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 11.2M 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; queueing, waiting time; urgent care; equity.

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Introduction

In many healthcare settings, patients join queues to wait for assessment or treatment. Healthcare staff manage these queues dynamically by prioritising patients. In health systems where access to care is universal and grounded on a principle of equal treatment for equal need, the prioritisation process should reflect only differences in clinical urgency and severity. Hence, for a given level of patient severity, factors such as ethnicity, socioeconomic status, or gender should therefore not determine the decisions of staff to prioritise one patient over another (Gravelle, Morris, and Sutton 2012). However, in practice the prioritisation process generates the potential for re-ordering of patients based also on non-clinical patient characteristics, which could contribute to creating or reinforcing inequalities in health and healthcare. The process of prioritising patients becomes increasingly necessary when the hospitals are busy, generating more opportunities for potentially unjust re-ordering (Weber 2019).

The emergency department (ED) waiting room offers a relevant setting to study this prioritisation process. Patients arrive unscheduled 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). When queues form in EDs, clinicians must choose who to treat first. Demand for emergency care services has increased sharply in recent decades in several high-income countries (Berchet 2015). The rise in demand has not been matched by increases in supply, resulting in growing waiting times in many settings including in England (Boyle 2023), Italy (Vainieri, Panero, and Coletta 2020) and America (Hsia et al. 2023). Concerns have been raised that detrimental effects of this growing strain on EDs are likely to disproportionately affect those from deprived and minority backgrounds, whose primary source of care is often the ED (The King's Fund 2022).

In this paper, we investigate how patients are prioritised by healthcare staff in a high-pressure working environment where delays may be most important for health outcomes: emergency department queues. We exploit plausibly exogenous demand shocks that we measure with changes in daily attendances. Such shocks trigger reprioritisation of patients queuing in the ED, and allow us to identify potential inequalities based on three non-need patient characteristics: ethnic background, biological sex, and socioeconomic status proxied by neighbourhood-level income deprivation.

To examine this prioritisation process, we calculate how many other patients are seen from the queue while each patient is waiting. This variable represents the rank order in which patients were attended to after their arrival. Since this should reflect patient severity, which we can measure only partially, we consider the effects of plausibly exogenous daily demand shocks. We do this by employing a feasible linear estimator to efficiently partial out 11,340 fixed effects representing ED-specific seasonality by month and day-of-the-week. We study whether patients living in more deprived neighbourhoods, those from minority ethnic backgrounds, and females, are prioritised or deprioritised when EDs face these 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 inequalities disadvantageous to these patient groups. Compared to patients from a White background[1], we find that following initial assessment Asian patients face about 0.41 additional patients in front of them in the queue for treatment (or, equivalently, 2 more patients for every 5 joining the queue), whilst Black patients have 1 more patient in front of them every 3 joining this queue. Compared to patients from the most affluent neighbourhoods, patients from neighbourhoods in the poorest quintile have 1 more patient in front of them for every 4 joining this second queue. We also find smaller but still statistically significant differences by biological sex, with women falling slightly behind in the queue. The patterns of inequalities are analogous but more compressed when looking at patients in the shorter, first queue between arrival and initial assessment.

We further unpack the mechanisms behind this de-prioritisation by decomposing the effect into two contributions. The first is the number of patients who joined the queue after a patient arrives but are seen before the same patient is attended to, which we refer to as the number of patients who "move ahead" in the queue. The second measures the index patient's failure to be prioritised before others in the queue. We capture this by measuring the number of patients who were in the queue at the time of patient arrival and "remain ahead". Our empirical findings show that the small observed inequalities are due to patients from ethnic minority (or deprived) groups having more White (or affluent) patients "remaining ahead" of them in the queue. We do not find evidence of patients "moving ahead". In simpler terms, consider a patient from an ethnic minority who arrives at the ED. On average, this patient will be seen later and more patients will be attended beforehand relative to a White patient. This delay does not arise

[1] We follow this style guide when writing about ethnicity: https://www.ethnicity-facts-figures.service.gov.uk/style-guide/writing-about-ethnicity/

because new patients arrive in the ED and are attended earlier, but because White patients who were already in the queue are seen earlier. This could reflect for example communication barriers, different tolerance levels to pain or other cultural differences while waiting in the ED room. Our large battery of robustness checks supports the validity of our main findings.

We also explore the potential drivers for the differences by running analyses stratified by the shares of non-native English speakers attending each hospital. The results of these explorative analyses suggest that language barriers may explain the differences in ED prioritisation.

Finally, focusing on mortality within 30 days and ED reattendance within 7 days, we find no evidence that these prioritisation inequalities are detrimental for health outcomes.

We make three contributions to the literature. First, we propose a new measure of patient prioritisation that focuses on the reordering of patients in a queue. This adds to the substantial strand of literature focused on 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) (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, this existing literature does not analyse the dynamics of the queue at patient-level. It therefore fails to unpack the prioritisation that may happen while patients are queueing and how these (re)prioritisation decisions contribute to the distribution of waiting times.

Second, we use a causal framework to test for socioeconomic inequalities in access, where we exploit shocks in demand to quantify the effect on prioritisation across different groups while controlling for unobserved factors (e.g. differences in severity, thresholds for seeking care, or differential opportunities to access care).

Third, we focus specifically on ethnic inequalities in healthcare, which has received less attention relative to income-related inequalities, especially in the setting of the English NHS (Nazroo et al. 2009). Disparities in 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). Some recent literature in the U.S. and South East Asia has focus on identifying causal estimates of the effect of race/ethnicity concordance on treatments and outcomes of patients in preventative, maternity and emergency

care (Corredor-Waldron, Currie, and Schnell 2024; Hill, Jones, and Woodworth 2023; Ye and Yi 2023; Alsan, Garrick, and Graziani 2019; Greenwood et al. 2020). Compared to these studies, the English NHS offers a setting where access to care is free from financial barriers and egalitarian by construction.

Health and care inequalities based on gender have also been documented. 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 (Cabral and Dillender 2024) find that gender disparities disadvantaging women are largely explained by the gender-match between patients and doctors. However, causal evidence linking these patterns to prioritisation in ED settings remains limited.

Institutional setting

In the English NHS, emergency care is free at the point of use, funded through taxation. There are therefore no barriers to access due to insurance coverage or lack of ability to pay.

During the time period captured in our data, English hospitals were reimbursed retrospectively for each ED attendance based on 11 healthcare resource groups (HRGs). HRGs are set to provide higher reimbursement for attendances involving more resource-intensive investigations and treatments (Parkinson, Meacock, and Sutton 2019). Staffing and infrastructural constraints for specific ED are determined by those of the corresponding NHS Trusts (R. Jones 2010), as well as availability of trained staff in the local labour market (Propper and Van Reenen 2010).

Our focus is on large EDs (known as "Type 1" in England). These are 24-hour multi-specialty consultant-led departments with full resuscitation facilities accounting for 99% of all emergency admissions via ED. Patients attending a Type 1 ED and not arriving by ambulance are required to register at reception, provide personal information and explain the reason for attending. Registration is followed by a triaging process; this entails an initial assessment performed by either a medic or a nursing professional, and aims to assign a level of priority for the patient. According to national guidelines, triage may require a brief check of the patients' medical history, and the assessment of pain and early warning scores and vital signs (Department of Health 2010). For patients arriving at the ED by ambulance, the triage assessment is typically performed in advance by ambulance staff. 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).

After triage, patients who do not proceed immediately to treatment join virtual queues and wait to be attended by a senior clinician. Providers may decide to re-order or re-prioritise the queue of patients they face, for example in response to unplanned shifts in demand. Whilst initial screening and triaging happens for all patients visiting an ED, re-ordering patients involves an effort for ED staff. When seen, patient may undergo a series of investigations to aid diagnosis (e.g., via blood tests and X-rays), before eventually being delivered a treatment, if needed (Department of Health 2010). Finally, upon completing investigations and required treatments, a senior clinician defines the type of discharge destination for the patient, choosing between: admission for inpatient care, discharge either with no follow-up or with follow-up by GPs in primary care, transfer to another provider for additional treatment, or referral for less urgent treatment to an outpatient clinic or another provider.

Patients can decide to leave the ED before being assessed or treated, or may refuse the offered treatment. Walk-outs are often linked to lengthy waits (Turner et al. 2020). In the time frame captured in our data, English EDs followed an operational standard requiring them to conclude attendances for 95% of patients within four hours of arrival. Breaches of this four-hour target and longer waiting times caused by crowding have been found to harm patients' health, including evidence of increased mortality (Gruber, Hoe, and Stoye 2023; Guttmann et al. 2011; S. Jones et al. 2022).

Data

Data sources

Our main source of data are the attendance records of all 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. Crucially for our study, HES contains detailed time stamps for key stages in the ED treatment pathway, including arrival time, initial assessment time and treatment initiation time.

These HES attendance records also contain an extensive range of information about patients, including the hospital site, diagnostic procedures codes, and a comprehensive set of demographic information, including age and biological sex. Ethnic background is recorded across 16 categories. For consistency with ethnicity recording adopted by the Office of

National Statistics, we recoded ethnicity to four large groups: White, Black, Asian and Mixed/other ethnicity. We code patients with missing or non-stated ethnicity as a fifth separate group (see Appendix A for further details). HES does not include individual level socioeconomic information. We therefore measure socioeconomic status using granular data on neighbourhood-level deprivation using the income-specific component of the English Index of Multiple Deprivation, as in exiting studies (Gaynor, Propper, and Seiler 2016; Turner et al. 2022). Neighbourhoods are defined as Lower-layer Super-Output Areas containing 1,500 people on average. This neighbourhood income variable represents the proportion of households receiving social welfare benefits and/or tax credits because of low income. We classified neighbourhoods into deprivation quintiles.

We focus on data for between 11.2M and 12.7M patients (depending on the analysis) visiting 135 EDs in England between 1st April 2017 and 31st March 2018. This period is interesting because it is not affected by the disruptions caused by the COVID-19 pandemic, and 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 patients attending Type 2 and Type 3 EDs tend to be less urgent. We excluded attendances of patients who were dead upon arrival, and planned follow-up attendances as these do not represent unexpected demand and may therefore be prioritised differently. If the same patient attended any ED more than once in the same day, we included only the first attendance.

We further excluded attendances with outlier or implausible recorded values for the relevant waiting times by trimming observations with values larger than the 99th percentile. The few excluded values were mostly at the maximum value allowed in the data-entry system (i.e. 1,439 minutes), which we recoded to 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 the time each patient arrives at the ED and their ranking in the queue upon arrival. We can also see the time each patient is (1) first assessed, (2) starts treatment, and (3) is discharged, or (4) leaves the ED before receiving treatment. The time variables in the attendance records are defined as follows. The *arrival time* is defined as the time when a patient self-presented or arrived in an ambulance at the ED. The *initial assessment time* is defined as the time when a patient is first assessed by medical or nursing staff in the ED to determine priority and type of treatment required. The *treatment initiation time* is the 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

The simplest way to define the level of queue priority assigned to a patient is the number of patients seen between the time the patient joins a queue and when they leave the queue. We look at two queues along the patient pathway. The first is the queue from arrival in the ED to the initial assessment. The second queue is from initial assessment to treatment initiation.

More formally, for each patient *i* we define R_i as the number of patients seen between time t_i^a when patient *i* joins a queue in the ED and time t_i^s when patient *i* leaves that queue. We then divide R_i into two components. First, whilst waiting in the queue, some patients may arrive at the ED after the index patient and move ahead of the them in the queue, therefore succeeding in being prioritised over the index patient due to patient re-prioritisation. Let us define N_i^M as the number of patients who arrived after the index patient *i* but who were served before patient *i*. We refer to this group as patients who 'moved ahead' in the queue (hence the superscript *M*).

Second, 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 the queue. Unless some reordering of patients takes place, these patients are naturally seen before the index patient. Let us define N_i^S as the number of patients who arrive before the index patient and that patient *i* does not manage to move ahead of. We refer to this group as the number of patients who 'stayed ahead' (hence the superscript *S)*.

The mapping between these prioritisation variables is a simple identity:

$$R_i = N^M{}_i + N^S{}_i. \quad (1)$$

Whether prioritisation of patients over the index patient *i* 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 more or less 'moved ahead' or 'stayed ahead' patients will influence their order in the queue.

Figure 1: Example of waiting time decomposition and prioritisation variables

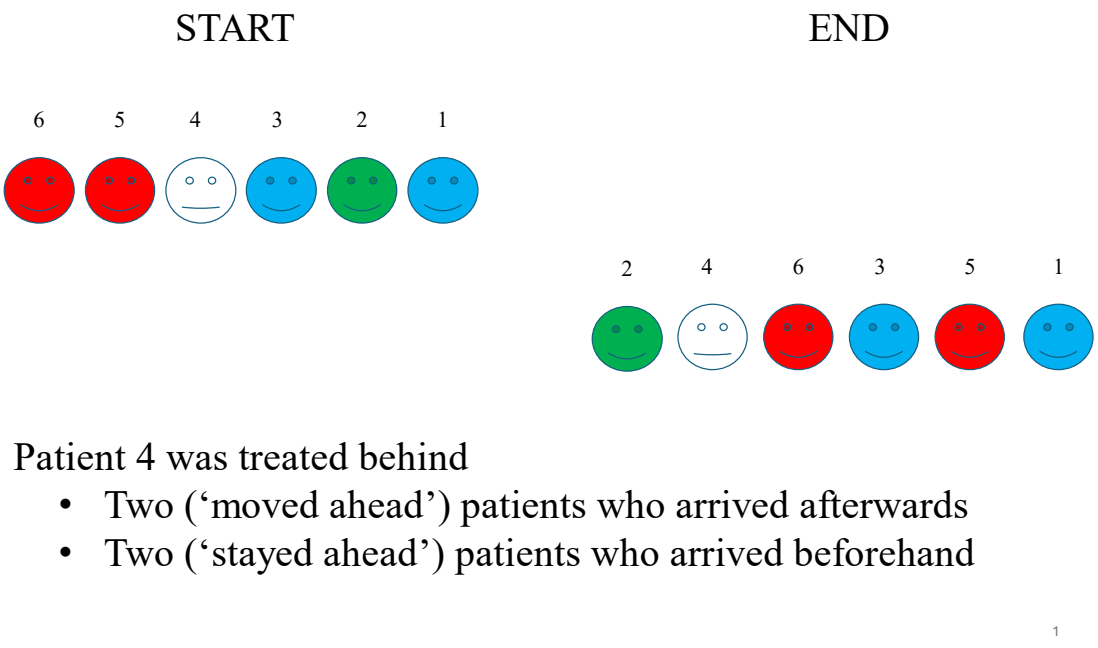


Figure 1 illustrates with a simple example the concepts of counting the number of patients who 'moved ahead' and who 'stayed ahead'. Our index patient is ranked 4 at arrival. When they arrive at the ED and start waiting, they have three patients ahead of them in the queue (1, 2 and 3). Two patients arrive shortly after (5 and 6). The final order in which these patients are seen by a healthcare provider 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 them. 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 they were seen, which gives our key measure $R_i = 4$. Two of these patients (5 and 6) arrived after the index patient but were prioritised and 'moved ahead' in the queue, so that $N^M{}_i = 2$. Two patients (1 and 3) had arrived before the index patient at the ED and 'stayed ahead' of the index patient, so that $N^S{}_i = 2$.

In summary, for each patient we construct three different dependent variables measuring their prioritisation. We focus mainly on the queue from initial assessment to start of treatment

because this longer period offers more scope for re-prioritisation. For this queue we define: i) the number of other patients starting treatment before patient *i* after patient *i* had been assessed, R_i; ii) the number of patients who 'moved ahead', N_i^M, and iii) the number of patients who 'stayed ahead', N_i^S. We obtain analogous measures for the first queue (from arrival to initial assessment).

Methods

Baseline specification

Our main goal is to study whether EDs – when presented the opportunity to reorder patients by changes in demand - prioritise patients based on three non-need characteristics: ethnic background, neighbourhood deprivation, and biological sex. We examine this conditional on other observables that may legitimately determine triage-based prioritisation (e.g. age, health condition, arrival mode). However, patients may also differ in unobservable clinical urgency patterned by the non-need characteristics. By focusing on orthogonal demand shocks as triggers for reordering, we circumvent this potential source of confounding.

Our baseline specification is:

$$y_{iht}^{p} = \delta\, Demand_{ht} + \psi\, Inequality_{it} + \gamma\, (Demand_{ht} \times Inequality_{it}) + Patient_{it}'\beta + Attendance_{iht}'\omega + \alpha_{it} + \varepsilon_{iht} \quad (2)$$

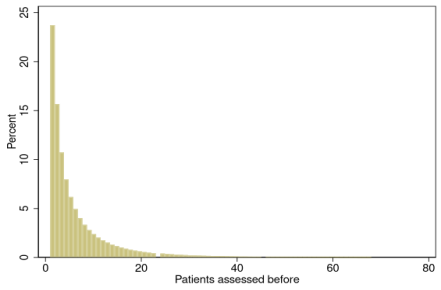
where y_{iht}^{p} is the prioritisation outcome of interest for patient *i*, in ED *h* on day *t*. We estimate model (2) for two separate queues: a) waiting for initial assessment after arrival, and b) waiting for treatment after initial assessment. For each queue, we explore *p=3* different outcomes $y^{p}{}_{iht}$: (i) number of patients being served while patient *i* is in the queue, R_i, (ii) number of patients who moved ahead of patient *i* in the queue $N^{M}{}_{i}$; and (iii) number of patients who stayed ahead of patient *i* in the queue $N^{S}{}_{i}$. Figure ***2*** shows the distributions of the of R_i for the two queues we study.

$Patient_{it}$ is a vector of observable patient characteristics including age (coded to five-year bands), the number of previous ED attendances in 12 months prior to the attendance day, number of emergency admissions in the previous year, and the sum of Elixhauser comorbidities (Gutacker, Bloor, and Cookson 2015) based on inpatient visits in the previous 12 months. $Attendance_{iht}$ is a vector of characteristics of patient *i*'s attendance at ED *h* on day *t*, including indicators for the type of incident leading to the attendance (road traffic accident, assault, self-

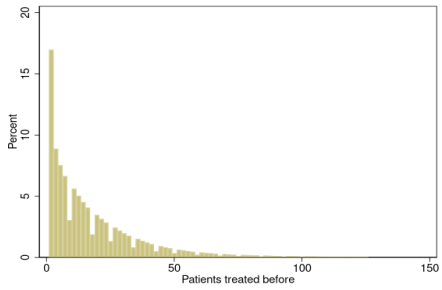
harm, sports accident, other accidents, unknown), indicators for combinations of referral and arrival mode (i.e. whether the patient arrived by ambulance or not, and whether they were self-referred or sent by a GP, emergency service, police, healthcare provider, or other), time of day of the attendance, and 41 indicators for primary ED diagnosis (provided in Appendix A).

Figure 2: Distribution of key dependent variables

a) Patients seen before *i* in the queue for initial assessment



b) Patients treated before *i* in the queue between assessment and treatment



The key coefficients of interest are γ, on the interactions 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). We initially consider our dimensions of inequality individually, running separate models focusing on each. Later in the paper, we consider the potential intersectional nature of inequality by sex and ethnicity.

The interpretation of γ depends on the outcome variable. For the count variables, the coefficient represents the average differences – for a one standard deviation (SD) change in unexpected demand – attributable to the inequality dimension of interest (e.g. having a Black compared to a White ethnic background). For R_i, a positive coefficient represents the additional number of patients seen before patient *i* in the queue. For $N^M{}_i$, a positive coefficient represents the success of other patients who arrived after the index patient to be prioritised and move ahead in the queue. For $N^S{}_i$, a positive coefficient represents the inability of the index patient to be prioritised over other patients who stay ahead in the queue when the index patient arrives at the ED. Notably, all our measures are increasing in de-prioritisation. The interpretation of ψ is analogous, but relates to baseline differences and not to differences associated with 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 $Inequality_{it}$.

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 is because EDs are required to accept all attending patients, who arrive unscheduled and receive healthcare free at point of use. The nature of emergency care makes patient selection into a specific hospital very unlikely, especially for urgent circumstances. This is 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, and Monday evenings are typically less busy than Friday evenings. The volume of attendances faced by an ED in a coastal town is 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. 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 ψ and 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. 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 staffing shifts throughout the year (Graff and Radford 1990), which we use to proxy variation in staffing in the absence of more refined workforce data. We operationalise the seasonal component with a set of fully interacted fixed effects for $135\ EDs \times 12\ months \times 7\ days = 11{,}340$, 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 and γ avoiding the potential endogeneity due to α_{it}. 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.

Figure 3: Distribution of unexpected demand and residual variation in prioritisation measures

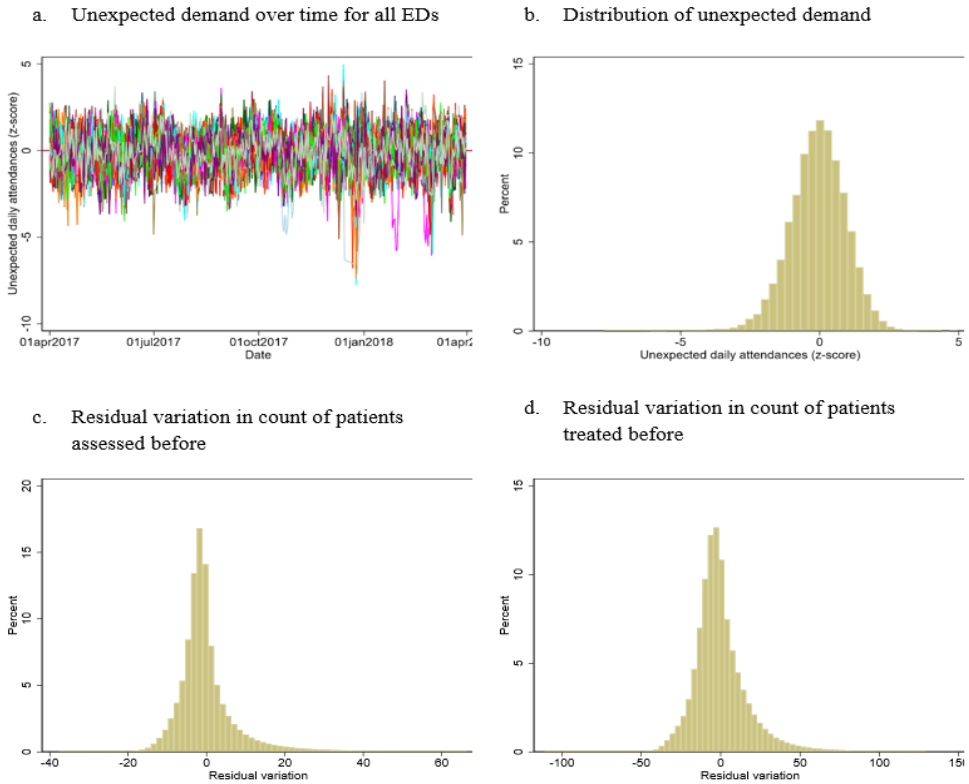


Figure *3* shows the distribution of our measure of unexpected demand (i.e. the residual variability in z-score normalised daily ED demand after partialling out ED-specific seasonality), and the residual variability in our main prioritisation measures. One standard deviation in our unexpected demand measure is equivalent to approximately 24 unexpected daily attendances, or 6.7 percent of the average attendance volumes of 365 per day.

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 comprehensive 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. In the robustness checks section, we provide evidence to support this claim.

The estimation of an extended version of equation (2) including 11,340 dummy variables capturing ED-specific seasonality 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 other recent literature (Francetic, Meacock, and Sutton 2024; Hoe 2022; Turner et al. 2020). Our inference is based on standard errors clustered at ED-level (Abadie et al. 2023).

Heterogeneity analysis and health outcomes

We complement our main approach with three additional sets of analyses, which we expand on in the relevant section below.

First, to explore mechanisms for our findings, we provide tentative evidence on the mediating role of language barriers by running separate analyses for subsamples defined by the share of the neighbourhood population not speaking English.

Second, we explore the potential intersectional nature of ethnic and sex inequalities by estimating models stratified by biological sex.

Third, we explore whether patient health outcomes are affected by prioritisation by examining three outcomes: waiting time in minutes, mortality within 30-days of the attendance; and an unplanned second attendance at an emergency department within 7-days. We run reduced form models that mimic our baseline specification, replacing the prioritisation measures as dependent variables with the measures of patient outcomes.

Results

Table 1 provides descriptive statistics for our core sample (see Appendix A for a full table of descriptive statistics, including a detailed list and distribution of primary ED diagnoses). Our main focus is on the interval between initial assessment and treatment initiation. In this queue, patients wait for treatment behind approximately 17 other patients on average, 10 of whom have stayed ahead and six who have moved ahead. Our secondary focus is on the interval between arrival and initial assessment. During this period, typically five other patients are assessed by healthcare staff, including three who stayed ahead in the queue and two who are prioritised and move ahead.

The patients in our sample are divided equally between males and females, and have an average age of 41 years. In our core sample, one quarter of patients are from ethnic minority groups or did not report their ethnic background. Seven percent of patients are from an Asian background, 4% have Black backgrounds, and 4.2% have other or mixed backgrounds. 50.9% of patients live in areas in the two most deprived quintiles of income deprivation.

The first column of **Table 2** reports our main results. A one-SD increase in unexpected daily demand adds 2.8 other patients in front of each patient in the queue on average (about 15 percent relative to the mean).

There are no systematic baseline differences in prioritisation between patients with White and other ethnic backgrounds. However, the reordering of patients in response to unexpected demand disadvantages ethnic minorities compared to White patients. Compared to patients with White background, Asian patients have about 0.41 additional patients in front of them in

the queue or, equivalently, 2 in every 5 Asian patients joining the queue face an additional patient in front of them. Similarly, 1 in every 3 Black patients joining the queue will have an additional patient in front of them.

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

	Mean	SD
Time to assessment		
Count of patient seen before i (R_i)	5.365	7.8
Moved ahead patients (N_i^M)	2.146	4.56
Stayed ahead patients (N_i^S)	3.218	4.14
Time from assessment to treatment		
Count of patient treated before i (R_i)	17.782	18.4
Moved ahead patients (N_i^M)	6.209	9.86
Stayed ahead patients (N_i^S)	10.572	10.5
Ethnic background		
White	0.744	
Asian	0.069	
Black	0.039	
Other and Mixed	0.042	
Not stated or Missing	0.106	
Deprivation quintile		
Least deprived	0.144	
2	0.165	
3	0.183	
4	0.221	
Most deprived	0.288	
Female	0.506	
Age (years)	41.337	27.4
Nr. of emergency admissions in past year	0.717	2.03
Nr. of ED attendances in past year	0.925	4.01
Daily attendances	365.033	171
Unexpected daily attendances	-0.230	23.9
Z-score demand	-0.007	.996
Observations	11,049,931	

We find a gradient in relation to neighbourhood income deprivation with patients from more deprived neighbourhoods (quintiles 3-5) having on average more patients ahead of them in the queue compared to patients from the most affluent neighbourhoods. Our coefficient of interest confirms this pattern of inequality also in response to unexpected shifts in demand. For a one-SD increase in daily demand, one in every four patients from the most deprived neighbourhoods who join the queue at times of higher unexpected demand face an additional patient in front of them being treated before they are, compared to patients from the most affluent neighbourhoods.

Our analysis also shows that females are generally disadvantaged in ED queue prioritisation. Compared to males, one in every two female patients who joins the queue tends to wait behind

one more patient. This gap increases slightly in response to unexpected demand; one in every ten females joining the queue waits behind one more patient, compared to males.

Columns (2) and (3) in **Table 2** decompose the findings for the overall prioritisation measure into the patients who moved ahead in the queue and those who stayed ahead. We find that prioritisation inequalities by ethnic background are twice as large in terms of patients staying ahead in the queue as opposed to patients jumping ahead in the queue. Focusing on neighbourhood income deprivation, inequalities to the disadvantage of quintiles 4 and 5 are positive and significant (compared to quintile 1) in terms of both patients moving ahead and patients staying ahead, with the latter being a larger contribution to the total (about 1.5 times bigger). The inequalities by biological sex are equally distributed between other patients moving ahead and other patients staying ahead in the queue. The results for the initial queue between patient arrival and initial assessment are reported in **Table 3**. A one-SD change in unexpected demand adds on average one other patient in front of each person in the queue. Overall, compared to **Table 2**, we find similar but attenuated patterns. In this first queue, differences in prioritisation by area deprivation in response to unexpected demand are only evidence for the most deprived quintile.

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 2: Effect of unexpected demand on prioritisation between initial assessment and treatment by area deprivation quintile, sex, and ethnicity

	(1) Count of patients seen before (R_i)	(2) Moved ahead patients (N_i^M)	(3) Stayed ahead patients (N_i^S)
Model A: Ethnic group (reference: White)			
Unexpected demand	2.821***	0.922***	1.852***
	(19.61)	(19.65)	(20.20)
Asian, Asian British, or Asian Mixed	0.197	0.0536	0.118
	(0.88)	(0.44)	(1.23)
Black, Black British, or Black Mixed	0.291	0.144	0.137
	(1.52)	(1.34)	(1.44)
Other, or Other Mixed	0.103	0.0329	0.0678
	(0.71)	(0.43)	(1.06)
Not stated/missing	-0.152	-0.0725	-0.0816
	(-1.46)	(-1.39)	(-1.59)
Asian, Asian British, or Asian Mixed # Z-score demand	0.414***	0.103*	0.271***
	(4.19)	(2.22)	(4.23)
Black, Black British, or Black Mixed # Z-score demand	0.368***	0.101**	0.242***
	(3.81)	(2.65)	(4.04)
Other, or Other Mixed # Z-score demand	0.240**	0.0470	0.155***
	(3.24)	(1.45)	(4.07)
Not stated/missing # Z-score demand	-0.0758	-0.0208	-0.0464
	(-1.48)	(-1.19)	(-1.23)
r2	0.345	0.169	0.415
Model B: IMD quintiles (reference: Least deprived)			
Unexpected demand	2.728***	0.877***	1.798***
	(17.08)	(17.70)	(18.82)
Income deprivation quintile=2	0.141	0.0792	0.0567
	(1.89)	(1.93)	(1.89)
Income deprivation quintile=3	0.213*	0.117*	0.0954*
	(2.33)	(2.28)	(2.42)
Income deprivation quintile=4	0.319*	0.164*	0.158**
	(2.49)	(2.22)	(2.97)
Income deprivation quintile=5	0.347*	0.165	0.190**
	(2.34)	(1.92)	(3.06)
Income deprivation quintile=2 x Demand	0.0171	0.0123	0.0107
	(0.40)	(0.89)	(0.46)
Income deprivation quintile=3 x Demand	0.0897	0.0347	0.0526
	(1.68)	(1.89)	(1.71)
Income deprivation quintile=4 x Demand	0.169*	0.0676**	0.102*
	(2.57)	(2.93)	(2.54)
Income deprivation quintile=5 x Demand	0.287**	0.112***	0.175**
	(2.99)	(3.76)	(2.98)
r2	0.345	0.169	0.415
Model C: Biological sex (reference: Male)			
Unexpected demand	2.811***	0.906***	1.852***
	(19.25)	(18.75)	(20.05)
Female	0.108***	0.0521***	0.0568***
	(7.01)	(5.60)	(8.11)
Female=1 x Demand	0.413***	0.210***	0.203***
	(10.96)	(10.25)	(11.43)
r2	0.345	0.169	0.415
Outcome sample average	18.53	6.352	10.75
N	11203320	11203303	11207321

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 (in 5y bands), 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 for initial assessment by area deprivation quintile, sex, and ethnicity

	(1) Count of patients seen before (R_i)	(2) Moved ahead patients (N_i^M)	(3) Stayed ahead patients (N_i^S)
Model A: Ethnic group (reference: White)			
Unexpected demand	1.015***	0.379***	0.617***
	(18.97)	(20.18)	(16.97)
Asian, Asian British, or Asian Mixed	0.145	0.0695	0.0462
	(1.53)	(1.01)	(1.32)
Black, Black British, or Black Mixed	0.0330	0.0400	0.00741
	(0.32)	(0.63)	(0.24)
Other, or Other Mixed	-0.0298	-0.00812	-0.0130
	(-0.30)	(-0.14)	(-0.38)
Not stated/missing	-0.111	-0.0551	-0.0657**
	(-1.88)	(-1.56)	(-2.66)
Asian, Asian British, or Asian Mixed # Z-score demand	0.224**	0.0697***	0.133***
	(3.29)	(3.58)	(3.50)
Black, Black British, or Black Mixed # Z-score demand	0.126	0.0276	0.0903*
	(1.98)	(0.98)	(2.51)
Other, or Other Mixed # Z-score demand	0.128***	0.0348*	0.0760***
	(3.58)	(2.43)	(3.47)
Not stated/missing # Z-score demand	0.0202	0.0123	0.0107
	(0.73)	(1.01)	(0.64)
r2	0.324	0.163	0.424
Model B: IMD quintiles (reference: Least deprived)			
Unexpected demand	1.012***	0.383***	0.609***
	(18.86)	(18.80)	(17.15)
Income deprivation quintile=2	0.0343	0.0246	0.0103
	(0.75)	(0.79)	(0.75)
Income deprivation quintile=3	0.0816	0.0529	0.0284
	(1.29)	(1.24)	(1.47)
Income deprivation quintile=4	0.0668	0.0467	0.0206
	(0.92)	(0.95)	(0.97)
Income deprivation quintile=5	0.0975	0.0539	0.0389
	(1.00)	(0.80)	(1.37)
Income deprivation quintile=2 x Demand	-0.0131	-0.00978	-0.00444
	(-0.79)	(-1.17)	(-0.50)
Income deprivation quintile=3 x Demand	0.00894	0.000140	0.0106
	(0.46)	(0.02)	(0.90)
Income deprivation quintile=4 x Demand	0.0286	0.00149	0.0304
	(1.04)	(0.13)	(1.64)
Income deprivation quintile=5 x Demand	0.0906*	0.0221	0.0597*
	(2.02)	(1.16)	(2.42)
r2	0.324	0.163	0.424
Model C: Biological sex (reference: Male)			
Unexpected demand	1.021***	0.379***	0.621***
	(18.66)	(20.28)	(16.61)
Female	0.112***	0.0528***	0.0541***
	(6.63)	(5.94)	(7.25)
Female=1 x Demand	0.0436***	0.0175***	0.0254***
	(6.04)	(4.56)	(6.66)
r2	0.324	0.163	0.424
Outcome sample average	6.097	2.465	3.502
N	12779238	12783829	12783475

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 (in 5y bands), 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 4: Balancing regressions

	Daily attendance (z-score)	*t-stat*	R-squared
Ethnic group:			
White	-0.000105	(-0.43)	0.168
Asian	0.0000205	(0.16)	0.101
Black	0.000155	(1.89)	0.0851
Other	0.000359***	(3.61)	0.0415
Not stated/missing	-0.000429*	(-1.98)	0.168
IMD quintile			
Least deprived	0.000210	(1.60)	0.0854
2	-0.0000871	(-0.51)	0.0338
3	-0.000236	(-1.40)	0.0257
4	0.000208	(1.21)	0.0291
Most deprived	-0.0000950	(-0.50)	0.139
Female	0.000303	(-1.28)	0.00168

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. N=13336962. 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, whereas the main effects of the inequality dimensions are affected, the effects of the interactions between unexpected demand and the inequality dimensions are fully consistent when models are estimated with and without detailed patient and attendance controls. This provides further support to our reliance on the interactions with unexpected demand as evidence of prioritisation.

Fourth, our approach uses plausibly exogenous demand shifts to measure patterns of inequalities in unplanned prioritisation. However, this does not remove the risk of model misspecification. Following (Feigenberg, Ost, and Qureshi 2023), we assess the extent of omitted variable bias due to not accounting for differential effects of the controls across the inequality dimensions of interest. We do so by estimating an extended model fully interacting the inequality dimensions of interest with all covariates included in the main model.

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

In Appendix B (**Figure B2**) we report estimates of δ and γ from the standard model in equation (2) and $\tilde{\delta}$ and $\tilde{\gamma}$ from the extended model in (3) including interactions between $Inequality_{it}$ and all covariates included in the same table. This allows direct comparisons of the relative sizes of the coefficients. The differential effects of unexpected demand on prioritisation by dimensions of inequality are stable whether or not we include interactions between inequality

dimensions and all other covariates included in the model. The results do not therefore suffer from omitted variable bias.

Fifth, our preferred specifications control for age and ambulance arrival, which are two predictors of high patient priority. Regarding age, infants and children are systematically prioritised over adults and elderly (see Appendix A). We show in **Figure B4** that our results are unchanged when we exclude infants and children. Regarding mode of arrival, ambulance patients are more urgent on average and are put in a different queue compared to patients arriving autonomously. To examine whether our inequality results apply to both modes of arrival, we repeat our analyses separating patients who arrive by ambulance and those that arrive autonomously. The results in Appendix B (**Figure B3**) suggest that differences in patient priority by ethnic background and neighbourhood income deprivation are smaller but broadly consistent for patients arriving by ambulance.

To further reduce concerns of unobserved severity across ethnic groups (e.g. ethnic minorities visit EDs for systematically less urgent conditions), we propose one additional analysis. We select patients whose primary diagnoses with a balanced prevalence and similarly low mortality between White and minority ethnic groups (see Appendix C). In our case, these are Sprain/ligament injury, Muscle/tendon injury, Obstetric conditions, Gynaecological conditions, Ophtalmological conditions, which we pool ensure a sufficiently powered analysis. The results of this sub-sample analysis (see Appendix C) are reassuringly similar to our main findings, suggesting that unobserved severity is unlikely to be driving our findings.

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 from **Table 2**. 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 or 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 B5**). The patterns in our main analysis are mostly unchanged

across 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" – conditions that are arguably easier to diagnose and less urgent than the other two 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.

Heterogeneity and mechanisms

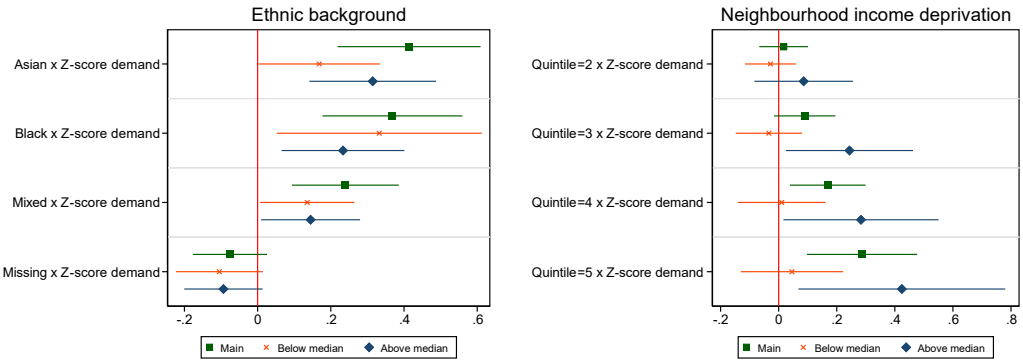
To further unpack the mechanisms behind our results, we conduct three sets of heterogeneity analyses, focusing on the longer queue from assessment to treatment.

First, communication barriers may be one of the channels through which inequalities emerge. Poor English language proficiency may limit the extent to which a patient is able to express the urgency of her condition to staff. Poor language skills are more likely amongst deprived populations (e.g. due to low education attainment) and ethnic minorities (e.g. first generation migrants or second generation but segregated ethnic groups). Our administrative data do not include information on the language skills of patients. However, we conduct an indirect tentative test for this mechanisms by dividing patients based on level of English proficiency in their LSOA of residence, proxied by the share of population reporting English not being their main language. We divide patients based on their neighbourhoods being below and above the median English proficiency. We report the results in panel A of **Figure 4**. For patients who are Asian or from neighbourhoods in the top three quintiles of income-deprivation we find lower coefficients for residents of areas with a higher English proficiency.

Second, our main approach ignores the potential intersectional nature of inequalities across our dimensions of interest. There is evidence that ethnic disparities in healthcare affect females differently than males (Akinade et al. 2023; Lett, Dowshen, and Baker 2020), which would imply a substantial heterogeneity masked behind our estimates. To explore the potential intersectional nature of ethnic and sex inequalities, we estimate stratified models by biological sex of the patients. The results are reported in Appendix D (**Figure D2)**. Although the

magnitudes are marginally larger for females compared to males, the differences are negligible and not statistically significant.

Figure 4: Ethnicity and socioeconomic inequalities
by neighbourhood share of non-English speaking patients



Note: The models were estimated with the feasible estimator developed by Correia (2016) partialling out ED fixed effects and reflect equation (2), stratified by the hospitals below or above the median in the ED population of the relevant statistic. Covariates included in the model are: age (5 year bands), 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Prioritisation and patient health outcomes

Our main and heterogeneity analyses suggest small but significant inequality in the level of prioritisation assigned by ethnic minority, neighbourhood income deprivation and biological sex for patients visiting EDs in England. Previous literature has shown the detrimental health effects of excessively long waiting times in emergency care (Gruber, Hoe, and Stoye 2023; Hill, Jones, and Woodworth 2023; S. Jones et al. 2022). It is therefore natural to ask whether the prioritisation inequalities are linked to worse patient health outcomes.

We estimate reduced form models that mimic our main specification but substitute prioritisation indicators with patient outcomes. We focus on two patient outcomes that we can objectively measure in our data: all causes mortality within 30 days of the ED visit, and ED reattendance within 7 days. To give a sense of the differences in waiting times implied by the prioritisation inequalities, we also show reduced form estimates for the differences in minutes waited in the queue.

Table 5: Reduced form results for patient outcomes

	(1) Waiting time (mins)	(2) 30 days mortality	(3) 7 days re-attendance
Model A: Ethnic group (reference: White)			
Unexpected demand	7.737***	-0.0000462	-0.0000285
	(31.56)	(-0.65)	(-0.54)
Asian, Asian British, or Asian Mixed	0.232	-0.00209***	-0.000394
	(0.33)	(-6.36)	(-1.33)
Black, Black British, or Black Mixed	2.071	-0.00210***	-0.00118**
	(1.08)	(-6.76)	(-3.00)
Other, or Other Mixed	0.0610	-0.000744***	-0.000447
	(0.10)	(-3.95)	(-1.57)
Not stated/missing	-0.990	0.000920**	-0.00287***
	(-1.78)	(2.78)	(-7.23)
Asian, Asian British, or Asian Mixed # Z-score demand	0.204	0.00000511	-0.0000912
	(0.79)	(0.04)	(-0.78)
Black, Black British, or Black Mixed # Z-score demand	-0.201	0.000201	-0.000286
	(-0.49)	(1.45)	(-1.87)
Other, or Other Mixed # Z-score demand	0.00896	-0.0000310	-0.000108
	(0.04)	(-0.25)	(-0.74)
Not stated/missing # Z-score demand	0.0943	0.0000231	-0.0000469
	(0.44)	(0.16)	(-0.39)
r2	0.404	0.0640	0.0180
Model B: IMD quintiles (reference: Least deprived)			
Unexpected demand	7.634***	-0.0000753	-0.0000551
	(26.43)	(-0.56)	(-0.61)
Income deprivation quintile=2	0.489	0.000947***	0.0000223
	(1.56)	(4.83)	(0.10)
Income deprivation quintile=3	1.121	0.00123***	0.0000439
	(1.89)	(6.23)	(0.21)
Income deprivation quintile=4	1.455	0.00165***	0.0000890
	(1.83)	(7.26)	(0.36)
Income deprivation quintile=5	1.560	0.00131***	0.000484
	(1.65)	(5.82)	(1.62)
Income deprivation quintile=2 x Demand	-0.183	0.000120	-0.000156
	(-1.69)	(0.80)	(-1.43)
Income deprivation quintile=3 x Demand	0.0761	-0.0000538	0.0000228
	(0.58)	(-0.36)	(0.21)
Income deprivation quintile=4 x Demand	0.131	-0.0000837	0.0000945
	(0.67)	(-0.54)	(0.79)
Income deprivation quintile=5 x Demand	0.383	0.000163	0.0000103
	(1.82)	(1.05)	(0.09)
r2	0.404	0.0640	0.0180
Model C: Biological sex (reference: Male)			
Unexpected demand	7.664***	-0.000133	-0.0000656
	(31.95)	(-1.90)	(-1.05)
Female	1.597***	-0.00508***	-0.000377***
	(9.97)	(-24.59)	(-4.03)
Female=1 x Demand	0.176*	0.000200*	0.0000249
	(2.55)	(2.57)	(0.38)
r2	0.404	0.0643	0.107
Outcome sample average	81.98	0.0179	0.0127
N	11312273	11203320	10743611

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 the same as those in the main models. *t* statistics in parentheses, standard errors were clustered at the ED level. Stars, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The results are reported in **Table 5** below, focusing on the longer queue between assessment and treatment initiation. The interaction between demand and our inequality dimensions of interest – our key coefficients – are very close to zero and not significant. The only exception is biological sex, where we find a very small mortality difference disadvantaging women (about 1 percent of the baseline mortality rate). A one-SD change in unexpected demand increases the waiting time by about 7 minutes on average. We find no relevant differences between our groups of interest for the waiting time between assessment and treatment initiation. The main coefficients for our inequality dimensions of interest are suggestive of mild patterns of selection. Ethnic minorities and females tend to be positively selected; these groups have lower baseline 30 days mortality. These patterns are fully aligned with ethnic differences in baseline all causes age-standardised mortality (Mirza and Warwick 2024) [2].

Discussion

We have proposed a new measure of prioritisation in health care provision, which counts the number of other patients served while a patient is waiting to be served. We then decomposed this measure into two components, representing the number of patients who joined the queue *after* the index patient but "moved ahead" and those who joined the queue *before* the index patient and "stayed ahead". In a setting where emergency department care is free at the point of use, we examined whether three population groups, defined by neighbourhood deprivation, biological sex or ethnic background, were prioritised differently. Since these populations may differ in unmeasured urgency, we then examined the effect of prioritisation triggered by unexpected demand. We find evidence of systematic prioritisation by these characteristics, mostly generated by patients "staying ahead" rather than "moving ahead" in the queue. This leads to longer waiting times but patient outcomes in the following days are not affected. All robustness checks seem to confirm the validity of our main results.

Focusing on the ethnic disparities, we find a difference in priority for ethnic minority patients (compared to White) of about 1.2 to 2.2 percent. The magnitude of this gap is consistent with estimates from different settings in the literature on differences in care. For example, Ye and Yi (2023) find 2.3 percent longer consultations in emergency departments for race-concordant patient-doctor interactions compared to race-discordant interactions in South East Asia. In the US, Schrader and Lewis (2013) found a 6.4 percent lower triage score given to African

[2] See here: https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/datasets/mortalityfromleadingcausesofdeathbyethnicgroupenglandandwales

American patients in emergency departments, compared to White patients. On the other hand, Lu et al. (2021) find no difference in probability of being assigned lower priority, but waiting times of 6.8 to 36 percent longer (depending on triage category) for ethnic minorities.

There are different possible explanations for our findings. First, there may be communication barriers disadvantaging ethnic minorities in their interactions with staff, resulting in lower priority. For example, first generation ethnic minority migrants whose native language is not English may find it more difficult to express their health problems clearly compared to a White British patient. As a result, these individuals could be systematically assigned a lower priority. Two features in our results point to this as a likely channel. Firstly, our findings are mainly driven by other patients staying ahead of ethnic minority and deprived patients, rather than by people moving ahead of them in the queue. This would be consistent with ethnic minorities and deprived patients being less able to express their urgency or being less assertive, with the result that a greater number of White or affluent patients stay ahead of them in the queue. Secondly, inequalities by income deprivation are most pronounced for patients living in neighbourhoods with a higher than median share of non-native English speakers. The differences are also larger for patients with Asian backgrounds compared to Black or Other/Mixed backgrounds. People with Asian backgrounds are least likely to be native English speakers and most likely to have poor English language skills[3]. Language barriers have been suggested as probable drivers of inequalities in other recent work on emergency care (Ye and Yi 2023; Hill, Jones, and Woodworth 2023).

A second interpretation of our result relates to possible mismatch between ethnic backgrounds of patient and healthcare professional. A growing body of literature points to match between patient and provider characteristics such as gender and ethnic background as a driver for disparities in treatment and patient outcomes (Cabral and Dillender 2024; Hill, Jones, and Woodworth 2023; Ye and Yi 2023; Greenwood et al. 2020; Alsan, Garrick, and Graziani 2019). We do not have data on the characteristics of staff in emergency departments to unpack the role of such patient-provider mismatches. Unfortunately, we could not explore this mechanism.

A third possible interpretation relates to direct patient discrimination based on ethnicity. Intuitively, the most direct form of discrimination would be represented by a reordering of patients that favours White individuals compared to ethnic minorities, given a same level of

[3] See here: https://www.ethnicity-facts-figures.service.gov.uk/uk-population-by-ethnicity/demographics/english-language-skills/latest/.

severity. However, we find little evidence that ethnic minorities experience more patients "moving ahead" of them in the queue compared to White patients, providing suggestive evidence against direct discrimination as a core channel for our findings.

Overall, our findings paint a positive picture of triage and patient prioritisation practices in English EDs. The explanations for the small gaps in prioritisation for ethnic minorities and deprived patients are most likely linked to demand side factors outside of the direct control of ED staff. This can be taken as a reflection of the egalitarian spirit of the NHS.

Unjustified differences in prioritisation could lead to different health outcomes across different groups. We find no evidence this is the case, as ethnic and socioeconomic disparities in response to unexpected demand do not lead to differential increases in mortality or rates of re-attendance. Therefore, even if inequalities in prioritisation are economically and statistically significant, they are not sufficient to translate into differences in health outcomes. This null finding on health outcomes is consistent with previous work on the English NHS (Turner et al. 2022; Francetic, Meacock, and Sutton 2024), but contrasts with US studies highlighting mortality gaps of up to 27 percent for ethnic minorities relative to baseline mortality (Hill, Jones, and Woodworth 2023; Jenkins et al. 2023).

Our study has some limitations. First, despite having detailed information on patient characteristics, our data may still fail to accurately identify the level of severity of different patients, leaving room for potential confounding due to unobserved severity. Nevertheless, our robustness checks substantially reduce concerns over a substantial bias from unobservables. Second, the lack of data on staffing limits the extent to which we can adjust for capacity and therefore the need for more prioritisation at times of high unexpected demand. Third, we also miss interaction level data on the patient-doctor relationship, preventing us from exploring ethnicity-match between patients and staff or communication barriers.

Despite these limitations, we believe our proposed measures of patient prioritisation are important complements to existing ways of examining inequalities in access to care. Future work could explore the link between prioritisation and patient outcomes, for example studying whether hospitals that engage in more re-ordering of the queue have better outcomes because they are prioritising more effectively.

Appendix available here:

https://www.dropbox.com/scl/fi/c0fwdpqzd4g06xcd5f3di/Appendix.pdf?rlkey=nt9pr7zuw8r3b5scjh2migbm3&st=yabzwqsd&dl=0

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