007
	5—very high occupancy	0.985	0.970 to 0.999	0.990	0.980 to 0.999
Maternity inpatient occupancy quintiles	1—very low occupancy	0.991	0.977 to 1.005	0.994	0.985 to 1.003
	2—below average occupancy	1.003	0.989 to 1.017	1.002	0.993 to 1.011
	3—average occupancy (ref)	1.000		1.000	
	4—above average occupancy	1.007	0.994 to 1.022	1.005	0.996 to 1.014
	5—very high occupancy	1.015	1.001 to 1.030	1.010	1.001 to 1.020
Overnight elective inpatient occupancy quintiles	1—very low occupancy	1.002	0.986 to 1.017	1.001	0.991 to 1.012
	2—below average occupancy	1.001	0.987 to 1.016	1.001	0.992 to 1.010
	3—average occupancy (ref)	1.000		1.000	
	4—above average occupancy	0.990	0.976 to 1.004	0.993	0.984 to 1.003
	5—very high occupancy	1.016	1.001 to 1.032	1.011	1.001 to 1.021
Elective day-case inpatient occupancy quintiles	1—very low occupancy	0.957	0.941 to 0.974	0.971	0.959 to 0.982
	2—below average occupancy	0.964	0.949 to 0.980	0.976	0.965 to 0.987
	3—average occupancy (ref)	1.000		1.000	
	4—above average occupancy	1.029	1.012 to 1.046	1.019	1.008 to 1.030
	5—very high occupancy	1.058	1.038 to 1.078	1.038	1.025 to 1.051

elective and day-case and maternity case are high. However, an admission is less likely when ED occupancy is high, when day-case numbers are low and emergency inpatient occupancy is either very high or very low.

### Relation to existing literature

Our results with respect to admission thresholds when ED is crowded concur with a 2019 US study that found that ED crowding was associated with reduced likelihood of admission.<sup>12</sup> An earlier US study found no association between crowding and admission thresholds, but this study did not control for a number of important case-mix variables.<sup>13</sup> Our results with respect to admission thresholds when emergency inpatient occupancy is high concur with the results of a 2014 Swedish study.<sup>14</sup>

### Possible mechanisms

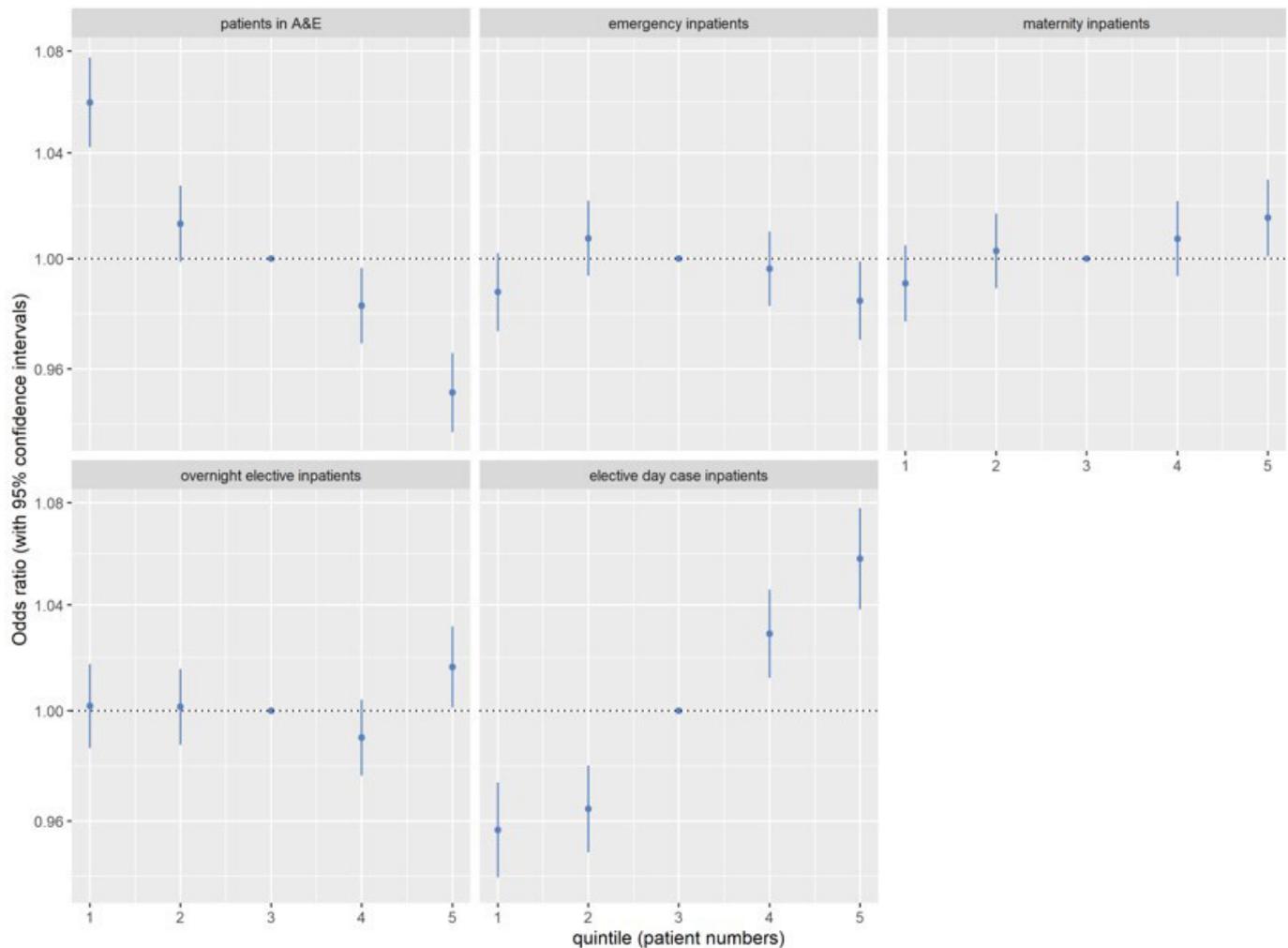
Our observational study offers no direct insight into mechanisms that may underpin these relationships. We can nonetheless hypothesise some mechanisms which appear consistent with the observed data.

The effects of ED crowding on admission thresholds that we have estimated are independent of inpatient occupancy levels. So although ED crowding might often coincide with high inpatient occupancy, the ED crowding effect cannot be explained with reference to inpatient occupancy. Reductions in the probability of admission when ED occupancy is high may, however, be explained with reference to attendance duration. As ED occupancy increases, staff to patient ratios fall, and so the time that it takes to manage the components of patient care (triage, tests and investigations, treatments, decision to admit/discharge) increases. As the average duration of patient stays increases, so

too does the potential for the results from complex tests to be returned while the patient is still in the department. Given that most test results are negative, this increases the opportunity for clinicians to conclude a patient's treatment pathway without the need for admission. Furthermore, the longer a patient spends in ED the greater the opportunity for their condition to improve of its own accord, although the spike in admissions at the 4-hour target threshold is a well-known artefact.

The observed parabolic-shaped relationship between the probability of admission and emergency inpatient occupancy might be explained by two competing effects. As emergency inpatient occupancy increases, the opportunity cost of admitting a patient also increases. When inpatient bed occupancy is high, for example, clinicians and managers may trade off the benefits of admitting a current patient with that of an unknown patient who might arrive in the next hour (in the circumstances it may be feasible, although suboptimal to complete a patient's care in ED). As such, the value of an empty bed increases as occupancy levels rise, and admission thresholds rise in response. This would fit with Roemer's law which suggests that 'in an insured population, a hospital bed built is a filled bed'.<sup>15</sup>

Staff working in ED often request the support of specialists to confirm a diagnosis, and whether admission is required. These specialists balance their time between theatres, wards, clinics and ED. As inpatient occupancy rises, so the availability of specialists to support decisions in ED falls, and without support, ED clinicians may take more risk-averse decisions and admit at lower thresholds. These two effects (bed availability and specialist availability) act in opposite directions. We propose that when bed occupancy is high, the bed availability factor dominates and when bed occupancy is low, the specialist availability factor takes



**Figure 2** The relationship between ED and inpatient occupancy levels and the probability of admission whiskers denote 95% CIs.

precedence. In both cases, high and low inpatient occupancy would result in increased admission thresholds.

We found that the probability of admission from ED rose when elective and maternity occupancy rates were high, given the time of day and day of week. While patients in ED tend to not compete for bed space with elective and maternity patients, they may compete for diagnostic capacity. If consultants in ED are unable to rapidly rule out high-risk conditions because diagnostic capacity is being consumed by elective and maternity patients, then they may choose to admit the patient until the test can be carried out.

Qualitative research or more targeted quantitative studies may be able to test these hypotheses and establish the causal mechanisms that underpin our findings.

### Limitations

While our models adjusted for a wide range of patient and attendance characteristics, they did not include any direct measure of patient acuity such as triage score or the national early warning score because such data were not consistently available in our study datasets. Our study is based on attendances at consultant-led EDs in 13 NHS Trusts in 2019. These trusts were selected based on data availability and while attendances at these trusts are broadly similar to attendances in England as a whole in terms of the age and sex profile, there were some notable differences in the ethnicity, deprivation and regional profile. The

approach used to determine whether a patient was admitted to hospital following attendance at ED relied on linkage between ED and inpatient datasets. The approach may not deliver accurate results in rare situations when a patient attends ED twice in the same day and is discharged after one of these attendances and admitted after the other.

### Implications for policy

Decisions to admit patients are based on the potential benefits of anticipated clinical interventions, and the potential risks of discharging a patient to a location where medical input may not be readily available. If our proposed mechanisms are valid then admission thresholds may operate at similar levels when emergency inpatient occupancy is low and high, these two circumstances are qualitatively different. Heightened admission thresholds when emergency inpatient occupancy is low may be driven by the increased availability of specialists to advise on admission decisions, whereas heightened admission thresholds when emergency inpatient occupancy is high may be driven by necessity (ie, a lack of available beds). We might therefore expect the quality of admission/discharge decisions to be clinically optimal in times of low emergency inpatient occupancy. The long-term upward trend in acute bed occupancy may therefore give rise to safety concerns.

If the relationship between increased probability of admission and increased elective and maternity occupancy is indeed

mediated by diagnostic capacity, then efforts to reduce unnecessary admissions from ED would be aided by adequate and dedicated emergency diagnostic capacity.

Many policy initiatives seek to reduce the numbers of patients attending ED, by increasing the proportion of ambulance patients who are treated at scene and by diverting patients to other settings such as walk-in centres and primary care. Our study suggests that if these initiatives are successful then admission thresholds may fall, and the number of admissions may rise, unless other compensating changes are made simultaneously.

Our observational study is unable to determine whether the relationship between occupancy and admission thresholds is causal. If however, the relationship is causal, and providers are able to actively manage ED and inpatient occupancy levels (eg, by adopting strategies to discharge more patients before noon), then this might provide a mechanism to safely reduce emergency admissions. With these caveats in mind, our analysis suggests that 5.5% of admissions might be avoided if hospitals could replicate occupancy conditions that are most conducive to safe discharge from ED.

**Contributors** SW conceived and conducted the analysis. JMM assembled and sought permissions to share datasets for a preliminary analysis. RJ, JMM and MAM reviewed and commented on the interim findings. SW produced the draft paper and RJ, JMM and MAM offered comments. MAM revised the final draft of the paper. All authors reviewed and agreed on amendments following peer review.

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#### ORCID iD

Steven Wyatt <http://orcid.org/0000-0002-3332-0866>

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## Supplementary file 1

Table A – Characteristics of attendances at study sites and all sites

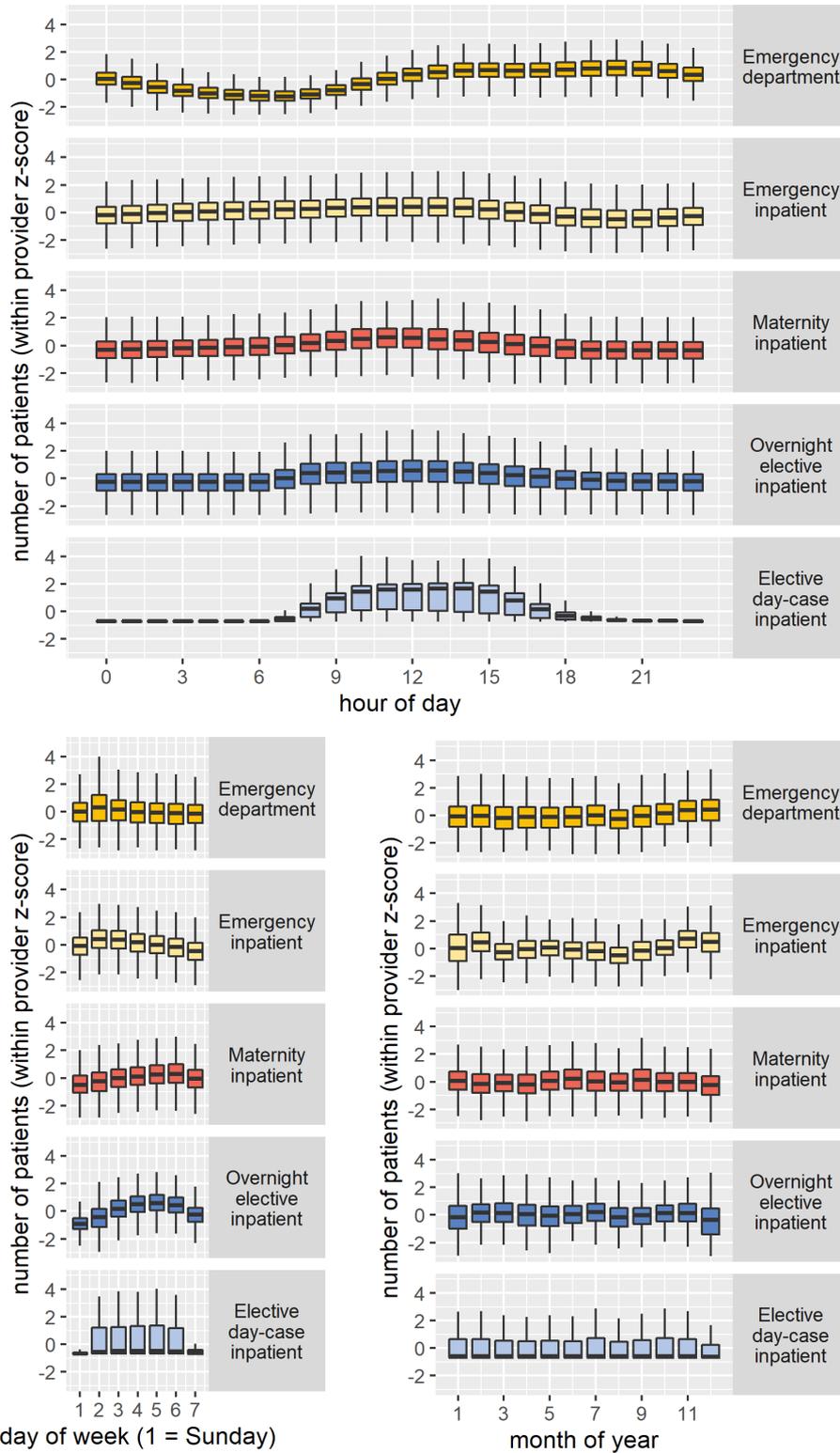
Category	Subgroup	Attendances at study sites	Attendances at all sites
sex	Male	48.8%	48.8%
	Female	51.2%	50.8%
	Not Known	0.0%	0.4%
Age group	0 To 19	26.7%	25.3%
	20 To 29	23.3%	25.0%
	40 To 59	19.3%	20.0%
	60 To 79	18.1%	18.0%
	80+	12.6%	11.7%
Ethnicity	White	76.5%	73.0%
	Black	2.5%	3.7%
	Asian	4.4%	7.1%
	Mixed parentage	1.8%	1.7%
	Other	2.6%	3.3%
	Not known /not stated	12.2%	11.2%
Deprivation quintile (IMD2015)	1 – most deprived	18.2%	26.4%
	2	20.6%	21.7%
	3	18.9%	18.6%
	4	19.9%	16.6%
	5 – least deprived	20.9%	14.6%
	Not known	1.5%	2.1%
Region of provider	North West	8.2%	14.1%
	North East and Yorkshire	3.2%	16.9%
	Midlands	14.3%	17.9%
	East of England	26.1%	11.1%
	London	17.9%	17.3%
	South West	13.9%	8.6%
	South East	16.4%	14.2%

## Supplementary file 2

Table B: Mean (SD) occupancy over 12 months taken at 15-minute intervals over the study period

Provider	ED patients		Emergency inpatients		Overnight elective inpatients		Elective day case inpatients		Maternity inpatients	
	mean	(sd)	mean	(sd)	mean	(sd)	mean	(sd)	mean	(sd)
provider 1	61	(26)	585	(42)	78	(15)	20	(31)	37	(7)
provider 2	48	(17)	1173	(79)	204	(29)	34	(51)	50	(8)
provider 3	45	(16)	653	(41)	23	(8)	10	(14)	46	(9)
provider 4	64	(21)	1178	(70)	58	(11)	22	(29)	34	(8)
provider 5	35	(15)	602	(32)	38	(11)	20	(27)	58	(9)
provider 6	63	(27)	1018	(50)	76	(16)	17	(24)	34	(7)
provider 7	29	(11)	620	(38)	36	(10)	11	(15)	11	(3)
provider 8	44	(14)	866	(51)	99	(15)	21	(29)	33	(6)
provider 9	46	(19)	710	(41)	62	(17)	22	(33)	35	(6)
provider 10	19	(8)	509	(33)	35	(13)	14	(23)	20	(5)
provider 11	79	(25)	1285	(70)	76	(19)	35	(49)	36	(7)
provider 12	54	(21)	1203	(67)	60	(16)	34	(47)	40	(8)
provider 13	61	(18)	662	(37)	51	(12)	21	(33)	19	(5)
<b>All providers</b>	<b>647</b>	<b>(198)</b>	<b>11065</b>	<b>(426)</b>	<b>894</b>	<b>(154)</b>	<b>282</b>	<b>(394)</b>	<b>454</b>	<b>(46)</b>

Figure 3 - Numbers of patients by setting, by hour of day, day of week and month of year  
 15-minute intervals in 2019 | within provider z-score | whiskers denote 1.5 IQR | outliers not shown



## Supplementary file 3

Table B: Model Covariates and Coefficients

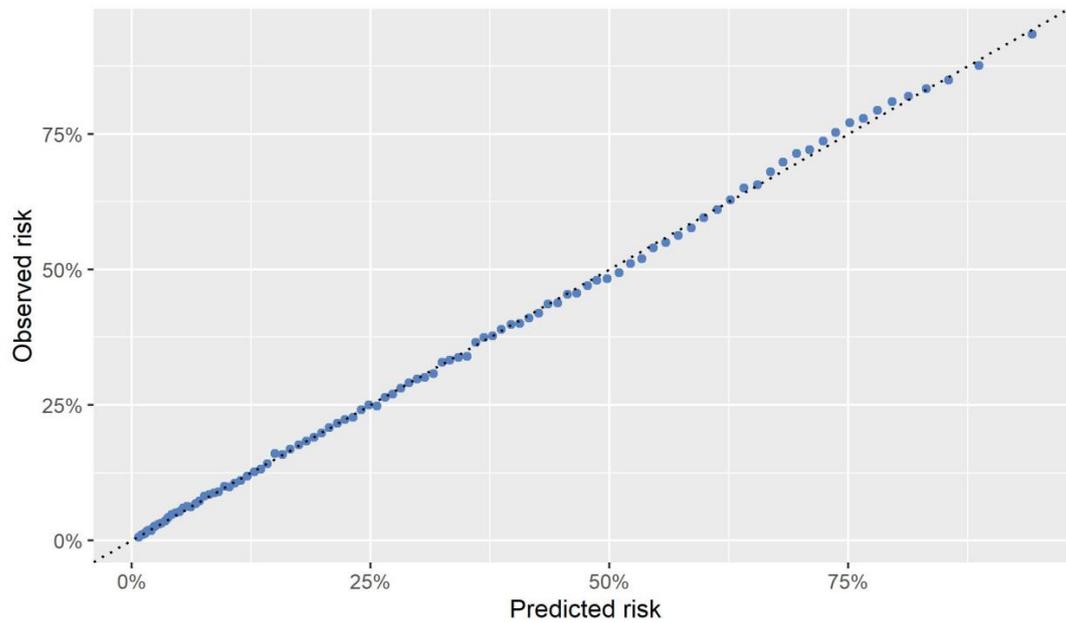
Fixed effects		OR	std error	p-value
(Intercept)		1.40	0.05	0.000
Sex	male (ref)	1.00		
	female	0.97	0.01	0.000
Deprivation quintile	1 (ref)	1.00		
	2	0.99	0.01	0.181
	3	1.00	0.01	0.616
	4	1.00	0.01	0.559
	5	1.01	0.01	0.498
Ethnicity	white (ref)	1.00		
	asian	0.89	0.01	0.000
	black	0.88	0.02	0.000
	mixed parentage	0.90	0.02	0.000
	not know / not stated	0.85	0.01	0.000
	other	0.82	0.02	0.000
Arrival mode	ambulance (ref)	1.00		
	walk-in	0.34	0.01	0.000
Arrival month	Jun (ref)	1.00		
	Jan	1.00	0.01	0.885
	Feb	0.97	0.01	0.005
	Mar	0.97	0.01	0.005
	Apr	0.97	0.01	0.013
	May	0.98	0.01	0.086
	Jul	1.00	0.01	0.918
	Aug	1.01	0.01	0.344
	Sep	1.02	0.01	0.156
	Oct	1.00	0.01	0.849
	Nov	0.98	0.01	0.101
	Dec	0.95	0.01	0.000
	Arrival weekday	Mon (ref)	1.00	
Tue		1.05	0.01	0.000
Wed		1.06	0.01	0.000
Thu		1.07	0.01	0.000
Fri		1.07	0.01	0.000
Sat		1.08	0.01	0.000
Sun		0.99	0.01	0.189
Arrival hour	12 (Ref)	1.00		
	0	0.84	0.02	0.000
	1	0.83	0.02	0.000
	2	0.83	0.02	0.000
	3	0.84	0.02	0.000
	4	0.89	0.02	0.000
	5	0.97	0.02	0.182
	6	1.04	0.02	0.049
	7	1.02	0.02	0.274
	8	0.87	0.02	0.000
	9	0.89	0.01	0.000
	10	0.95	0.01	0.000
	11	0.99	0.01	0.371
	13	0.96	0.01	0.004
	14	0.91	0.01	0.000
	15	0.88	0.01	0.000
	16	0.89	0.01	0.000
	17	0.89	0.01	0.000
	18	0.87	0.01	0.000
	19	0.76	0.02	0.000
	20	0.80	0.02	0.000

<b>Fixed effects</b>		<b>OR</b>	<b>std error</b>	<b>p-value</b>
	21	0.87	0.02	0.000
	22	0.86	0.02	0.000
	23	0.82	0.02	0.000
Prior activity (28 days)	none (ref)	1.00		
	attended % admitted	1.76	0.01	0.000
	attended only	0.91	0.01	0.000
Prior activity (29-365 days)	none (ref)	1.00		
	attended % admitted	1.36	0.01	0.000
	attended only	0.85	0.01	0.000
Diagnosis:ambulance conveyed	Respiratory conditions (ref)	1.00		
	Not known / recorded	1.40	0.02	0.000
	Laceration	0.21	0.03	0.000
	Contusion/abrasion	0.20	0.02	0.000
	Soft tissue inflammation	0.37	0.03	0.000
	Head injury	0.29	0.02	0.000
	Dislocation/fracture/joint injury/amputation	1.07	0.02	0.001
	Sprain/ligament injury	0.18	0.03	0.000
	Muscle/tendon injury	0.26	0.04	0.000
	Nerve injury	1.00		
	Vascular injury	0.55	0.16	0.000
	Burns and scalds	0.67	0.07	0.000
	Electric shock	0.47	0.09	0.000
	Foreign body	0.00		
	Bites/stings	0.84	0.02	0.000
	Poisoning	1.67	0.33	0.120
	Visceral injury	3.08	0.09	0.000
	Infectious disease	1.61	0.03	0.000
	Local infection	1.40	0.04	0.000
	Septicaemia	7.78	0.05	0.000
	Cardiac conditions	0.93	0.02	0.000
	Cerebro-vascular conditions	1.17	0.02	0.000
	Other vascular conditions	0.73	0.05	0.000
	Haematological conditions	1.41	0.03	0.000
	Central Nervous System conditions (exc. strokes)	0.71	0.02	0.000
	Gastrointestinal conditions	0.90	0.02	0.000
	Urological conditions	0.89	0.02	0.000
	Obstetric conditions	1.62	0.17	0.005
	Gynaecological conditions	1.06	0.04	0.136
	Diabetes and other endocrinological conditions	2.21	0.04	0.000
	Dermatological conditions	0.43	0.07	0.000
	Allergy	0.40	0.05	0.000
	Facio-maxillary conditions	0.34	0.13	0.000
	ENT conditions	0.32	0.03	0.000
	Psychiatric conditions	0.56	0.02	0.000
	Ophthalmological conditions	0.15	0.12	0.000
	Social problem	1.34	0.04	0.000
	Nothing abnormal detected	0.31	0.02	0.000
Diagnosis:walk-in	Respiratory conditions (ref)	1.00		
	Not known / recorded	1.70	0.02	0.000
	Laceration	0.78	0.03	0.000
	Contusion/abrasion	0.43	0.03	0.000
	Soft tissue inflammation	1.05	0.04	0.187
	Head injury	0.85	0.03	0.000
	Dislocation/fracture/joint injury/amputation	0.24	0.03	0.000
	Sprain/ligament injury	0.24	0.05	0.000
	Muscle/tendon injury	0.52	0.05	0.000
	Nerve injury	0.00		
	Vascular injury	1.26	0.22	0.287
	Burns and scalds	0.52	0.08	0.000
	Electric shock	0.57	0.10	0.000
	Foreign body	3.69		
	Bites/stings	1.80	0.03	0.000

<b>Fixed effects</b>	<b>OR</b>	<b>std error</b>	<b>p-value</b>
Poisoning	0.53	0.60	0.299
Visceral injury	1.11	0.11	0.377
Infectious disease	0.62	0.03	0.000
Local infection	0.54	0.05	0.000
Septicaemia	2.76	0.08	0.000
Cardiac conditions	1.80	0.02	0.000
Cerebro-vascular conditions	1.29	0.03	0.000
Other vascular conditions	1.06	0.06	0.375
Haematological conditions	2.13	0.05	0.000
Central Nervous System conditions (exc. strokes)	1.66	0.03	0.000
Gastrointestinal conditions	1.63	0.02	0.000
Urological conditions	1.23	0.02	0.000
Obstetric conditions	1.72	0.19	0.004
Gynaecological conditions	1.42	0.04	0.000
Diabetes and other endocrinological conditions	1.44	0.05	0.000
Dermatological conditions	0.92	0.07	0.235
Allergy	0.98	0.06	0.798
Facio-maxillary conditions	1.01	0.13	0.936
ENT conditions	1.57	0.04	0.000
Psychiatric conditions	1.63	0.03	0.000
Ophthalmological conditions	0.52	0.13	0.000
Social problem	0.94	0.07	0.420
Nothing abnormal detected	1.54	0.02	0.000

<b>Random effect</b>	<b>Estimated df</b>	<b>Residual df</b>	<b>p-value</b>
Provider	11.962	12.000	0.000

<b>Non-parametric (smoothed) term</b>	<b>Estimated df</b>	<b>Residual df</b>	<b>p-value</b>
(age-55):sex(male)	8.88	8.987	0.000
(age-55)::sex(female)	8.841	8.978	0.000
ED patients	4.516	5.500	0.000
emergency inpatients	3.433	4.321	0.044
overnight elective inpatients	7.518	8.317	0.000
elective day case in patients	6.424	7.382	0.000
maternity inpatients	3.646	4.547	0.022

**Supplementary file 4***Figure 4 - Calibration plot – Logistic general additive model**Figure 5: Receiver Operating Characteristic Curve – Logistic general additive model*