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DISORDERLY QUEUES: HOW DOES UNEXPECTED DEMAND AFFECT QUEUE PRIORITISATION IN EMERGENCY CARE?

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ABSTRACT

The sharp increase in emergency department (ED) use in England has created long queues at busy times. Care professionals may prioritize some patients in these queues, increasing delays for others and potentially impacting both equity and efficiency. We calculate a measure of queue prioritisation for all 11M attendances at an ED in England in 2017/18, and examine whether some patient groups (ethnic minorities, females, and residents of deprived neighbourhoods) are discriminated against in this prioritisation process. We reduce the risk of unobservable confounding by examining how patient re-ordering responds to unexpected demand surges. To do so, we leverage high-dimensional fixed effects to partial out hospital-specific month-day-of-the-week seasonality to obtain plausibly exogenous daily demand shocks. We further reduce the risk of observable confounding by including detailed severity adjusters. We find that females, ethnic minorities and residents of deprived neighbourhoods are all systematically deprioritised, especially when EDs are busy. Our findings highlight the importance of queue prioritization as a contributor to ED inequities in access to care.

Keywords: prioritisation; waiting time; urgent care; equity.

Introduction

Across most high income countries, demand for emergency care services has increased sharply in the last decades (Berchet 2015). In most cases, the rise in demand has not been matched by increases in supply, resulting in growing waiting times in Emergency Departments (EDs). Waiting times increased more vigorously in the most capacity-constrained health systems, such as the English National Health Services (NHS). Recent efforts and political pledges to reduce waiting times within the NHS in England have yielded modest improvements for emergency hospital treatments. Research from the Royal College of Emergency Medicine (RCEM) suggests that excessively long delays in emergency departments (EDs) cause a significant increase in mortality (Jones et al. 2022). The detrimental effects of the growing strain on emergency departments are likely to disproportionately affect those from deprived and minority backgrounds (The King's Fund 2022). This links to a second major policy area for the NHS and policy makers in England, namely health equity (Kmietowicz 2020; Marmot 2020).

When queues form in EDs, clinicians must choose who to treat first. Providers may decide to re-order or re-prioritise the queue of patients they face, for example in response to unplanned shifts in demand. Re-ordering of patients generates opportunities for discrimination – i.e. prioritisation based on non-clinical patient characteristics - which could contribute to fostering of inequality in health and healthcare, including disparities between patients of different ethinic backgrounds. Despite this triaging stage is a crucial prioritisation process, and a contributor to equity and efficiency of ED care, it has received very little attention in research.

Our study aims to fill this gap in the literature, shedding light on prioritisation-based inequalities. In this paper, we consider how individuals are prioritised by healthcare staff in a high-pressure working environment where ordering may be most important for outcomes: emergency department queues. We examine both the number of patients that an individual waits behind in the queue (failure of the patient to be prioritised) and the number of patients who jump ahead of them in the queue (success of other patients to be prioritised). We focus on how patient sex, ethnicity and neighbourhood deprivation affect their prioritisation. We exploit plausibly exogenous changes in daily attendances – triggering more reordering of patients queuing for an ED visits – to identify potential discrimination based on non-need patient characteristics (ethnic background, biological sex and neighbourhood-level deprivation). We use a feasible linear estimator to efficiently partial out 11,340 fixed effects representing ED-specific seasonality by month and day-of-the-week, which allows us to isolate plausibly exogenous daily demand shocks. We then study whether female patients, those from minority ethnic backgrounds, and those living in more deprived neighbourhoods are prioritised or deprioritised when EDs reorder patients in response to plausibly exogenous changes in demand. This allows us to overcome potential confounding due to unmeasured clinical urgency across these patient characteristics. We find evidence of small but significant discrimination against these patient groups.

The Emergency Department (ED) waiting room offers a relevant setting to study the prioritisation process. We focus on EDs in England where user charges and health insurance restictions do not apply, and where there is very little pre-screening of attending patients (Francetic, Meacock, and Sutton 2024). Patients arrive at the ED at a quasi-random rate every day, with a broad spectrum of health conditions, and are initially triaged upon arrival. The triage process assigns patients to more homogeneous groups with similar levels of urgency, aiming to ensure prioritisation by clinical need and helping an appropriate organisation of ED services (FitzGerald et al 2010). Completing the triage process takes clinician time away from providing patient care and its limited sensitivity and specificity in detecting severe cases has been criticised (Weber 2019).

Prioritisation becomes increasingly necessary when the ED is busy (Weber 2019). Turner et al (2020) examined how EDs in England responded to higher than expected demand for care. In contrast to the findings of Martins and Filipe (2020) in a Lisbon-based ED, ED staff in England not only rationed care but also allowed average waiting times for initial assessment and for subsequent treatment to increase. Whether this was achieved by explicitly de(prioritising) some patients is unknown, though inequalities in waiting times between patients from less deprived and more deprived areas increased slightly at busy periods (Turner et al, 2022).

Operational research methods have also been used to model the ED queing process at the system level (Lakshmi and Sivakumar 2013). This approach does not focus on prioritisation decisions and consequences for individual patients, but instead models processes for queue optimisation at the level of the ED in order to informe decisions regarding the level of capacity needed to achieve minimum service standards for treating patients. Queues are simulated, with parameters including arrival time and patient severity sampled from distributions, and waiting times most often the outcome of interest.

Following a principle of equal treatment for equal need, prioritisation should reflect only differences in urgency and severity. However, whilst initial screening and triaging happens for all patients visiting an ED, re-ordering patients involves an effort for ED staff. Some providers may not be willing or able to re-order the queue as much as they should, compared to what would be optimal to minimise the impact of delays on patients' health. Prioritisation may also affect patient experience (a sense that others are jumping ahead in the queue) and ultimately might affect patient demand, for example patients leaving without being seen (Sivey 2018).

Inequalities in health and healthcare across ethnic groups are clearly intertwined with broader socioeconomic conditions. In both the US and the UK, various studies highlight how some of the racial disparities detected can be explained by income, education or broader area-level factors including deprivation (Nazroo et al. 2007; Delgado-Angulo, Mangal, and Bernabé 2019; Baicker et al. 2004; Chandra and Skinner 2003). Focusing on the UK, small but economically significant inequalities in outcomes, access and treatments have been measured amongst patients living in the least and most deprived areas, where population from various ethnic minorities often live (Moscelli et al. 2018; Cookson et al. 2016; Turner et al. 2022). Whether these inequalities can be explicitly linked to prioritisation in ED, however, remains an open empirical question.

Health and care inequalities based on gender have also been documented, although convincing causal evidence linking these patterns to prioritisation in ED settings remains limited. In England, Watkinson et al. (2021) document wider inequalities in health-related quality of life amongst women than men from ethnic minorities in England. In the context of a workers' compensations program in Texas, Cabral and Dillender (2021) find that gender disparities disadvantaging women are largely explained by the gender-match between patients and doctors. Focusing on differences in care and priority across age groups a qualitative study of patients' perception about who should be prioritised showed that – other than clinical needs – the only group that patients were willing to prioritise were children (Cross et al. 2005).

Assuming that access to healthcare in the NHS follows a principle of equal treatment for equal need (Morris, Sutton, and Gravelle 2005), only observable legitimate indicators of patient urgency and severity should feed into the decision-making process defining prioritisation of patients in an ED queue. For a given level of patient severity, factors such as ethnicity, socioeconomic status, or gender should therefore not determine the decisions of ED staff to prioritise one patient over another. Any influence of these "non-need" variables on the level the prioritisation process in EDs may reflect ED staff own perceptions, biases, views or preconceptions about a specific socioeconomic profile, ultimately causing an instance of discrimination.

Methods

Data

Our main source of data is the attendance records of patients visiting EDs in England from the Hospital Episode Statistics (HES). These are routinely collected administrative data covering all procedures and treatments for all patients visiting secondary care facilities across England, tracking the patients' pathway from arrival to discharge. These HES attendance records contain an extensive range of information about patients, including the hospital site, diagnostic procedures codes (OPCS codes), and a comprehensive set of demographic information including an indicator of deprivation for their area of residence. Crucially for our study, they also contain detailed time stamps for key stages in the ED treatment pathway including arrival time, initial assessment time and treatment insitiation time.

We focus on data for about 10.5M to 11.9M patients (depending on the analysis) visiting 135 EDs in England between 1st April 2017 and 31st March 2018. This period is interesting because (1) it is not affected by the disruptions caused by the COVID-19 pandemic, and (2) operational standards for waiting times were still in place. These standards required that no patient was faced with a time between arrival and conclusion of the attendance longer than six hours, and that the 95th percentile of ED length of stay did not exceed four hours. The operational standard also set targets on time to initial assessment for patients arriving by ambulance (no longer than 15 minutes), and for treatment initiation for all patients (no longer than 60 minutes), alongside measures aimed at minimising the number of patients leaving without treatment, and patients re-attending ED for unplanned follow-up care (Turner et al. 2020). We restricted our sample to focus only on patients attending Type 1 EDs because the type of patients attending Type 2 and Type 3 EDs tend to be systematically less urgent. Type 1 EDs are consultant-led, multi-specialty 24-hour services with full resuscitation facilities. We also (1) excluded individuals who were dead upon arrival at the ED; (2) excluded planned follow-up attendances; and (3) in instances where the same patient attends any ED more than once in the same day we focused only on the first observed attendance.

We further excluded patient visits with outliers or inplausible recorded values for the relevant waiting times by trimming observations larger than the 99th percentile in the distribution of raw values of the dependent variables. Trimmed observations mostly included values for the waiting time variables set close to the maximum value allowed in the data-entry system (i.e. 1,439 minutes), which we assume to be missing values for the purpose of our analyses.

Finally, we excluded all observations for one relatively small hospital Trust which reported an average waiting time for initial assessment across all patients of precisely zero, which we assumed to be implausible.

Using these data we can identify:

- What time each patients arrives at the ED and their ranking in the queue upon arrival
- The time when patients are (1) first assessed, (2) start treatment, (3) are discharged, or (4) leave the ED before receiving treatment
- Some key patient demographic and socioeconomic characteristics
- Primary diagnosis as a proxy indicator for the patients' severity

The time variables in the attendance records are defined as:

- Arrival time = When a patient self-presented or arrived in an ambulance at the ED
- Initial assessment time = When a patient is assessed by medical or nursing staff in the ED to determine priority for and type of treatment
- Treatment initiation time = When a patient is seen by a healthcare professional to initiate treatment, which may include undertaking diagnostic tests and the provision of a diagnosis

Defining queue prioritisation

For each (index) patient we first define two queue-related concepts. Firstly, upon arrival at the ED at time t_i^a, the patient starts waiting and finds a given number of patients who are already waiting in line. Unless some reordering of patients is enacted, these patients are naturally seen before the index patients. The index patient is eventually seen (or served) at time t_i^s. Let us define N_i^I as the number of patients who had arrived before the index patient *i* and who were served before patient *i,* but after *i* had arrived. We refer to the first group as 'in-order' patients (hence the superscript *I)* because entered the queue before the index patient.

Whilst waiting in queue, some other patients may arrive at the ED and jump ahead of the index patients in the queue, resulting in de-prioritisation for the index patient. This happens because of patients' reordering of some sort. Let us define N_i^O as the number of patients who arrived after the index patient *i* but who were served before patient *i*. We refer to the second group as 'out-of-order patients' because these patients go ahead of the index patient in the queue and are seen by a healthcare worker before the index patient, despite arriving after them.

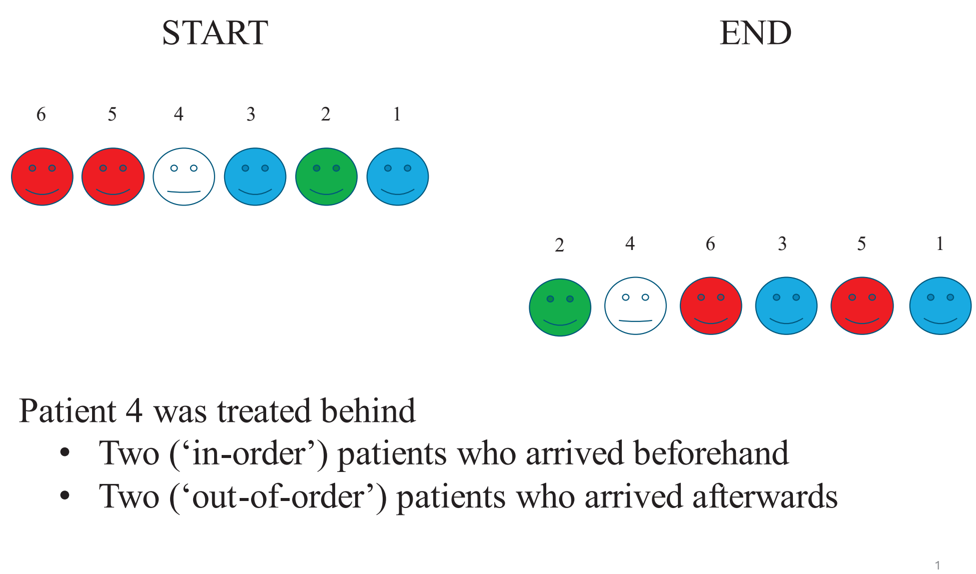
Whether de-prioritisation of the index patient is appropriate or not depends on the underlying reasons for this queue re-prioritisation. For example, a very severe patient with major trauma may be given priority over a patient with a minor injury, which is a clinically legitimate form of prioritisation. In other cases, for a given level of urgency, some patients may be more active complainers and be prioritised ahead in the queue without a clinical justification.

The extent to which the index patient faces in-order and out-of-order patients will influence her total waiting time. In our notation, the total waiting time for patient i is equal to the difference between arrival and service time

$$w_i = t_i^s - t_i^a \qquad (1)$$

Figure 1 illustrates with a simple example the concepts of counting in-order and out-of-order patients. Our index patient is 4. When she arrives at the ED and starts waiting, she has 3 patients ahead of her in the queue (1, 2 and 3). Two patients arrive shortly after (5 and 6). The final order in which these patients are seen by a healthcare provided differs from the initial order defined when the index patient started to wait. Patients 1 and 3 maintained their order in the queue and were seen before patient 4. However, the two patients who arrived shortly after the index patient were more urgent and jumped ahead of her. At the same time, patient 4 was seen before patient 2, who had arrived before the index patient. In short, the index patient waited behind four patients overall before she was seen. Two of these patients were prioritised over the index patient (out-of-order patients), and two had arrived before her at the ED (in-order patients), whist she was prioritised over patient 4.

Figure 1: Example of waiting time decomposition and prioritisation variables



Based on the above information, in relation to the queue for initial assessment, for each patient we construct three different dependent variables capturing prioritisation outcomes: i) waiting time between the time the patient arrives at the ED and the time the patient is seen by a healthcare worker for initial assessment, w_i; ii) the number of 'in-order' patients, N_i^I, and iii) the number of 'out-of-order' patients, N_i^O. We obtain analogous measures for the second queue (time between assessment and treatment).

Baseline specification

Given the prioritisation variables defined above, our main goal is to study whether EDs – when presented the opportunity to reorder patients by changes in demand - prioritise patients based on non-need patients' characteristics, independently of other observables that may determine triage-based prioritisation (e.g. health condition, arrival mode, etc.). Patients may also differ in unobservable clinical urgency across our non-need characteristics of interest, namely biological sex, ethnic background, neighbourhood deprivation. However, by focusing on orthogonal demand shocks as triggers for reordering we circumvent this potential source of confounding. Our baseline specification reads as follows:

$$y_{iht}^{p} = \delta\, Demand_{ht} + \psi\, Inequality_{it} + \gamma\,(Demand_{ht} \times Inequality_{it}) + \boldsymbol{Patient}_{it}'\boldsymbol{\beta} + \boldsymbol{Attendance}_{iht}'\boldsymbol{\omega} + \alpha_{it} + \varepsilon_{iht} \tag{2}$$

where y_{iht}^{p} is the prioritisation outcome of interest for patient *i*, in ED *h* on day *t*. We estimate model (2) for two separate ED queues: a) waiting for initial assessment after arrival, and b) waiting for treatment after initial assessment. For each ED queue, we explore *p=3* different outcomes ${y^p}_{iht}$: (i) total waiting time in queue (in minutes), (ii) in-order count of patients seen before patient *i*, (iii) out-of-order count of patients seen before patient *i*. Figure ***2*** shows the distribution of all dependent variables in our analytical samples.

$\boldsymbol{Patient}_{it}$ is a vector of observable patient characteristics including age and the number of ED attendances in the previous year, number of emergency admissions in the previous year, and the sum of Elixhauser comorbidities based on inpatient visits in the previous 12 months. $\boldsymbol{Attendance}_{iht}$ is a vector of characteristics of patient *i*'s attendance at ED *h* on day *t*, including dummies for the type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown), dummies for combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other), time of attendance, primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group).

Our key coefficients of interest relate to the interaction between $Demand_{ht}$ and $Inequality_{it}$. $Demand_{ht}$ captures the volume of attendances at the ED during the day of patient i's attendance. $Inequality_{it}$ represents our non-need characteristic of interest (ethnic background, biological sex, neighbourhood deprivation). The information on patients' ethnic background included in HES was recoded to White, Asian, Black, Other and Not stated/Missing. Biological sex is coded to either Female or Male. To capture neighbourhood deprivation we use the quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (Turner et al. 2022), measured at the level of Lower layer Super Output Areas (LSOAs). In our analyses, we consider our dimensions of inequality individually, running separate models focusing on each.

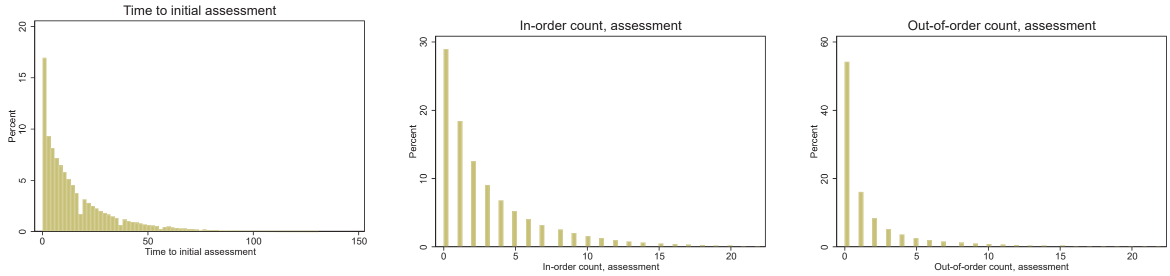
The interpretation of γ depends on the outcome variable. For waiting times, it represents the average number of extra minutes waited for a one SD change in unexpected demand that can be independently attributed to the inequality dimension of interest (e.g. living in of the most deprived neighbourhoods compared to patients from one of the least deprived neighbourhoods, or having a Black compared to a White ethnic background).

For the count variables, the coefficient represents the average difference in the count of in-order (out-of-order) patients – for a one SD change in unexpected demand – that is attributable to the inequality dimension of interest (e.g. having a Black compared to a White ethnic background). For the count of in-order patients, a positive coefficient represents failure to be prioritised over patients ahead in the queue. For the count of out-of-order patients, a positive coefficient represents the success of others to be prioritised in the queue. In all cases, our measures are increasing in discrimination. The interpretation of ψ is analogous but relates to baseline differences and not to differences for a one SD change in unexpected demand.

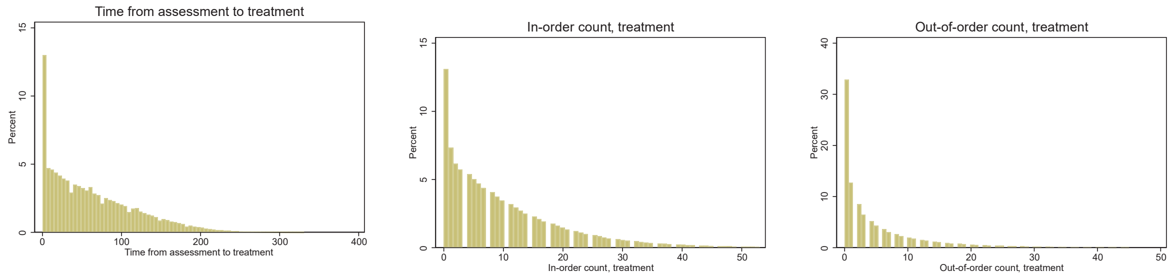
Equation (2) includes an idiosyncratic error term ε_{iht} and the time-varying unobservable individual characteristics α_{it} that are unobservable to the econometrician and potentially correlated with $Inequality_{it}$.

Figure 2: Distribution of key dependent variables

(a) Time to initial assessment



(b) Time to treatment



Identification

Given the institutional setting of the English NHS, daily demand for emergency care at a given ED can be seen as a quasi-random process (Hoe 2022). This stems from the fact that EDs are required to accept all attending patients, who receive healthcare free at point of use. The nature of emergency care makes patients selection to particular hospitals very unlikely, especially for urgent circumstances. This was further strengthened by two additional institutional features during our study period: patients had no means to know about the waiting times at a given ED prior to arrival, and ambulances were by default directed to the nearest ED, except for extremely rare circumstances of major incidents that prevented an ED from receiving patients (NHS England and North West Ambulance Service 2019; Mackway-Jones, Marsden, and Windle 2013; Dark et al. 2021).

However, in general, seeking ED care is not a random event. Some incidents are more likely to happen on specific days and times, and for the same incident the propensity of an individual to visit the ED is higher on some days compared to others (Meacock et al. 2017). For example, sports accidents tend to be more likely during weekends, a Monday evening being typically less busy than a Friday evening, or the volume of attendances faced by an ED in a coastal town being higher in the summer compared to the winter. Similarly, social stratification, culture and other factors may result in differences in the likelihood to attend and the severity of attendances during the week across our non-need characteristics. For example, individuals following

Muslim religious rules may experience increased risk during the Ramadan period. These factors suggest that the nature of ED attendances may be different between days and times of year for different population groups introducing correlation between α_{it} and our characteristics of interest, biasing coefficients δ, ψ, γ estimated using a simple OLS regression on model (2).

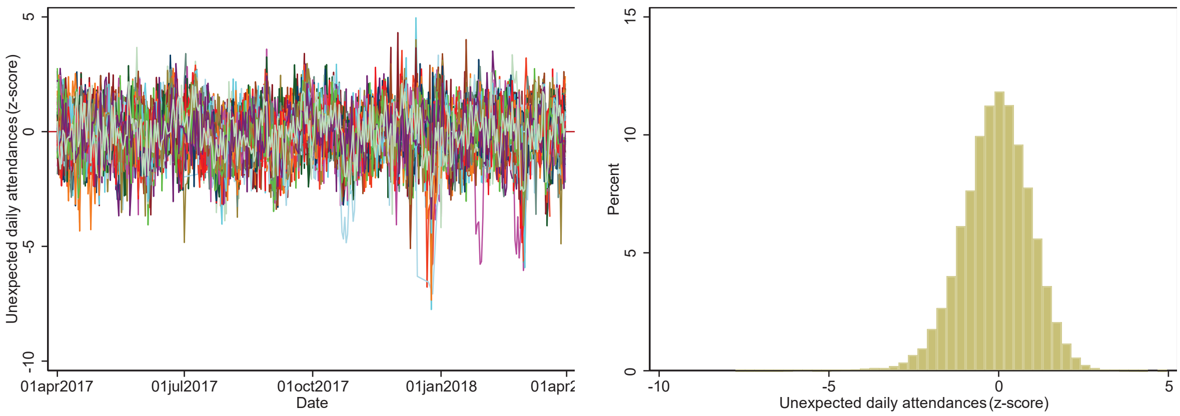
To obtain an orthogonal ED-specific measure of daily unexpected attendances, we rely on a design-based approach that uses high-dimensional fixed effects (HDFE) (Turner et al. 2020; 2022; Hoe 2022; Martins and Filipe 2020; Francetic, Meacock, and Sutton 2024). We argue that deviations in daily ED attendances from an ED-specific seasonal component accounting for month of the year and day of the week represents a plausibly exogenous demand shock for both EDs and patients. On the demand side, this seasonality accounts for predictable patterns in ED attendances (e.g. flu season, infectious respiratory illnesses in the winter, population migration in summer months, ED-specific seasonal variation in patients, patients' day-of-the-week preferences across different EDs and months). On the supply side, these known patterns are also used to plan ED shifts throughout the year (Graff and Radford 1990), which we use to proxy variation in staffing in the absence of more refined staffing variables. We operationalise the seasonal component with a set of fully interacted fixed effects across 135 Emergency Departments, months and days of the week ($135\ EDs \times 12\ months \times 7\ days = 11{,}340$) that enriches our baseline specification in (2). Following recent work on design based approaches to identification (Borusyak and Hull 2020; Borusyak, Hull, and Jaravel 2023), we also recentre our daily count of attendances. Specifically, we obtain ED-specific z-scores for daily attendances by de-meaning (using the ED-specific mean volume of daily attendances) and normalizing by the ED-specific standard deviation of daily attendances. Given the z-score transformation, δ should be interpreted as the effect of a one standard deviation (SD) change in unexpected demand on the outcome of interest.

Focusing on orthogonal demand shocks allows us to identify the vectors δ, ψ, γ – our main coefficients of interest - avoiding the potential endogeneity due to α_{it}. One notable advantage of design-based approaches over model-based approaches that restrict how potential outcomes relate to unobservables is that the former are not prone to the "negative weighting" issues that emerged, recently, in the difference-in-differences literature (Borusyak and Hull 2024).

Figure *3* shows the distribution of our measure of unexpected demand (i.e. the residual variability in daily z-score normalised ED demand after partialling out our ED-specific seasonality). To further reduce concerns in relation to observed and unobserved confounding, we include a set of patient- and attendance-level control variables that account for differences in severity that may be associated with daily ED demand and our characteristics of interest. Our key identifying assumption hence requires the error term ε_{iht} to be independent of $Demand_{ht}$ and $Inequality_{it}$, conditional on a comprehensive set of control variables. Our approach to ensure that the assumption holds relies on three main elements. Firstly, by focusing on plausibly exogenous deviations from predicted daily demand we exclude the influence of supply-side adaptations that may be correlated with both prioritisation and with demand. Secondly, our measure of unexpected demand and empirical approach excludes selection of patients into days of the week, reducing concerns of correlation between the unobservable individual component α_{it} and $Demand_{ht}$. Finally, our exhaustive set of covariates at both patient and attendance level – including the time of day – accounts for patients' severity levels that may again drive both the priority given to patient i and decisions to attend ED h on a specific day and time. Taken together, these elements suggest that we can treat our measure of unexpected demand as plausibly exogenous for both EDs and patients, limiting concerns about bias in our coefficient of interest from both reverse causality and omitted variable bias.

Figure 3: Distribution of unexpected demand

(a) Unexpected demand over time for all Eds (b) Distribution of unexpected demand



The estimation of an extended model (2) including 11,340 dummy variables capturing the ED-specific seasonality that allows us to isolate plausibly exogenous shifts in demand is both inefficient and computationally demanding. We therefore rely on the feasible linear estimator developed by Correia (2016), which allows us to partial out the seasonal component. At its core, the estimator relies on the Frisch-Waugh-Lovell theorem (Lovell 2008). Firstly, the seasonal component is partialled out from both left- and right-hand side variables. Secondly, the residualised version of the variables is used in a modified regression model that only relies on the variability in the variables that is not explained by the seasonality. Similar approaches have been used in Francetic et al (2024), Hoe (2022) and Turner et al (2020). Our inference is based on standard errors clustered at ED-level (Abadie et al. 2023).

Results

In **Table 1** we show descriptive statistics for the variables included in our empirical model (in the interest of space, the list and distribution of primary ED diagnoses is reported in Appendix A). The average waiting time for assessment in our sample is 16 minutes. On average, there are three patients in front of them when they join the queue. Almost 2 patients (1.8) who arrive after the index patient are prioritised in the queue ahead of the index patient. In the interval between assessment and treatment, people wait on average 64 minutes. Patients wait for treatment behind 10 "in-order" patients on average, and approximately 5 patients are prioritised and seen before them despite being assessed after. In our analytical sample, our z-score-standardised measure of unexpected demand has an average of -0.019 and has a SD of 0.995. The patients in our sample are equally split between males and females, and half are aged 16 to 59. They are more likely to live in more deprived areas (50.8 percent in quintiles 4 and 5). One fourth are from ethnic minorities or did not report their ethnic background.

In **Table 2** and **Table 3** we show how prioritisation linked to unexpected demand changes by IMD quintile, biological sex and age group. For time to initial assessment (**Table 2**) we find no evidence of a socioeconomic gradient by IMD quintile. On the other hand, we observe mild signs of a widening gap between the least deprived and other IMD quintile in terms of number of in-order patients generating these waits in response to unexpected demand. Females tend to wait slightly longer and the difference increases by a further 20 percent in response to unexpected demand; these differences are very small in magnitude, however. Waiting times for initial assessment are not significantly different between patients of different ethnic backgrounds. However, for all (stated) ethnic groups (in contrast with White background) we find a mildly positive coefficient for the number of in-order patients, suggesting an underlying failure to be prioritised over White patients.

These patterns of inequalities are clearer when focusing on the time window between assessment and treatment (**Table 3**), despite similarly moderate magnitudes. Patients in the most deprived IMD quintile wait about 1m20s more for treatment and wait behind one additional patient every six/seven in the queue (in- and out-of-order), compared to patients living in the least deprived areas. Their waiting times increases slightly in response to unexpected demand, and they wait behind one additional patient every seven(sixteen) in(out-of)-order patients in the queue for a one SD increase in unexpected demand. Females wait up to 1m30s more, have almost one additional patient every five remaining or jumping ahead of them in the queue compared to males. This gap becomes about 20 percent wider on days of higher than expected demand. Waiting times are slightly but systematically longer for Chinese patients, but not for other ethnic backgrounds. However, the reordering of patient in response to unexpected demand seems again to disadvantage ethnic minorities compared to White patients. These effects are again small in magnitude (about one more patient every five remains ahead if the index patients has an Asian or Black background, compared to a White background), but larger compared to those found for area-level deprivation and sex.

Table 1: Descriptive statistics for dependent variables and covariates for core sample

	Mean	SD
Time to assessment		
Time to initial assessment	15.870	17.7
In-order count, assessment	3.040	3.67
Out-of-order count, assessment	1.786	3.27
Time from assessment to treatment (N=10,507,071)		
Time from assessment to treatment	63.735	55.7
In-order count, treatment	10.137	9.88
Out-of-order count, treatment	5.405	7.81
IMD quintile		
Least deprived	0.145	
2	0.165	
3	0.183	
4	0.222	
Most deprived	0.286	
Ethnic group:		
White	0.740	
Asian	0.072	
Black	0.044	
Other	0.037	
Not stated/missing	0.107	
Female	0.505	
Child	0.111	
Adult	0.495	
Elder	0.284	
Referral/mode of arrival group:		
GP referral-Ambulance	0.010	
GP referral-Non-Ambulance	0.060	
Self-referral Ambulance	0.109	
Self-referral-Non- Ambulance	0.515	
EMS- Ambulance	0.114	
EMS-Non- Ambulance	0.007	
Police- Ambulance	0.001	
Police-Non- Ambulance	0.004	
Healthcare prov.- Ambulance	0.038	
Healthcare prov, Non-Ambulance	0.046	
Other- Ambulance	0.030	
Other-Non- Ambulance	0.065	
Patient type:		
Road traffic accidents	0.010	
Assault	0.006	
Self-harm event	0.006	
Sports accident	0.013	
Other accidents	0.192	
Other problem (not accidents)	0.758	
Unplanned follow-up visit	0.016	0.126
Nr. of emergency admissions in past year	0.707	2.01
Nr. of ED attendances in past year	0.928	4.04
z-score Demand	-0.019	0.996
Observations	11857588	

Table 2: Effect of unexpected demand on prioritisation for initial assessment by IMD quintile, sex, and ethnicity

	(1) Waiting time	(2) Nr. in-order	(3) Nr. out-of-order
Model A: IMD quintiles (reference: Least deprived)			
Unexpected demand	1.459***	0.494***	0.245***
	(18.26)	(18.82)	(24.25)
Income deprivation quintile=2 x Demand	0.0106	0.00874	-0.00566
	(0.43)	(1.52)	(-1.36)
Income deprivation quintile=3 x Demand	0.0292	0.0142	0.000124
	(1.02)	(1.67)	(0.03)
Income deprivation quintile=4 x Demand	0.00826	0.0291*	0.00000157
	(0.22)	(2.36)	(0.00)
Income deprivation quintile=5 x Demand	-0.00832	0.0365*	-0.00150
	(-0.16)	(2.29)	(-0.18)
Income deprivation quintile=2	-0.0104	0.00347	0.00840
	(-0.10)	(0.29)	(0.42)
Income deprivation quintile=3	0.0565	0.00762	0.0135
	(0.39)	(0.47)	(0.45)
Income deprivation quintile=4	0.0369	-0.00174	0.00909
	(0.22)	(-0.09)	(0.25)
Income deprivation quintile=5	0.128	0.0191	0.0262
	(0.62)	(0.74)	(0.57)
r2	0.216	0.389	0.134
Sample average	15.87	3.040	1.788
N	11878926	11878926	11878926
Model B: Biological sex (reference: Male)			
Unexpected demand	1.442***	0.506***	0.238***
	(18.98)	(19.75)	(25.76)
Female=1 x Demand	0.0487***	0.0173***	0.0102***
	(3.53)	(5.87)	(3.45)
Female	0.236***	0.0433***	0.0373***
	(10.85)	(8.65)	(8.10)
r2	0.216	0.390	0.134
Sample average	15.87	3.040	1.786
N	11857588	11857588	11857588
Model C: Ethnic group (reference: White)			
Unexpected demand	1.461***	0.505***	0.241***
	(19.23)	(19.68)	(26.85)
Asian, Asian British, or Asian Mixed # Z-score demand	-0.0633	0.0612**	0.00713
	(-1.34)	(3.24)	(0.71)
Black, Black British, or Black Mixed # Z-score demand	0.00746	0.0649**	0.0177
	(0.11)	(3.14)	(1.43)
Chinese, Other, or Other Mixed # Z-score demand	0.0134	0.0612***	0.0117
	(0.25)	(3.72)	(1.14)
Not stated/missing # Z-score demand	0.0839	0.00425	0.00900
	(1.79)	(0.33)	(1.25)
Asian, Asian British, or Asian Mixed	0.269	0.0491	0.0596
	(1.56)	(1.85)	(1.62)
Black, Black British, or Black Mixed	0.0325	-0.0158	0.00795
	(0.16)	(-0.51)	(0.16)
Chinese, Other, or Other Mixed	0.0530	0.00740	0.0253
	(0.40)	(0.33)	(0.82)
Not stated/missing	-0.210	-0.0471**	-0.0318
	(-1.75)	(-2.67)	(-1.44)
r2	0.216	0.389	0.134
Sample average	15.87	3.040	1.788
N	11878926	11878926	11878926

Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2). Covariates included in the model are: age, biological sex, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). *t* statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Effect of unexpected demand on prioritisation between initial assessment and treatment by IMD quintile, sex, and ethnicity

	(1) Waiting time	(2) Nr. in-order	(3) Nr. out-of-order
Panel A: IMD quintiles (reference: Least deprived)			
Unexpected demand	5.905***	1.654***	0.664***
	(19.95)	(20.36)	(20.60)
Income deprivation quintile=2 x Demand	-0.00873	0.0120	0.0138
	(-0.08)	(0.61)	(1.07)
Income deprivation quintile=3 x Demand	0.0790	0.0495	0.0267
	(0.67)	(1.85)	(1.81)
Income deprivation quintile=4 x Demand	0.0630	0.0819*	0.0372*
	(0.42)	(2.37)	(2.08)
Income deprivation quintile=5 x Demand	0.204	0.146**	0.0607*
	(0.99)	(2.92)	(2.55)
Income deprivation quintile=2	0.382*	0.0422	0.0532*
	(2.56)	(1.71)	(2.04)
Income deprivation quintile=3	0.675**	0.0729*	0.0779*
	(3.15)	(2.20)	(2.14)
Income deprivation quintile=4	0.916***	0.122**	0.111*
	(3.48)	(3.21)	(2.52)
Income deprivation quintile=5	1.341***	0.177***	0.144**
	(4.31)	(4.19)	(2.77)
r2	0.192	0.407	0.159
Sample average	63.73	10.14	5.405
N	10507066	10507066	10507066
Panel B: Biological sex (reference: Male)			
Unexpected demand	5.933***	1.702***	0.683***
	(22.79)	(21.93)	(24.81)
Female=1 x Demand	0.121**	0.0444***	0.0262***
	(3.23)	(7.06)	(3.48)
Female	1.526***	0.188***	0.176***
	(17.04)	(12.50)	(12.61)
r2	0.193	0.408	0.159
Sample average	63.76	10.14	5.401
N	10485995	10485995	10485995
Panel C: Ethnic group (reference: White)			
Unexpected demand	5.990***	1.701***	0.696***
	(23.10)	(21.99)	(25.11)
Asian, Asian British, or Asian Mixed # Z-score demand	-0.193	0.188***	-0.0115
	(-0.82)	(3.47)	(-0.42)
Black, Black British, or Black Mixed # Z-score demand	0.0681	0.207***	0.0258
	(0.35)	(3.66)	(1.16)
Chinese, Other, or Other Mixed # Z-score demand	-0.0705	0.137***	0.0130
	(-0.40)	(3.44)	(0.51)
Not stated/missing # Z-score demand	0.112	-0.0293	0.000384
	(0.67)	(-0.85)	(0.03)
Asian, Asian British, or Asian Mixed	0.578	0.151*	0.0612
	(1.54)	(2.22)	(0.86)
Black, Black British, or Black Mixed	0.749	0.102	0.100
	(1.43)	(1.53)	(1.38)
Chinese, Other, or Other Mixed	0.680*	0.123*	0.0837
	(1.98)	(2.03)	(1.33)
Not stated/missing	-0.481	-0.0617	-0.0507
	(-1.50)	(-1.28)	(-1.15)
r2	0.192	0.407	0.159
Sample average	63.73	10.14	5.405
N	10507066	10507066	10507066

Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2). Covariates included in the model are: age, biological sex, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Robustness checks

Our main empirical approach rests on conditional mean independence of our residualised demand measure. Whilst this assumption is formally untestable, we start by showing descriptive statistics of our covariates of interest across tertiles of unexpected demand. This first check verifies a necessary (but not sufficient) condition for unconfoundedness, namely that the exogenous regressor is plausibly independent of observable confounders. In Appendix B (**Table B1**) we report summary statistics of our key covariates across tertiles of unexpected demand. The characteristics of patients visiting EDs in our sample are remarkably balanced across different levels of unexpected demand, supporting the validity of our empirical approach.

Secondly, in the spirit of balancing regressions (Pei, Pischke, and Schwandt 2019), we test whether unexpected demand is associated with our inequality dimensions of interest. This analysis serves as a second stricter test of unconfoundedness of unexpected demand in relation to our dimensions of inequality of interest. The results in **Table 4** suggest that, even without controlling for additional patient- and attendance-level covariates, the correlation between our measure of unexpected demand and our dimensions of inequality of interest is negligible.

Table 4: Balancing regressions

	Daily attendance (z-score)	*t-stat*	Constant		*N*
IMD quintile					
Least deprived	0.000389*	-2.46	0.143***	-41668	12481418
2	0.0000728	-0.4	0.165***	-41737.5	12481418
3	-0.000188	(-1.04)	0.183***	-46628.2	12481418
4	0.000135	-0.74	0.222***	-56076.4	12481418
Most deprived	-0.000409	(-1.43)	0.287***	-46092.8	12481418
Ethnic group:					
White	0.00024	-0.64	0.739***	-90631.2	12481418
Asian	-0.000177	(-0.84)	0.0711***	-15501.8	12481418
Black	0.000254**	-2.78	0.0443***	-22376.6	12481418
Other	0.000106	-0.92	0.0370***	-14747.7	12481418
Not stated/missing	-0.000424	(-1.87)	0.109***	-22045.3	12481418
Female	-0.000311	(-1.22)	0.505***	-87361.8	12411351

Note: Coefficients estimated using the same models as main results, using the *reghdfe* command to partial out our ED-specific seasonality. No covariate was included. Stars indicate significance as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Third, given our claim of quasi-exogeneity in the daily demand shifts, we compare our main results (conditional on patient- and attendance-level controls) to models without any control variables (i.e. just including ED-standardized demand fully interacted with the inequality dimension of interest). In Appendix B (**Figure B1**) we show that our results are fully consistent when models are estimated with and without detailed patient and attendance controls.

Fourth, our design-based approach isolates plausibly exogenous demand shifts which we use to measure patterns of inequalities in unplanned prioritisation. However, this does not remove the risk of model misspecification. Following Feigenberg et al. (2023), we assess the extent of omitted variable bias due to not accounting for differential trends in controls across the inequality dimension of interest, in our case neighbourhood income deprivation, sex, and ethnicity. We do so by estimating the following extended model using the same feasible linear estimator:

$$\begin{gathered} {y^p}_{iht} = \tilde{\alpha} + \tilde{\delta} Demand_{ht} + \tilde{\gamma}(Demand_{ht} \times Inequality_{it}) + \boldsymbol{Patient'}_{it}\tilde{\boldsymbol{\beta}} + \\ \boldsymbol{Attendance'}_{iht}\tilde{\boldsymbol{\omega}} + (\boldsymbol{Inequality_{it}} \times \boldsymbol{Patients_{it}})'\boldsymbol{\phi_1} \quad (3) \\ +(\boldsymbol{Inequality_{it}} \times \boldsymbol{Attendance'_{iht}})'\boldsymbol{\phi_2} + \tilde{\epsilon}_{iht}. \end{gathered}$$

We report estimates of δ and γ from the standard model in (2) and $\tilde{\delta}$ and $\tilde{\gamma}$ the extended model in (3) including interactions between $Inequality_{it}$ and all covariates included in the same table, allowing a direct comparison of their relative size of coefficients. In Appendix B (**Figure B2**) we report the results of this exercise.

Our interaction coefficients capturing differential effects of unexpected demand on prioritisation across age groups are stable when estimating an extended model that fully interacts ethnicity, deprivation and biological sex with all other covariates included in the model. These findings suggests that coefficients estimated with models only interacting unexpected demand with the dimension of inequality of interest are unlikely to suffer from omitted variable bias due to differential trends in covariates across levels of the inequality dimension.

Finally, despite conditioning on primary ED diagnosis in our main empirical approach, the level of heterogeneity in patient pathways across different diagnostic groups may limit the validity of our results. Bias could arise due to violations of the constant treatment effect assumption (Imbens and Rubin 2015), masking the fact that the results are concentrated in selected diagnostic groups. To rule out this latter possibility, we repeat our analysis restricting the index patients to three groups, namely those with a primary diagnosis classified as "Dislocation/Fractures", "Cardiac conditions", or "Gastrointestinal conditions".

We contrast the results of these subgroup analyses with the main findings in **Table 2** and **Table 3**. This allows us to focus on prioritisation decisions within more homogeneous patient groups. Moreover, given that cardiac conditions are on average more urgent than gastrointestinal conditions of dislocations and fractures, we also explore whether the results vary sensibly across conditions with different levels of expected urgency. The results of these analyses are included in Appendix B (**Figure B3**). The patterns in our main analysis are unchanged throughout the groups of patients whose primary ED diagnoses were either "Dislocation/Fractures", "Cardiac conditions", or "Gastrointestinal conditions". Confidence intervals around the point estimates are mostly overlapping, with no major differences. If anything, cardiac and gastrointestinal patients show slightly stronger de-prioritisation in response to unexpected demand against patients from more deprived areas, ethnic minorities, and females. Interestingly, "Dislocation/Fractures" – a diagnostic group that is arguably less urgent than cardiac conditions – shows point estimates very much in line with our main estimates and not substantially different from the other two diagnostic groups. In short, the results of all our robustness checks supports the validity of our identifying assumptions and our main results.

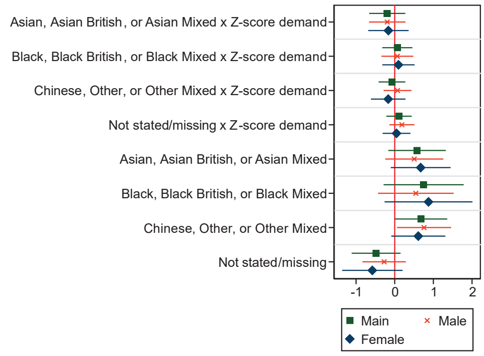
In next iterations of this work we will test the sensitivity of our estimates to estimation with non-linear models better suited to count variables (Mullahy 2023; 1997; Mullahy and Norton 2022), and with lower frequency for our ED-specific seasonality (e.g. month and hour-of-week). Preliminary analyses suggested that our results remain consistent under these alternative approaches.

Heterogeneity analyses

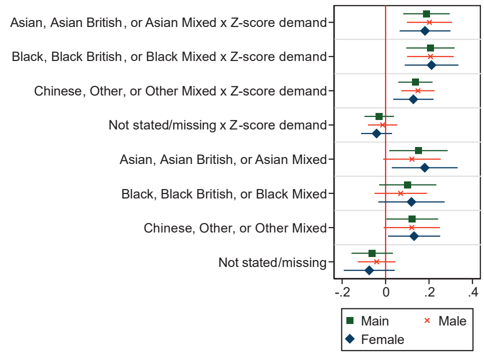
To further unpack the mechanisms behind our results, we conduct two additional heterogeneity analyses. Firstly, there is evidence that ethnic disparities in healthcare affect females differently than males (Akinade et al. 2023; Lett, Dowshen, and Baker 2020). We explore whether this is the case in our setting by running stratified models by biological sex. For this analysis we focus on the longer queue from assessment to treatment, where the effect sizes are larger, and differences are more likely to emerge. These results are reported in **Table 5** below; although the magnitudes are marginally larger for females compared to males, the differences are negligible and not statistically significant.

Table 5: Biological sex differences in the ethnicity gradient

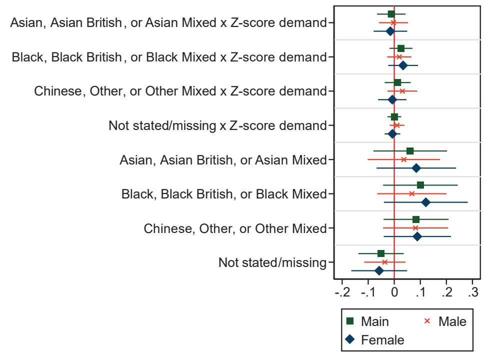
(a) Waiting time



(b) In-order count of patients



(c) Out-of-order count of patients



Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2), separately for males and females. Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Secondly, the extent to which non-need variables such as ethnicity or area-level deprivation can affect the level of prioritisation assigned to a patient may depend on the composition of patients seen at a specific hospital. This may be due to various factors, including being used to engaging with patients from a given socioeconomic profile or ethnic background, or other individual communication or cultural factors that may result in either discrimination or a poorer interaction between patient and staff. For example, staff in an hospital serving a catchment area with a relatively high share of patients from a Black background will have more experience of treating patients from a Black background. As a result, the staff will likely be influenced differently by the patients' background (if at all) compared to staff in an hospital where Black patients are rarely seen. For example, the match between patients and providers ethnicity is a known mechanism underpinning these differences in healthcare provision across ethnic groups (Hill, Jones, and Woodworth 2023; Ye and Yi 2023).

We test this hypothesis by repeating our analysis focused on the gradient linked to neighbourhood deprivation dividing hospitals by tertiles of the share of their yearly patients living in the most deprived neighbourhood (i.e. in the fifth quintile of the IMD distribution). Analogously, we repeat our analyses focused on the gradient linked to the patients' ethnic background dividing hospitals by tertiles of the share of their yearly patients with (i) Black and (ii) Asian backgrounds. Again, we only focus on the second more substantial queue between assessment and treatment. Unfortunately, we do not observe individual providers' characteristics such as gender or ethnicity in our dataset, preventing us from explicitly looking at patient-provider ethnicity-match. The results are presented in Appendix C. **Figure C1** shows that there is wide variability in the extent to which patients from most deprived neighbourhoods are concentrated across hospitals, with over 60% of the patients presenting at some EDs residing in LSOAs in the most deprived quintile of IMD. Despite this, the differences in prioritisation linked to deprivation across hospitals with different concentration of deprived patients (**Figure C2**) are consistent with our main results for the waiting time variables. Whilst point estimates differences are not statistically significant, the results for headcounts of in- and out-of-order patients jumping ahead suggest that, in hospitals seeing the largest shares of patients from deprived neighbourhoods, these latter patients tend to experience the same level of prioritisation as those from the least deprived neighbourhoods. The small but significant discrimination against most deprived patients seem concentrated in hospitals less used to seeing patients from deprived areas.

The EDs in our study sample also show substantial variability in the extent to which they serve catchment areas comprised of patients from Asian and Black backgrounds (up to a third of patients). The analyses splitting hospitals by tertiles of the share of yearly patients from both minority ethnic backgrounds are reported in **Figures C3 and C4**. In both cases, our findings seem driven by the middle group (tertile 2). Although - again - the difference in point estimates compared to tertile 2 are not statistically significant, the estimates for the two groups at the extremes (i.e. seeing the least and the most minority patients respectively) are very close to or precisely 0.

Discussion

We propose an approach to decompose the wait of an index patient queuing at the ED, counting the number of patients arrived before her that she waits behind (in-order patients), and the other patients arriving after her but being prioritised over the index patient (out-of-order patients). We then study how patients' prioritisation in English EDs responds to unexpected ED demand, which we measure as deviations from ED specific day-of-the-week and month of the year seasonal components. We explore whether prioritisation triggered by unexpected demand affects patients differently in three groups of interest defined by IMD of the area of residence, biological sex, and ethnic background.

Reprioritisation triggered by unexpected demand is small in magnitude (about 1m30s more for the queue to initial assessment and 6 for time between assessment to treatment). On average, a one standard deviation increase in unexpected demand causes one more patient every 4 to jump ahead of them. In the queue for treatment, almost one additional patients jumps ahead of the index patient in response to a one SD change in unexpected demand.

We found evidence of mild gaps in prioritisation by area-level deprivation, biological sex and ethnic background. Patients from more deprived areas and females tend to wait longer, and these differences increase in response to unexpected demand. These two groups are also less likely to be prioritised in the queue during demand peaks. Patients from minority ethnic backgrounds also appear slightly less likely to be prioritised over patients that were ahead of them in the queue. In most cases, unexpected demand increases waiting times proportionally to the baseline differences in waiting times and counts of in-order and out-of-order patients. This finding may be interpreted as suggestive evidence that the baseline de-prioritisation (i.e. the main effects for deprivation, biological sex, and ethnic background) are not substantially biased by unobservables. All robustness checks seem to confirm the validity of our main results. Overall, these patterns are fully consistent with previous work on English data (Turner et al. 2022; 2020) and point to very mild but significant deprioritisation against patients from most deprived neighbourhoods, females and to some extent ethnic minorities.

Although the available data do not allow to investigate individual patient-provider interactions, in the heterogeneity analysis section we tried to explore two mechanisms. We did not find strong evidence of heterogeneity between males and females in the results focusing on de-prioritisation linked to ethnic background. This suggests that the mild evidence of de-prioritisation against ethnic minorities is unlikely to be driven by differential treatment of women within those ethnic minorities. We also repeated our analysis splitting hospitals according to the concentration of yearly visiting patients from most deprived neighbourhoods, and with Asian and Black ethnic backgrounds. These findings seem to suggest that – in hospitals with the highest prevalence of patients from the most deprived neighbourhoods – the latter experience the same level of prioritisation of patients from affluent areas. On the other hand, in EDs that generally serve more affluent populations, deprived patients seem slightly more discriminated against. When looking at hospitals split by the prevalence of Asian and Black backgrounds in their yearly patients flow, we find our main results to be driven by hospitals with a middle-range concentration of these ethnic minorities. On the other hand - in hospitals with relatively few or relatively many patients with Asian and Black background – the latter experience the same level of priority to patients with a White background. This may be interpreted as evidence that being accustomed to a diverse patient population is positive for equity. Similarly, staff in hospitals that receive few patients from ethnic minorities may be more careful with avoiding differential treatment compared to the dominant group.

Our study is clearly linked to the substantial strand of literature focused on hospital and ED waiting times, including its determinants, its distribution and its consequences (Berchet 2015; Sivey 2018; Turner et al. 2020; Gaughan et al. 2020; Turner et al. 2022; Francetic, Meacock, and Sutton 2024). Whilst waiting time is informative of the overall care process, the literature has not unpacked the prioritisation that may happen while patients are queueing and how these (re)prioritisation decisions contribute to the distribution of waiting times. Specifically, existing waiting times studies do not analyse the dynamics of the queue at patient-level.

Our study has some relevant limitations. For example, despite detailed information, our data may still fail to accurately identify the level of severity of different patients, leaving room for potential confounding due on unobserved severity. Nevertheless, our robustness checks substantially reduce concerns over a substantial bias from unobservables. Furthermore, the lack of supply-side data on staffing limits the extent to which we can exactly obtain a measure of unexpected ED demand that accurately reflects EDs capacity, as well as race-match between patients and providers. Despite this, we believe that our proposed measures of patient prioritisation in ED are important complements to traditional studies of waiting times. Future work could bridge the link between prioritisation and patient outcomes, for example studying whether EDs that engage in more re-ordering of the queue have better outcomes because they are prioritising more effectively, or whether unjust de-prioritisation linked to non-need variables has clinically significant consequences for patient outcomes.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. 2023. 'When Should You Adjust Standard Errors for Clustering?*'. *The Quarterly Journal of Economics* 138 (1): 1–35. https://doi.org/10.1093/qje/qjac038.

Akinade, Temitope, Anna Kheyfets, Naissa Piverger, Tracy M. Layne, Elizabeth A. Howell, and Teresa Janevic. 2023. 'The Influence of Racial-Ethnic Discrimination on Women's Health Care Outcomes: A Mixed Methods Systematic Review'. *Social Science & Medicine*, Complex Effects of Racism and Discrimination on African Americans' Health and Well-Being: Navigating the Status Quo, 316 (January):114983. https://doi.org/10.1016/j.socscimed.2022.114983.

Baicker, Katherine, Amitabh Chandra, Jonathan S. Skinner, and John E. Wennberg. 2004. 'Who You Are And Where You Live: How Race And Geography Affect The Treatment Of Medicare Beneficiaries'. *Health Affairs* 23 (Suppl2): VAR-33. https://doi.org/10.1377/hlthaff.var.33.

Berchet, Caroline. 2015. 'Emergency Care Services: Trends, Drivers and Interventions to Manage the Demand'. OECD Health Working Papers 83. https://doi.org/10.1787/5jrts344crns-en.

Borusyak, Kirill, and Peter Hull. 2020. 'Non-Random Exposure to Exogenous Shocks: Theory and Applications'. w27845. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w27845.

———. 2024. 'Negative Weights Are No Concern in Design-Based Specifications'. Working Paper. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w32017.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2023. 'Design-Based Identification with Formula Instruments: A Review'. w31393. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w31393.

Cabral, Marika, and Marcus Dillender. 2021. 'Gender Differences in Medical Evaluations: Evidence from Randomly Assigned Doctors'. w29541. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w29541.

Chandra, Amitabh, and Jonathan Skinner. 2003. 'Geography and Racial Health Disparities'. w9513. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w9513.

Cookson, Richard, Carol Propper, Miqdad Asaria, and Rosalind Raine. 2016. 'Socio-Economic Inequalities in Health Care in England'. *Fiscal Studies* 37 (3–4): 371–403. https://doi.org/10.1111/j.1475-5890.2016.12109.

Cross, E., S. Goodacre, A. O'Cathain, and J. Arnold. 2005. 'Rationing in the Emergency Department: The Good, the Bad, and the Unacceptable'. *Emergency Medicine Journal* 22 (3): 171–76. https://doi.org/10.1136/emj.2004.020180.

Dark, Paul, Martin Smith, Harry Ziman, Simon Carley, and Fiona Lecky. 2021. 'Healthcare System Impacts of the 2017 Manchester Arena Bombing: Evidence from a National Trauma Registry Patient Case Series and Hospital Performance Data'. *Emergency Medicine Journal* 38 (10): 746–55. https://doi.org/10.1136/emermed-2019-208575.

Delgado-Angulo, Elsa K., Munisha Mangal, and Eduardo Bernabé. 2019. 'Socioeconomic Inequalities in Adult Oral Health across Different Ethnic Groups in England'. *Health and Quality of Life Outcomes* 17 (1): 85. https://doi.org/10.1186/s12955-019-1156-3.

Feigenberg, Benjamin, Ben Ost, and Javaeria A. Qureshi. 2023. 'Omitted Variable Bias in Interacted Models: A Cautionary Tale'. *The Review of Economics and Statistics*, July, 1–47. https://doi.org/10.1162/rest_a_01361.

FitzGerald, Gerard, George A. Jelinek, Deborah Scott, and Marie Frances Gerdtz. 2010. ‘Emergency Department Triage Revisited’. *Emergency Medicine Journal* 27 (2): 86–92. https://doi.org/10.1136/emj.2009.077081.

Francetic, Igor, Rachel Meacock, and Matt Sutton. 2024. ‘Free-for-All: Does Crowding Impact Outcomes Because Hospital Emergency Departments Do Not Prioritise Effectively?’ *Journal of Health Economics* 95 (May):102881. https://doi.org/10.1016/j.jhealeco.2024.102881.

Gaughan, James, Panagiotis Kasteridis, Anne Mason, and Andrew Street. 2020. ‘Why Are There Long Waits at English Emergency Departments?’ *The European Journal of Health Economics* 21 (2): 209–18. https://doi.org/10.1007/s10198-019-01121-7.

Graff, Louis G., and Martha J. Radford. 1990. ‘Formula for Emergency Physician Staffing’. *The American Journal of Emergency Medicine* 8 (3): 194–99. https://doi.org/10.1016/0735-6757(90)90320-Y.

Hill, Andrew J., Daniel B. Jones, and Lindsey Woodworth. 2023. ‘Physician-Patient Race-Match Reduces Patient Mortality’. *Journal of Health Economics* 92 (December):102821. https://doi.org/10.1016/j.jhealeco.2023.102821.

Hoe, Thomas P. 2022. ‘Does Hospital Crowding Matter? Evidence from Trauma and Orthopedics in England’. *American Economic Journal: Economic Policy* 14 (2): 231–62. https://doi.org/10.1257/pol.20180672.

Imbens, Guido W., and Donald B. Rubin. 2015. *Causal Inference in Statistics, Social, and Biomedical Sciences*. Cambridge University Press.

Jones, Simon, Chris Moulton, Simon Swift, Paul Molyneux, Steve Black, Neil Mason, Richard Oakley, and Clifford Mann. 2022. ‘Association between Delays to Patient Admission from the Emergency Department and All-Cause 30-Day Mortality’. *Emergency Medicine Journal* 39 (3): 168–73. https://doi.org/10.1136/emermed-2021-211572.

Kmietowicz, Zosia. 2020. ‘NHS Launches Race and Health Observatory after BMJ’s Call to End Inequalities’. *BMJ* 369 (June):m2191. https://doi.org/10.1136/bmj.m2191.

Lakshmi, C, and AI Sivakumar. 2013. ‘Application of Queueing Theory in Health Care: A Literature Review’. *Operations Research for Health Care* 2 (1–2): 25–39. https://doi.org/10.1016/j.orhc.2013.03.002.

Lett, Elle, Nadia L. Dowshen, and Kellan E. Baker. 2020. ‘Intersectionality and Health Inequities for Gender Minority Blacks in the U.S.’ *American Journal of Preventive Medicine* 59 (5): 639–47. https://doi.org/10.1016/j.amepre.2020.04.013.

Lovell, Michael C. 2008. ‘A Simple Proof of the FWL Theorem’. *The Journal of Economic Education* 39 (1): 88–91. https://doi.org/10.3200/JECE.39.1.88-91.

Mackway-Jones, Kevin, Janet Marsden, and Jill Windle, eds. 2013. *Emergency Triage: Manchester Triage Group*. 1st ed. Wiley. https://doi.org/10.1002/9781118299029.

Marmot, Michael. 2020. ‘Health Equity in England: The Marmot Review 10 Years On’. *BMJ* 368 (February):m693. https://doi.org/10.1136/bmj.m693.

Martins, Bruno, and Luís Filipe. 2020. ‘Doctors’ Response to Queues: Evidence from a Portuguese Emergency Department’. *Health Economics* 29 (2): 123–37. https://doi.org/10.1002/hec.3957.

Meacock, Rachel, Laura Anselmi, Søren Rud Kristensen, Tim Doran, and Matt Sutton. 2017. ‘Higher Mortality Rates amongst Emergency Patients Admitted to Hospital at Weekends Reflect a Lower Probability of Admission’. *Journal of Health Services Research & Policy* 22 (1): 12–19. https://doi.org/10.1177/1355819616649630.

Morris, Stephen, Matthew Sutton, and Hugh Gravelle. 2005. ‘Inequity and Inequality in the Use of Health Care in England: An Empirical Investigation’. *Social Science & Medicine* 60 (6): 1251–66. https://doi.org/10.1016/j.socscimed.2004.07.016.

Moscelli, Giuseppe, Luigi Siciliani, Nils Gutacker, and Richard Cookson. 2018. 'Socioeconomic Inequality of Access to Healthcare: Does Choice Explain the Gradient?' *Journal of Health Economics* 57 (January):290–314. https://doi.org/10.1016/j.jhealeco.2017.06.005.

Mullahy, John. 1997. 'Heterogeneity, Excess Zeros, and the Structure of Count Data Models'. *Journal of Applied Econometrics* 12 (3): 337–50. https://doi.org/10.1002/(SICI)1099-1255(199705)12:3<337::AID-JAE438>3.0.CO;2-G.

———. 2023. 'Analyzing Bounded Count Data'. w31814. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w31814.

Mullahy, John, and Edward Norton. 2022. 'Why Transform Y? A Critical Assessment of Dependent-Variable Transformations in Regression Models for Skewed and Sometimes-Zero Outcomes'. w30735. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w30735.

Nazroo, James, James Jackson, Saffron Karlsen, and Myriam Torres. 2007. 'The Black Diaspora and Health Inequalities in the US and England: Does Where You Go and How You Get There Make a Difference?' *Sociology of Health & Illness* 29 (6): 811–30. https://doi.org/10.1111/j.1467-9566.2007.01043.x.

NHS England and North West Ambulance Service. 2019. 'North West Divert & Deflection Policy'. Bolton: NWAS. https://www.england.nhs.uk/north-west/wp-content/uploads/sites/48/2020/01/north-west-divert-deflection-policy-version-60_final.pdf.

Pei, Zhuan, Jörn-Steffen Pischke, and Hannes Schwandt. 2019. 'Poorly Measured Confounders Are More Useful on the Left than on the Right'. *Journal of Business & Economic Statistics* 37 (2): 205–16. https://doi.org/10.1080/07350015.2018.1462710.

Sivey, Peter. 2018. 'Should I Stay or Should I Go? Hospital Emergency Department Waiting Times and Demand'. *Health Economics* 27 (3): e30–42. https://doi.org/10.1002/hec.3610.

The King's Fund. 2022. 'Health Inequalities: What Is Happening in Emergency Medicine'. The King's Fund. 2022. https://www.kingsfund.org.uk/insight-and-analysis/blogs/health-inequalities-what-happening-emergency-medicine.

Turner, Alex J., Laura Anselmi, Yiu-Shing Lau, and Matt Sutton. 2020. 'The Effects of Unexpected Changes in Demand on the Performance of Emergency Departments'. *Health Economics* 29 (12): 1744–63. https://doi.org/10.1002/hec.4167.

Turner, Alex J, Igor Francetic, Ruth Watkinson, Stephanie Gillibrand, and Matt Sutton. 2022. 'Socioeconomic Inequality in Access to Timely and Appropriate Care in Emergency Departments'. *Journal of Health Economics* 85 (September):102668. https://doi.org/10.1016/j.jhealeco.2022.102668.

Watkinson, Ruth Elizabeth, Matt Sutton, and Alex James Turner. 2021. 'Ethnic Inequalities in Health-Related Quality of Life among Older Adults in England: Secondary Analysis of a National Cross-Sectional Survey'. *The Lancet Public Health* 6 (3): e145–54. https://doi.org/10.1016/S2468-2667(20)30287-5.

Weber, Ellen J. 2019. 'Triage: Making the Simple Complex?' *Emergency Medicine Journal* 36 (2): 64–65. https://doi.org/10.1136/emermed-2018-207659.

Ye, Han, and Junjian Yi. 2023. 'Patient-Physician Race Concordance, Physician Decisions, and Patient Outcomes'. *The Review of Economics and Statistics*, May, 1–14. https://doi.org/10.1162/rest_a_01236.

APPENDIX

Appendix A: Primary ED diagnoses in our main sample

Diagnosis 1 - two digit code	Freq	Perc.	Cum. Perc.
Laceration	372540	3.14	3.14
Contusion/abrasion	366802	3.09	6.22
Soft tissue inflammation	308101	2.59	8.82
Head injury	295554	2.49	11.31
Dislocation/fracture	595597	5.01	16.32
Sprain/ligament injury	438795	3.69	20.01
Muscle/tendon injury	162536	1.37	21.38
Nerve injury	8100	0.07	21.45
Vascular injury	4555	0.04	21.49
Burns and scalds	52598	0.44	21.93
Electric shock	1828	0.02	21.95
Foreign body	86230	0.73	22.67
Bites/stings	28205	0.24	22.91
Poisoning (inc overdose)	159372	1.34	24.25
Near drowning	579	0.00	24.26
Visceral injury	6323	0.05	24.31
Infectious disease	207434	1.75	26.06
Local infection	150986	1.27	27.33
Septicaemia	67106	0.56	27.89
Cardiac conditions	426550	3.59	31.48
Cerebro-vascular conditions	101091	0.85	32.33
Other vascular conditions	48169	0.41	32.74
Haematological conditions	47715	0.40	33.14
Central nervous system conditions	213764	1.80	34.94
Respiratory conditions	629554	5.30	40.24
Gastrointestinal conditions	637658	5.37	45.61
Urological conditions (inc cystitis)	317672	2.67	48.28
Obstetric conditions	24284	0.20	48.49
Gynaecological conditions	110045	0.93	49.41
Diabetes and other endocrinological con	53597	0.45	49.86
Dermatological conditions	76418	0.64	50.51
Allergy (inc anaphylaxis)	52757	0.44	50.95
Facio-maxillary conditions	37258	0.31	51.27
ENT conditions	211652	1.78	53.05
Psychiatric conditions	149080	1.25	54.30
Ophthalmological conditions	138319	1.16	55.47
Social problems (inc chronic alcoholism)	36534	0.31	55.77
Diagnosis not classifiable	1781541	15.00	70.77
Nothing abnormal detected	326936	2.75	73.52
Missclassified	638166	5.37	78.90
No/missing diagnosis	2506925	21.10	100.00
Total	11878926		

Appendix B: Robustness

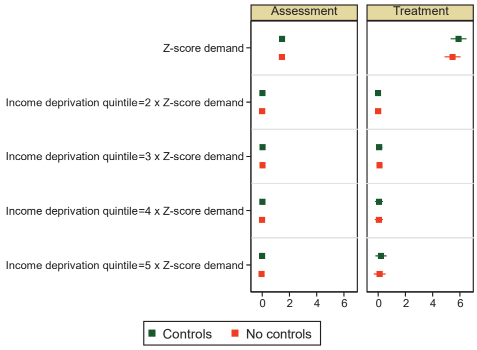
Table B1: Balance in covariates across tertiles of unexpected demand

	Tertile 1		Tertile 2		Tertile 3	
Variable	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
IMD quintile						
Least deprived	0.142	.349	0.149	.356	0.142	.35
2	0.163	.37	0.171	.376	0.163	.369
3	0.180	.385	0.188	.39	0.179	.384
4	0.222	.415	0.217	.412	0.222	.416
Most deprived	0.292	.455	0.276	.447	0.293	.455
Ethnic group						
White	0.736	.441	0.763	.425	0.737	.44
Asian	0.076	.265	0.060	.237	0.076	.265
Black	0.045	.208	0.036	.187	0.046	.21
Other	0.037	.189	0.032	.176	0.037	.189
Not stated/missing	0.105	.307	0.109	.311	0.104	.305
Female	0.504	.5	0.505	.5	0.503	.5
Child	0.105	.306	0.111	.314	0.119	.324
Adult	0.493	.5	0.481	.5	0.483	.5
Elder	0.287	.452	0.295	.456	0.279	.449
Referral/mode of arrival group						
GP referral-Ambulance	0.009	.0957	0.010	.0973	0.009	.0953
GP referral-Non-Ambulance	0.058	.234	0.058	.234	0.059	.236
Self-referral Ambulance	0.109	.312	0.112	.315	0.104	.306
Self-referral-Non- Ambulance	0.508	.5	0.512	.5	0.516	.5
EMS- Ambulance	0.119	.324	0.121	.327	0.114	.318
EMS-Non- Ambulance	0.007	.0817	0.007	.0824	0.007	.0827
Police- Ambulance	0.001	.034	0.001	.0331	0.001	.0317
Police-Non- Ambulance	0.004	.0621	0.004	.0626	0.004	.0627
Healthcare provider - Ambulance	0.039	.194	0.040	.195	0.038	.191
Healthcare provider - Non-Ambulance	0.044	.206	0.046	.208	0.044	.206
Other- Ambulance	0.032	.177	0.031	.172	0.032	.176
Other-Non- Ambulance	0.068	.252	0.060	.237	0.071	.256
Patient type						
Road traffic accidents	0.010	.101	0.010	.101	0.010	.1
Assault	0.007	.0807	0.007	.0808	0.007	.0811
Self-harm event	0.006	.0795	0.007	.0825	0.006	.0783
Sports accident	0.012	.111	0.014	.117	0.013	.115
Other accidents	0.195	.397	0.203	.402	0.195	.396
Other problem (not accidents)	0.757	.429	0.745	.436	0.755	.43
Not known	0.012	.107	0.015	.12	0.013	.115
Unplanned follow up visit	0.016	.126	0.016	.127	0.016	.126
Nr. of Emergency. Admissions. in previous year	0.720	2.05	0.718	2.01	0.695	1.99
Nr. of ED attendances in prevous year	0.939	4.07	0.903	3.89	0.908	3.95
Observations	3526160		3552400		3501141	

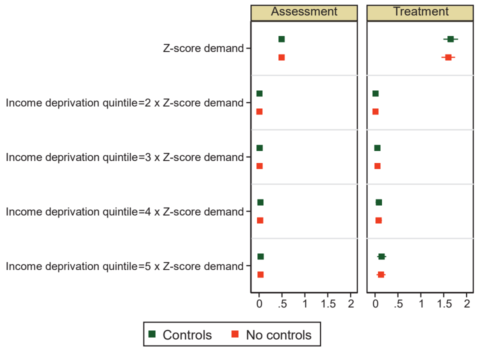
Figure B1: Models with and without controls

Deprivation

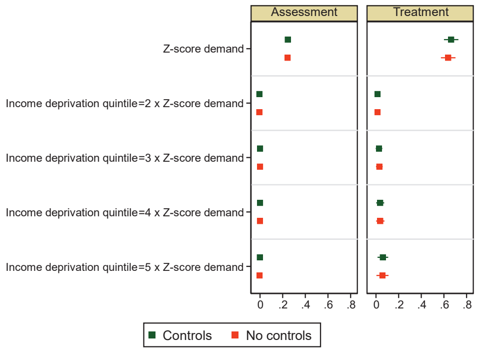
(a) Waiting time



(b) In-order count of patients



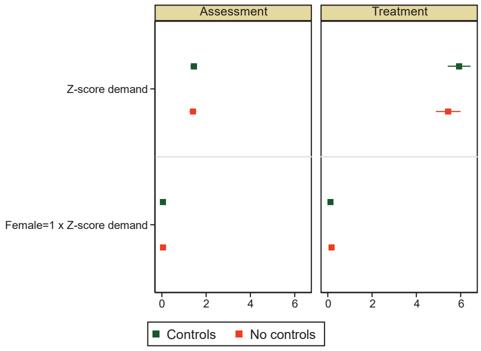
(c) Out-of-order count of patients



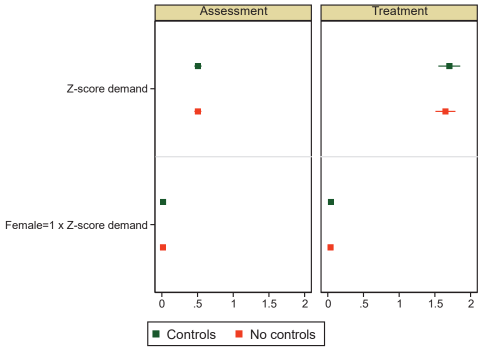
Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equations (2), with ("Controls") and without ("No controls") covariates. The covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Biological sex

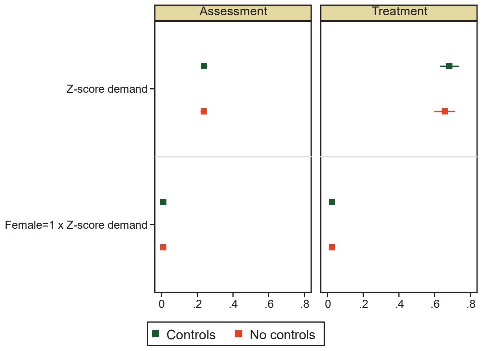
(a) Waiting time



(b) In-order count of patients



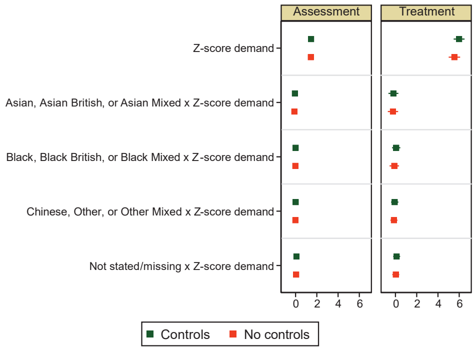
(c) Out-of-order count of patients



Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equations (2), with ("Controls") and without ("No controls") covariates. The covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

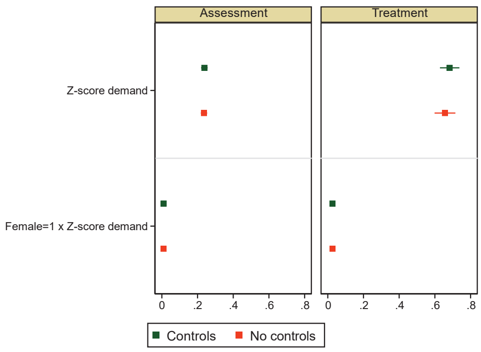
Ethnicity

(a) Waiting time



(b) In-order count of patients

(c) Out-of-order count of patients

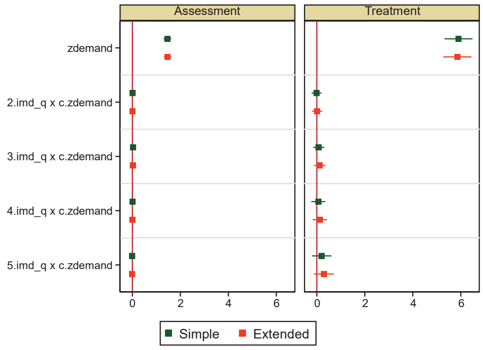


Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equations (2), with ("Controls") and without ("No controls") covariates. The covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

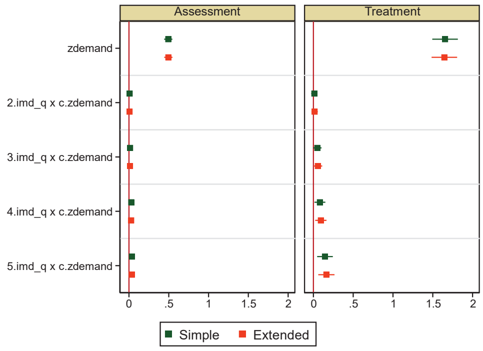
Figure B2: Comparison between main models and fully interacted models to check model misspecification

Deprivation

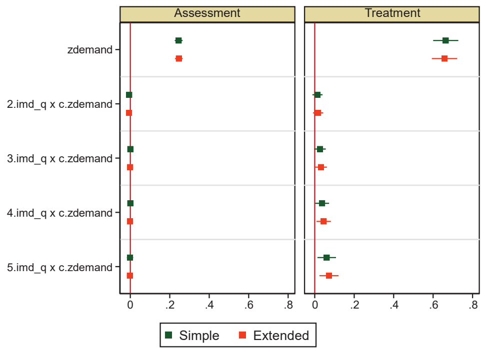
(a) Waiting time



(b) In-order count of patients



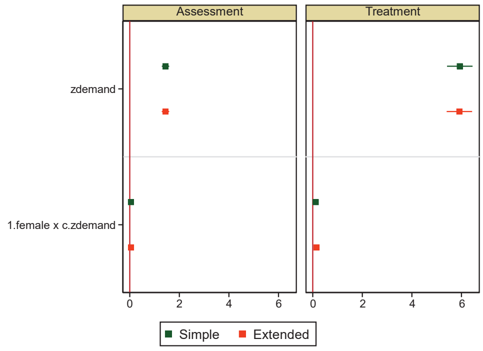
(c) Out-of-order count of patients



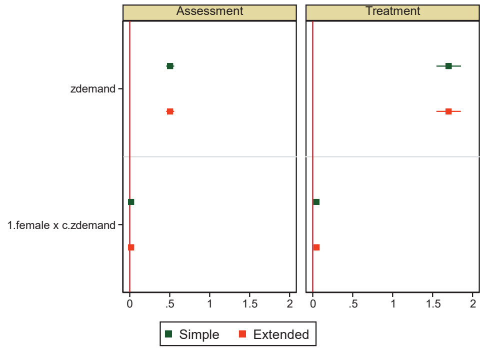
Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equations (2) for the "Simple" model and (3) for the "Extended" model that interacts the non-need variable of interest with all other covariates, following (Feigenberg, Ost, and Qureshi 2023). Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Biological sex

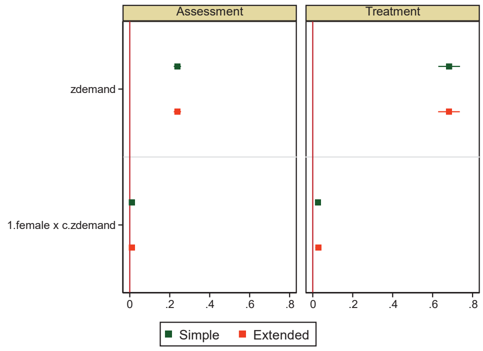
(a) Waiting time



(b) In-order count of patients



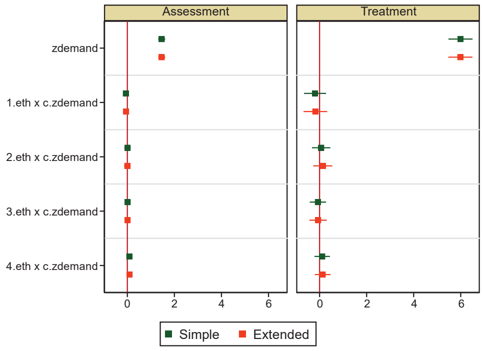
(c) Out-of-order count of patients



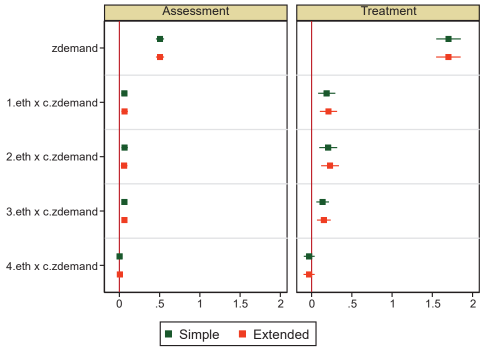
Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equations (2) for the "Simple" model and (3) for the "Extended" model that interacts the non-need variable of interest with all other covariates, following (Feigenberg, Ost, and Qureshi 2023). Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Ethnicity

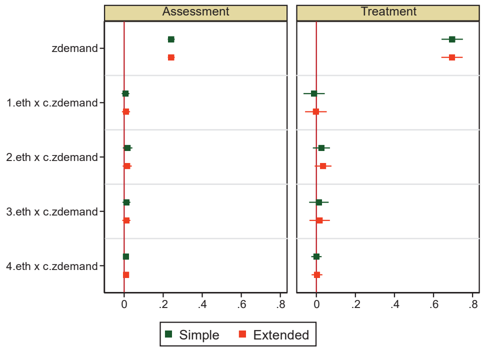
(a) Waiting time



(b) In-order count of patients



(c) Out-of-order count of patients

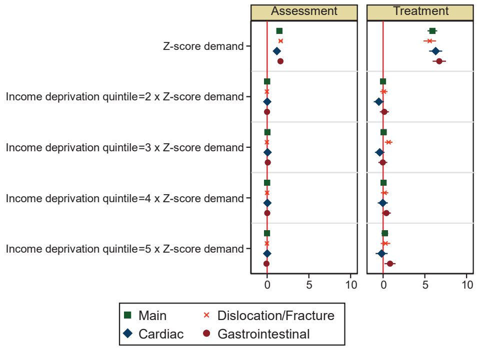


Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equations (2) for the "Simple" model and (3) for the "Extended" model that interacts the non-need variable of interest with all other covariates, following (Feigenberg, Ost, and Qureshi 2023). Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

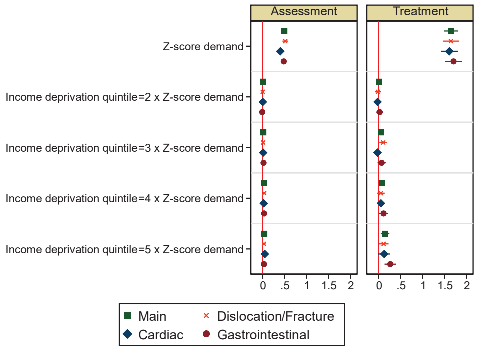
Figure B3: Comparison between main models and analyses within specific primary diagnoses

Deprivation

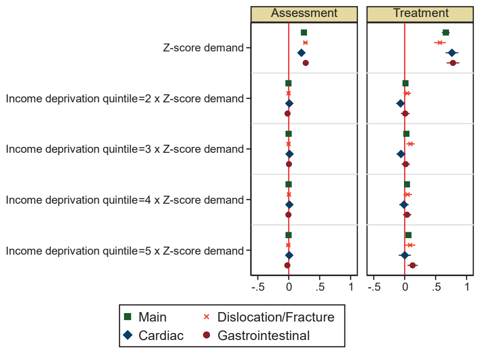
(a) Waiting time



(b) In-order count of patients



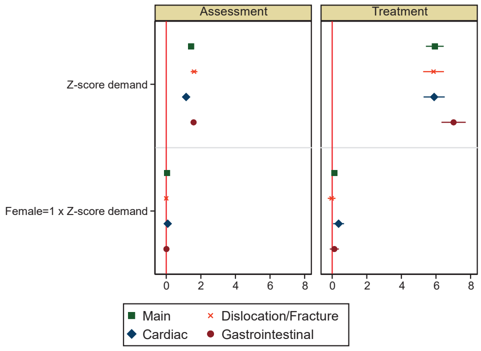
(c) Out-of-order count of patients



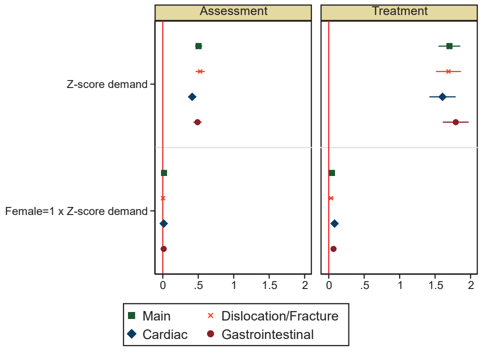
Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2). The main findings are to models estimated separately for patients whose primary ED diagnosis was "Disclocation/Fracture", "Cardiac condition", or "Gastrointestinal condition". Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Biological sex

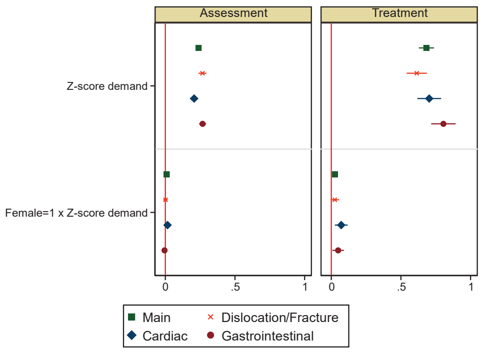
(a) Waiting time



(b) In-order count of patients



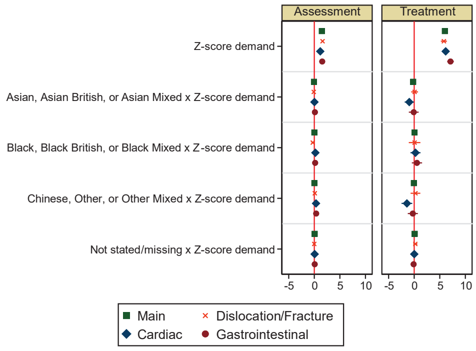
(c) Out-of-order count of patients



Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2). The main findings are to models estimated separately for patients whose primary ED diagnosis was "Disclocation/Fracture", "Cardiac condition", or "Gastrointestinal condition". Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

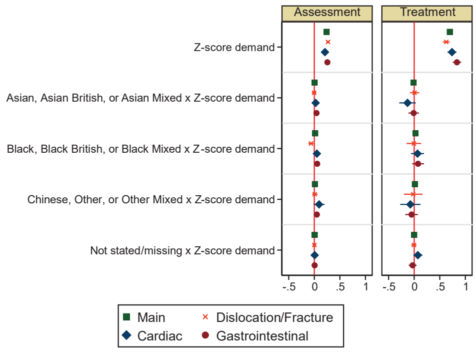
Ethnicity

(a) Waiting time



(b) In-order count of patients

(c) Out-of-order count of patients



Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2). The main findings are to models estimated separately for patients whose primary ED diagnosis was "Disclocation/Fracture", "Cardiac condition", or "Gastrointestinal condition". Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * p < 0.05, ** p < 0.01, *** p < 0.001.

Appendix C: Heterogeneity

Figure C1: ED-level variation in share of yearly patients from most deprived neighbourhoods (quintile 5 of IMD), and with Asian or Black backgrounds

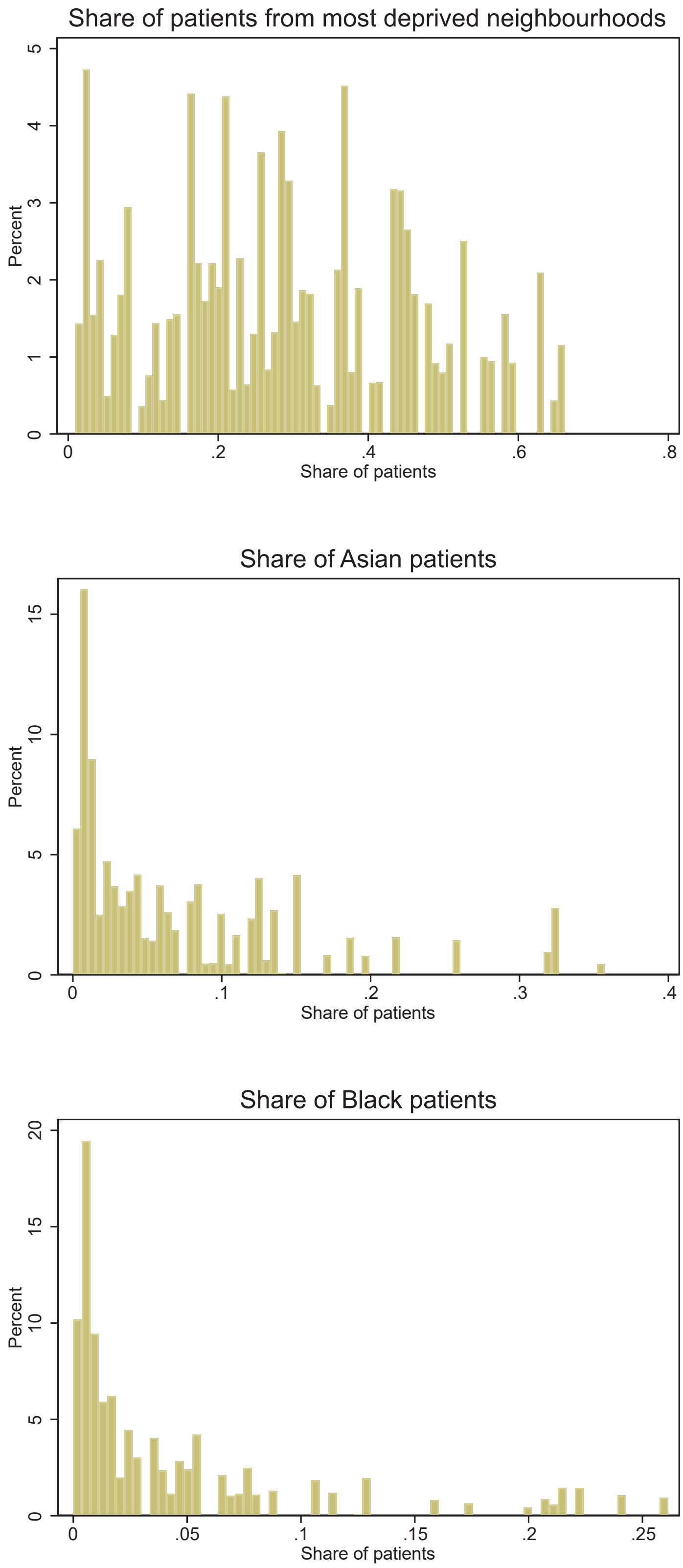
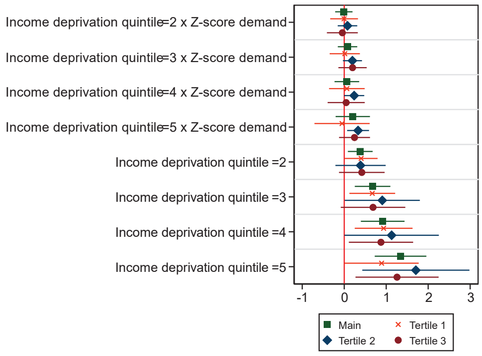


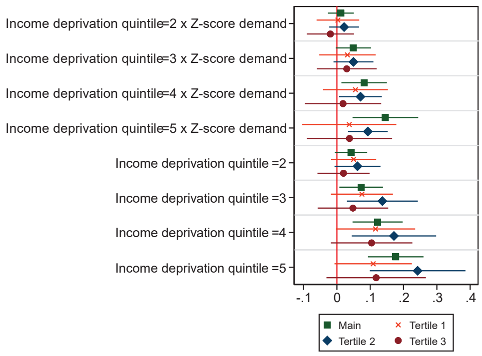
Figure C2: Comparison between main models and analysis by tertile of ED-level share of yearly patients from neighbourhoods in the most deprived quintile of IMD

Deprivation

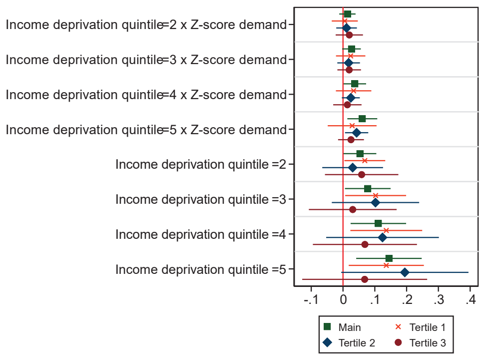
(a) Waiting time



(b) In-order count of patients



(c) Out-of-order count of patients

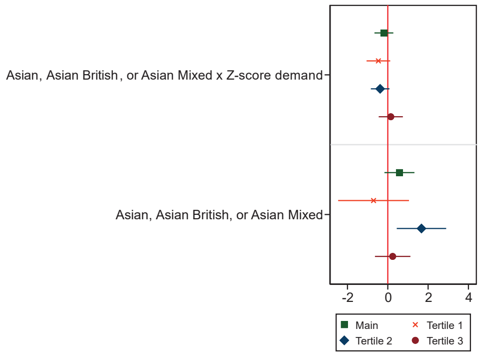


Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2), separately for hospitals in the 1st, 2nd and 3rd tertile of the yearly share of patients from the most deprived quintile of IMD over all visiting patients. Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

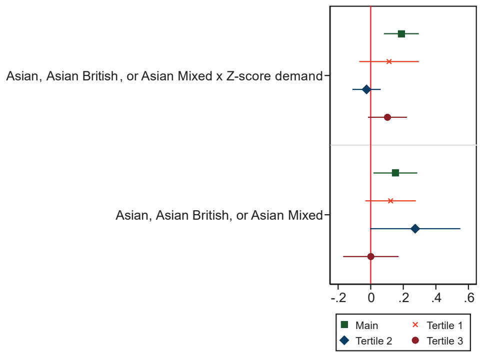
Figure C3: Comparison between main models and analysis by tertile of ED-level share of yearly patients with Asian background

Asian ethnic background

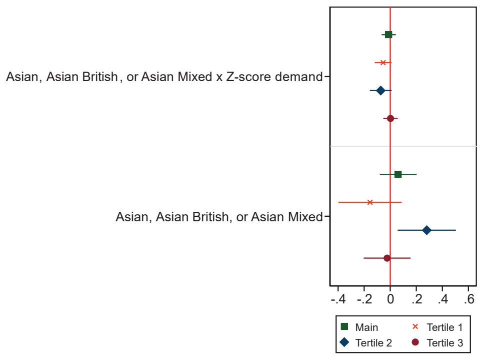
(a) Waiting time



(b) In-order count of patients



(c) Out-of-order count of patients

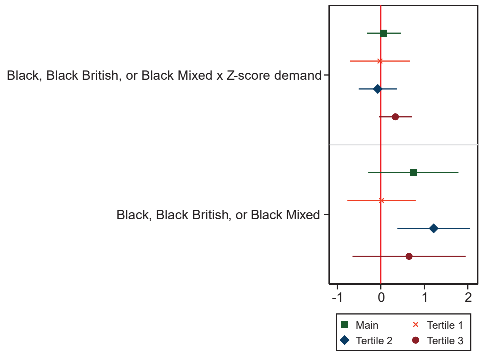


Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2), separately for hospitals in the 1st, 2nd and 3rd tertile of the yearly share of Asian patients over all visiting patients. Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

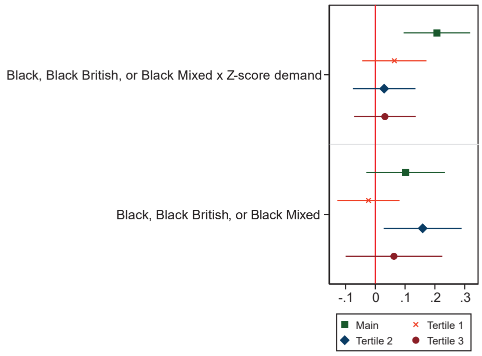
Figure C3: Comparison between main models and analysis by tertile of ED-level share of yearly patients with Black background

Black ethnic background

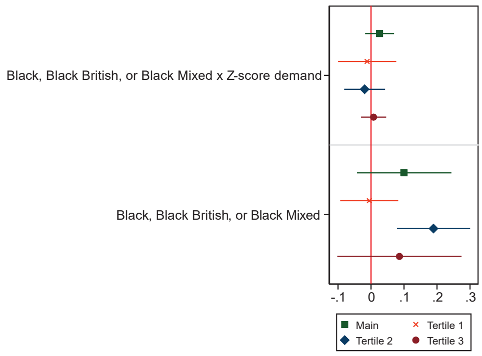
(a) Waiting time



(b) In-order wait



(c) Out-of-order wait



Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2), separately for hospitals in the 1st, 2nd and 3rd tertile of the yearly share of Black patients over all visiting patients. Covariates included in the model are: age, ethnic background (White, Asian, Black, Chinese/Other/Mixed or Missing; throughout the analyses we omit the dummy for White, the most prevalent category and our reference group), quintile of the income-component of the Index of Multiple Deprivation for the patient's area of residence (we use dummies and omit the least deprived quintile, setting it as reference group), type of incident leading to the attendance (road traffic accident, assault, self-harm, sports accident, other accidents, unknown; we use the most prevalent group – "other" – as reference), combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other; we use ambulance referrals from an emergency service as the omitted reference group), month (we use July as the omitted month of reference), day of the week (we use Thursday as the omitted day of reference), time of day (we use 5am as the omitted reference group), and primary ED diagnosis (a set of 41 dummies outlined in Appendix A; we use "Burns and scalds" as the omitted reference group). t statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.