The Impact of Ambulance Staff Shortage on Emergency Health Care: Evidence from English Administrative Data

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Abstract

Leveraging comprehensive administrative data on hospitals and ambulance stations, we estimate the causal effect of staff shortages in ambulance stations on patient mortality in emergency departments (EDs). We exploit quasi-random variation in worker shortages caused by unforeseen sickness absences across ambulance stations serving the same ED. We find a substantial and statistically significant effect: a one-standard-deviation increase in the sickness absence rate raises patient mortality within 24 hours of arrival at the ED by 0.78%. This result highlights the critical role of ambulance workers in emergency care quality and provides evidence on the damage caused by ambulance services understaffing.

Keywords: SICKNESS ABSENCES, STAFF SHORTAGES, AMBULANCE SERVICES, PATIENT MORTALITY.
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1 Introduction

The healthcare sector is among the most labour-intensive industries; yet the role of labour as a critical input in the health production function is not well understood. Specifically, the causal effect of staff shortage on patient outcomes is rarely isolated. Our paper aims to fill this gap by estimating a production function for emergency healthcare, where the input of interest is ambulance staff and the output is patient survival. In doing so, we not only emphasise the critical value of ambulance staff but also provide a novel methodological approach to evaluate how labour supply shocks affect health production.

An excess of emergency care demand relative to the available staff has become a global public concern, causing delays in ambulance transportation and emergency treatment (see Hoot and Aronsky 2008 and Darraj et al. 2023 for reviews). Minimising the waiting time for ambulance and emergency medical services is of paramount importance for reducing mortality in acute and life-threatening health conditions. In this paper, we identify the effect on patient mortality of a decrease in ambulance labour supply caused by unpredictable sickness absences.

Our work contributes to the growing body of literature that uses administrative data and quasi-experimental methods to identify the relationship between labour supply and health production. We extend the seminal work of Gruber and Kleiner (2012), Lin (2014), and Friedrich and Hackmann (2021), which primarily focused on the effects of nursing staff shortages on patient outcomes. Gruber and Kleiner (2012) found that nurse staffing reductions from strikes led to increased in-hospital mortality and 30-day readmissions in New York State. Similarly, Friedrich and Hackmann (2021) used a difference-in-differences approach to show that a parental leave program in Denmark led to a negative shock to the nursing labour supply, resulting in a substantial increase in 30-day readmission rates for patients with acute myocardial infarction. Lin (2014) exploited changes in minimum staffing requirements in the US as an instrumental variable to estimate the causal impact of nurse staffing on care quality, finding a significant positive effect.

Consistent with this body of work, our paper employs a quasi-experimental design using English administrative data to focus on the critical, yet unquantified, role of ambulance staff in emergency care. Our research exploits a unique, unpredictable

shock to the labour supply: unexpected staff sickness absences. A sudden reduction in staff caused by unpredicted sickness absences more accurately reflects a state of sustained understaffing than a planned absence such a parental leave or a strike, which can be strategically managed to minimize disruption.[1] Our estimated effect is also more generalizable because it avoids relying on variation caused by policies or strikes whose effects are difficult to extrapolate.

Our approach is also related to papers that analyse patients' demand shocks, such as Hoe (2022) and Francetic et al. (2024). These studies use English administrative data to evaluate the effect of unpredicted surges in healthcare demand in the trauma and orthopaedic departments (Hoe, 2022) and in the emergency department (Francetic et al., 2024) on patient outcomes; but they do not provide a direct measure of the causal effect of a reduction in labour supply. On the contrary, our paper isolate a supply-side shock—the unplanned absence of ambulance staff—to provide a direct estimate of how the unavailability of a critical labour input affects the production of emergency care.

We evaluate the effect of the sickness absence rate on the probability of death for patients transported to hospital emergency departments (EDs) by ambulance. Our analysis leverages a novel, linked set of English administrative datasets on hospitals, ambulance stations, staff absences, and mortality records. The central empirical challenge is the endogeneity of work absences, which we address by exploiting quasi-random variation across patients who arrive at the same hospital ED, but whose homes are located in different areas, giving them access to different ambulance stations.

More precisely, we isolate the quasi-random variation in the sickness absence rate by controlling for a comprehensive set of variables, including hospital fixed effects; time-of-day, day-of-week, month, and year fixed effects to capture seasonality; ED staff sickness absences; ambulance station size; and a rich set of patient characteristics. However, even after controlling for these variables, the variation in the ambulance staff sickness rate could still be partially anticipated by ambulance management

[1]Evidence that the effect of planned absences is mitigated is provided by Costa (2022), who found that physician strikes led to a modest increase in mortality for non-emergency patients in Portugal, and Stoye and Warner (2023), who also found no significant impact on the mortality of emergency patients in England.

through staff characteristics and patterns within their station over time. Furthermore, even if not anticipated, the variation in the ambulance sickness rate could still be related to unobserved ambulance station characteristics—for example, a negative work environment—which may directly affect both the quality of the ambulance service and patient mortality.

To isolate a more exogenous variation in sickness absences, we replace the observed sickness absence rate with the unexpected sickness rate. We define this as the ambulance staff absence rate net of observed ambulance staff characteristics, ambulance station fixed effects, and month and year fixed effects. This identification strategy is similar in spirit to controlling for high-dimensional fixed effects—see for example similar strategies exploited Francetic et al. (2024), to account for planned hospital capacity.[2]

We also run a set of sensitivity and placebo tests to show that our novel estimation method is robust to other potential endogeneity issues, such as changes in ambulance triage protocols during staff shortages and a potential spurious link between ambulance staff sickness absences and mortality, caused by an increase in patients with serious respiratory illnesses during flu epidemics. By isolating an unpredictable, supply-side shock, our analysis moves closer to identifying a true causal link, demonstrating the direct relationship between ambulance worker shortages and life-or-death outcomes in emergency healthcare.

We find that a one-standard-deviation increase in the ambulance sickness rate—from its baseline of approximately 6.4% to 14.7%—raises patient mortality within 24 hours of ED arrival by 0.78 percentage points. This is both an economically and statistically significant effect. The magnitude of this effect is about: 17% of the differential effect of an ED arrival in December compared to April, 16% of the differential effect of arriving at the ED during the night compared to the afternoon, and 17% of the differential effect of belonging to a minority group. Given that patient mortality is an extreme outcome, the presence of a statistically significant effect on this measure suggests that the impact on less severe outcomes—such as long-term illness, readmission, or extended hospitalisation—could be even greater.

This work contributes to several distinct but related strands of the economic

[2]For applications of this strategy to other empirical contexts, see Gazze et al. (2024), (Ireland et al., 2024) and (Escobar Carias et al., 2024).

literature. First, we add to the scarce research that quantifies the economic impact of work absences (e.g., Hansen, 2000; Pauly et al., 2002; Duflo et al., 2012; Herrmann and Rockoff, 2012; Grinza and Rycx, 2020). The economic costs of absenteeism are substantial, with estimated productivity losses of $225.8 billion annually in the US (Stewart et al., 2003) and 2.5% of the total gross domestic product in the European Union (Eurofound, 2010). In the healthcare sector, such reductions in productivity translate into worse patient health outcomes, raising serious public health concerns. However, the economics literature on losses caused by absences from work remains scant due to significant identification challenges. Previous studies in health economics have evaluated the effect of work absences by focusing on worker strikes (Gruber and Kleiner, 2012; Costa, 2022; Stoye and Warner, 2023). We advance this literature by focusing for the first time on the ambulance workers and by proposing a new identification strategy that relies on unpredictable sickness absence rates rather than planned absences like strikes, whose effects are often partially mitigated.

Second, our research speaks to the literature on the organization of emergency healthcare services and patient outcomes within publicly-funded systems like the English NHS (National Health Service).[3] By focusing on the short-term mortality of emergency patients, we provide a direct measure of the causal effect of emergency labour supply on a critical health outcome. A key finding of our analysis is that the impact of ambulance workers' shortages do not affect a patient's mortality risk beyond the first day. We document this by comparing patient mortality within 1 day of arrival at the ED to mortality at 2 and 7 days. This temporal specificity suggests the effect is driven by longer ambulance waiting times and delays in initial emergency treatment, highlighting the critical time-sensitivity of productivity in emergency care. Our results, therefore, empirically confirm that minimising delays in pre-hospital and early emergency care can directly save lives, especially for serious conditions requiring urgent response (e.g. blood poisoning, severe respiratory, and cardiac and vascular conditions such as emphysema, pneumonia and myocardial infarction). Furthermore, our heterogeneity analysis provides some suggestions to identify when and for whom the mortality risk caused by such delays is the highest. We find that the negative effect of unexpected ambulance sickness absences is the largest for patients aged 75

[3]For example, see Anselmi et al. (2017); Turner et al. (2020); Gruber et al. (2023); Turner et al. (2022); Francetic et al. (2024).

or older, or arriving at the ED in the morning or at night. On the contrary, arriving at an ED when there are high levels of avoidable emergency attendances[4] increases the risk of mortality only slightly and not statistically significantly. This evidence, coupled with the findings from Francetic et al. (2024), who find a limited impact of avoidable emergency visits, suggests that simply diverting avoidable attendances is an insufficient solution to the growing crisis in emergency departments.

Finally, we contribute to the broader literature on the relationship between healthcare labour supply and the health production (e.g. Propper and Van Reenen, 2010; Friedrich and Hackmann, 2021; Chan Jr and Chen, 2022; Zaranko et al., 2023; Moscelli et al., 2024). In particular, we extend the research on the relationship between staffing levels and patient health outcomes (e.g. Chen and Grabowski, 2015; Shen et al., 2022; Winter et al., 2020; Grabowski et al., 2023) by focusing on ambulance workers. By using pseudo-random variation in sickness absences rates that is unrelated to the ED and ambulance station characteristics and time patterns, we are able to identify the productivity of ambulance workers in terms of patient survival.

The remainder of the paper is organised as follows: Section 2 provides institutional background on the hospital and ambulance based emergency services in the English NHS. Section 3 presents the data used in our analysis, and Section 4 details our empirical strategy. The results are reported in Section 5, and Section 6 concludes.

2 Institutional Background

The English National Health Service (NHS) delivers urgent and emergency care through a complex and interdependent network of services. This network encompasses primary care (via General Practitioners or GPs), Urgent Treatment Centres (UTCs), ambulance services, and hospital-based Emergency Departments (EDs). Patients may access this system through any of the following access points, depending on the severity and immediacy of their condition. Ambulance services provide triage, initial treatment, and rapid transport to hospital facilities. In contrast, EDs serve as the primary site for life-saving medical intervention and treatment for a wide range of

[4]Avoidable attendances are ED visits for a medical condition that could be effectively managed by a general practitioner (GP) or in a primary care setting.

acute medical conditions.

2.1 Hospital-based Emergency Departments (EDs)

Emergency Departments (also known as Accident& Emergency) provide a free-of-charge, often unplanned, urgent medical care for patients in a hospital setting. There are various types of EDs with different care responsibilities. There were 161 NHS Trusts providing emergency care in March 2018, of which 137 were Type 1 (major) EDS, which provide 24/7 consultant-led services with full resuscitation facilities. In contrast, Type 2 EDs offer single-specialty care (e.g., ophthalmology or dental surgery), while Type 3 departments (minor injury units) provide urgent care for less complex conditions.

Demand for EDs has risen significantly, contributing to systemic delays. Between 2013/14 and 2017/18, attendance at major EDs rose by 7.8%, reaching 15,372,467 visits in 2017/18. This rising demand has coincided with a sharp increase in the proportion of patients waiting longer than the NHS's 4-hour target, increasing from 4.3% to 11.7% for the same period.

2.2 Ambulance services in the NHS

Ambulance services in England are organised into 10 NHS Ambulance Trusts (ATs), each covering a large geographical region, except for London, and serving over 55 million people in mainland England. These publicly funded services operate 24/7, are free at the point of use. The core function of NHS ATs is multifaceted: they serve as the initial responders to 999 emergency calls, coordinate with hospital services, and offer medical guidance for non-emergency incidents via the NHS 111 telephone system.

Rising demand has placed considerable pressure on NHS ambulance services. From 2011/12 to 2017/18, the demand for ambulance services has risen with an average annual rate of 5.2%, contributing to existing pressures in emergency services (National Audit Office, 2018) and workforce challenges. As of March 2018, there were 20,552 full-time equivalent NHS ambulance staff in England, comprising 1.9% of the NHS workforce and 3.6% of the professionally qualified clinical staff. With 85% of the staff

directly involved in operational services (Lord Carter of Coles, 2018), the ambulance workforce comprises a variety of roles from different professional groups. This includes paramedics, who make up 37.8% of all ambulance staff, ambulance technicians at 16%, and support staff, such as clerical and administrative personnel, accounting for 15.5%.

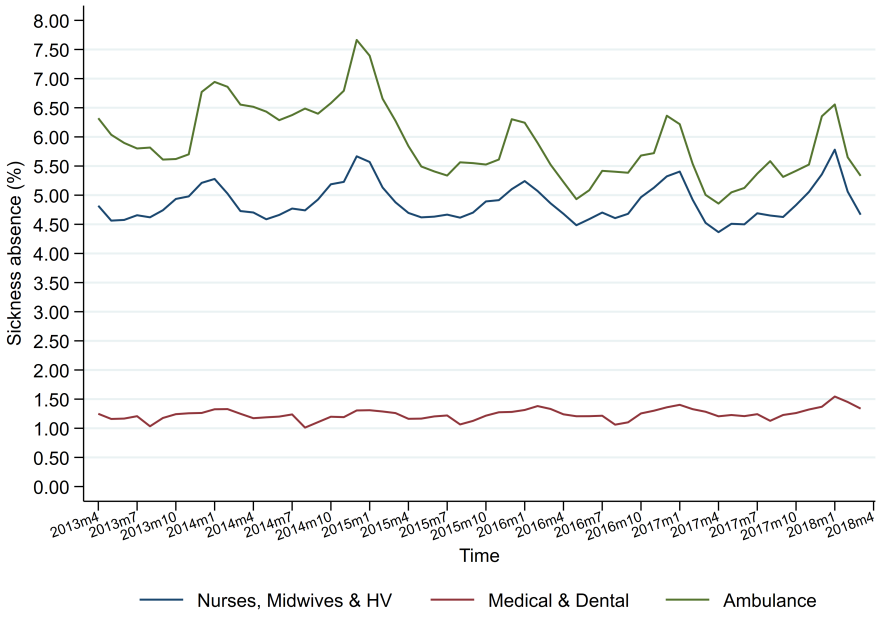
2.3 Workforce Pressures and Sickness Absences

Staff in ATs and EDs operate in high-pressure environments with long hours[5], frequent exposure to traumatic events, and face operational bottlenecks due to handover delays. These contribute to high burnout rates and staff attrition. In 2018, nearly 38% of ambulance staff considered leaving their roles, with 16% expressing a desire to exit the NHS or the healthcare sector altogether. This was also reflected in sickness absence rates as presented in Figure 1. From 2013/14 to 2017/18, monthly sickness absence rates of ambulance staff consistently exceeded those of nurses, midwives & health visitors and medical & dental staff, averaging 5.9% compared to 4.9% of nurses and 1.2% of medical staff.

Negative experiences in the workplace also remain a serious factor for AT staff: One in three ambulance staff reported experiencing physical violence from patients or their families. At the same time, 60% felt pressured into coming to work despite being unwell. These factors not only increase the risk of high staff turnover but also exacerbate workforce shortages by driving up sickness absence rates.

[5]In 2018, over 85% of staff in ATs worked extra hours. Authors' calculation from 2018 NHS Staff Survey (NHSSS) results available at `https://www.nhsstaffsurveys.com/results/results-archive/` (accessed in September 2024).

Figure 1. Sickness absence rates (in %) across NHS clinical workers



Notes. Authors' calculation from NHS Digital Sickness Absence Rates, November 2018 at `https://digital.nhs.uk/data-and-information/publications/statistical/nhs-sickness-absence-rates`. HV refer to Health Visitors.

3 Data

For our empirical analysis, we link a set of high-quality English administrative data and construct a multi-level panel spanning from April 2013 to March 2018. This panel is based on patient attendances to Type 1 Emergency Departments (EDs) in NHS hospitals in mainland England. The unit of observation is the ED attendance, which is clustered at three levels: the patient, the destination ED, and the nearest Ambulance Station (AS) to the patient. Our study sample is limited to patients who arrived at the ED via ambulance directly from their homes, enabling us to identify the nearest ambulance station to each patient's residence. An Ambulance Station (AS) is defined as a site within an Ambulance Trust (AT) that functions as an operational base where the majority of employees, hereafter referred to as *core staff*, are directly involved in delivering emergency patient care.[6]

[6]The definition of *core ambulance staff* includes individuals working as part of additional clinical services or allied health professionals whose primary area of work is clinical support (general acute)

ED attendance records come from the Hospital Episode Statistics Accident and Emergency (HES A&E) between 2013/14 and 2017/18. This administrative dataset provides detailed records on the timing, location, diagnosis, and discharge outcomes of ED visits in England.[7] We link this data with the Office for National Statistics (ONS) mortality data to derive mortality indicators following ED attendances.

We supplement the information on ED attendances from HES A&E by incorporating data on:

- Hospital ED Staff Absences: We derive monthly ED sickness (EDSA) and non-sickness absences for nurses and doctors whose secondary area of work is Accident & Emergency in an NHS acute care Trust from the NHS administrative payroll data, Electronic Staff Records (ESR).

- Socio-economic Deprivation: We use the income deprivation component of the 2015 English Index of Multiple Deprivation (IMD) to determine the proportion of residents on means-tested benefits within each Lower Super Output Area (LSOA)[8] associated with the ED patients.

The administrative patient-level ED attendance data in HES A&E, while comprehensive, lack information on the specific ambulance services used for patient transport. We address this gap by identifying the nearest ambulance station (AS) to the patient's home as a proxy for the actual AS responding to the patient. This assumption is based on the operational premise that ambulances are typically dispatched from the nearest available station to an emergency call, thereby minimizing response time.[9]

We link ED attendances with AS data constructed from two key micro-level datasets covering the same period, 2013/14 to 2017/18: Electronic Staff Records (ESR), a monthly administrative payroll database detailing staff demographics, and

and secondary area of work is ambulance services (or accident & emergency). We specifically include call operators, paramedics, ambulance drivers, and emergency medical dispatchers. The core staff make 76% of all AT employees across 10 NHS ATs.

[7] As realised ED visits, HES A&E data, by definition, exclude pre-hospital care (e.g., 999 or NHS 111 triage) or instances where patients were treated on site without transport to the ED.

[8] LSOAs are small, standardized geographical units created. Each LSOA has a consistent population, typically between 1,000 and 3,000 residents.

[9] We also conduct sensitivity analysis using the two closest ambulance stations to the patient to assess the robustness of our findings.

reference location data from the NHS Organisational Data Service (ODS). To link patients to their closest AS, we use the patients' (partial) postcode information from HES A&E and the AS postcodes collated from the ESR and the NHS Organisational Data Service (ODS).[10] The closest AS is the one with the shortest Pythagorean distance from the patient's home location, calculated using their geographic coordinates.

To measure fluctuations in the AS labour supply, we use staff absence data from the ESR and compute the following monthly workforce metrics for each ambulance station using the ESR: *Sickness Ambulance Absence Rate* (ASA), the share of days lost in a month because of sickness; *Non-Sickness Ambulance Absence Rate*, the share of days taken off in a month for reasons such as annual leave, study leave, or parental leave, which are generally planned; *Ambulance Turnover Rate*, the share of staff leaving their organisation, i.e.the ratio of the number of staff leaving their AS between month t and $t+1$ over the number of staff employed in the AS at t.

3.1 Auxiliary dataset: AS workforce

To address potential confounding factors and measure the effect of ambulance staff shortage on patients' mortality, we derive a measure of the ambulance sickness rate that is net of the effects of AS staff characteristics, time-invariant AS factors and time-specific patterns. This derived variable measures unexpected ambulance staff absences (UASA) (see for more details Section 4).

This UASA measure is computed using an auxiliary dataset, in which the unit of observation is ambulance stations.[11] This dataset contains monthly information on all AS recorded in ESR, validated with the ODS, and has a valid postcode. It includes several key variables on the AS workforce, such as the AS sickness absence rate, as defined above, and demographic and employment characteristics of their staff, including the proportion of staff by age group, ethnicity, nationality, gender, and contract type and the AS staffing levels.

[10] Despite containing site names, ESR provides limited geographical details. We cross-check and verify the postcodes for ambulance stations annually using reference location data from the NHS Organisational Data Service (ODS).

[11] This data is also used in identifying the closest AS to patients' residences as described above.

3.2 Estimation sample

Our analysis sample consists of patient attendances at Emergency Departments (EDs) in mainland England who were transported by ambulance from home between April 2013 and March 2018. We apply the following sample restrictions:

- Patients must have been alive upon arrival at the ED.[12]
- Patients must be younger than 97 years and residing in a non-rural area.[13]
- We focus on the first ED attendance of the day, which may include unplanned follow-ups.
- We exclude observations where the patient's travel distance to the ED was 57.7 km or more.[14]

The initial sample selection results in 11,217,507 attendances, representing 5,922,957 unique patients, 831 ASs, and 186 EDs (see the overall sample in Table A1, Column 1).

We further refine our sample by including only patients with at least one ambulance station (AS) located within 15 km of their residence. This restriction helps to maintain the validity of using the closest AS as a proxy for the one that provided care and ensures that the analysis focuses on cases where the operational logic of ambulance dispatch—minimising travel distance—is most likely to apply. This sample selection does not compromise the representativeness of our findings as we exclude only about 2% of total ED attendances (see Table A1, Column 2) while still including the same number of ASs and EDs as the overall sample (831 and 186).

This sample is then linked with the auxiliary dataset to add unexpected ambulance station sickness absences (UASA) for the closest AS to the patient. The resulting dataset is our estimation sample (Table A1, Column 3), which is negligibly smaller in size (lower than 0.1%) due to missing values in the unexpected ambulance staff absence rate (UASA).[15] Thus, the final sample consists of 11,018,201 ED visits from

[12] Approximately 2% of ED patients transported by an ambulance were recorded as deceased before ED arrival.

[13] Non-rural area is defined based on the rural-urban indicator available in the HES A&E data.

[14] Long-distance transports often involve air ambulances or pre-arranged transfers to highly specialised hospitals (e.g., major trauma centres).

[15] UASA is missing for ASs that are not observed in at least two different points in time.

5,834,187 patients who travelled to 186 EDs, transported by 818 closest ambulance stations.

3.3 Descriptive statistics

Table 1 presents the descriptive statistics of the main variables in our estimation sample.

The average patient mortality within 1 day of ED visit is 1.1%, rising slightly within 2 days to 1.5% and nearly tripling within 7 days (2.7%).[16] Compared to 124 thousand patients who died within 1 day of their ED visit, there were about 40 thousand more deaths on the second day of ED attendance, and the number of patients who died within a week of ED visit is 1.4 times that of one day. Table A3 displays the distribution of ED diagnoses among patients who died, by the timing of death, as well as those who survived. The timing of death for ED patients varied depending on the diagnoses they received, which is expected. For instance, cardiac conditions, which are one of the most common ED diagnoses, have an average 3.4% mortality rate within one day, which decreased to 1.1% in days 3 to 7. Similarly, vascular injury has slightly higher mortality closer to the ED visit (4.1% within 1 day vs. 2.3% in days 3-7).

[16]ED patient mortality at different time horizons is cumulative and not conditional on survival in previous days.

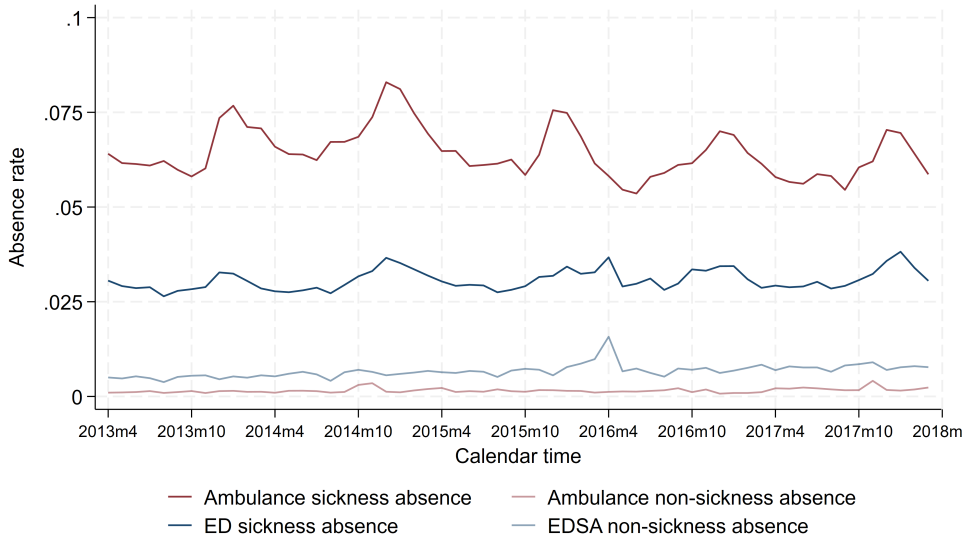
Table 1. Summary statistics, selected variables

Variable name	**Mean**	**Std. dev**
Patient mortality		
within 1 day	0.011	0.106
within 2 days	0.015	0.121
within 7 days	0.027	0.163
Ambulance station characteristics		
Sickness absence rate, ASA	0.064	0.073
Non-sickness (other) absence rate	0.002	0.008
Number of core staff	44.185	42.112
Churn rate	0.024	0.090
NHS leavers' rate	0.006	0.026
Leaver rate	0.030	0.094
ED characteristics		
ED staff sickness absence rate, EDSA	0.030	0.015
ED staff non-sickness (other) absence rate	0.007	0.008
GP-treatable attendances (AA_{GP})	0.226	0.106
Share of ED with above median AA_{GP}	0.475	0.499
No-treatment and discharge attendances (AA_{NTD})	0.145	0.099
Share of ED with above median AA_{NTD}	0.464	0.499
Patient characteristics		
Age [0-17]	0.087	0.282
Age [18-34]	0.124	0.330
Age [35-49]	0.116	0.321
Age [50-64]	0.142	0.349
Age 65 and above	0.530	0.499
Female	0.544	0.498
Black - Asian ethnic minority	0.105	0.307
Unknown ethnic minority status	0.075	0.263
Share of patients in income deprivation		
Least deprived 20%	0.136	0.343
Quintile 2	0.165	0.371
Quintile 3	0.194	0.395
Quintile 4	0.225	0.417
Most deprived 20%	0.281	0.449
Patient-ED distance in km	8.651	8.269
Diagnosed with a respiratory illness	0.082	0.274
ED waiting time to initial assessment, in minutes	34.745	142.467
ED waiting time to treatment, in minutes	88.468	105.530
Share of out-of-hours visits	0.644	0.479

Notes: Number of observations: 11,018,201. Patient characteristics are based on patients arriving at the ED by ambulance. See Table A2 for variable descriptions in detail.

The average sickness absence rate of the nearest ambulance stations to the ED patient was 6.4%, which is comparable to the NHS Digital statistic of 5.7% encompassing all ambulance staff (i.e., including core ambulance staff and support workers) for the same period.[17]

Figure 2. Monthly ambulance and ED staff absenteeism rates over time



Notes. Authors' calculation from the estimation sample. The monthly averages are based on 818 closest ambulance stations (to the patient) for ASA, and 138 NHS Trusts for EDSA. Non-sickness related absences include study leave, annual leave and parental leaves.

Figure 2 illustrates the monthly average rates of ambulance and ED staff absences over time. Similar to the NHS statistics depicted in Figure 1, the sickness absence rates for core ambulance staff have consistently been higher, more than double those of the ED nurses and doctors. In contrast, non-sickness absences among core ambulance staff were lower than those of ED staff throughout the observation period. On average, these planned absences were significantly lower in both ambulance stations and EDs, with monthly averages of 0.2% and 0.7%, respectively.

The most frequent ambulance users were patients aged 65 and above, who are likely to have a higher prevalence of chronic conditions and potentially lack immediate care for transportation. One in ten patients carried by an ambulance to an ED was

[17]The sickness absence rate is similar in the auxiliary AS panel, presented in Table A4, along with other AS workforce characteristics.

from an ethnic minority background, and almost 30% of the patients were from an income-deprived area. Over the years, 8.7% of ED patients were diagnosed with a respiratory condition, which includes flu and pneumonia, with around one-fifth of the cases occurring in December and January, i.e. the winter pressure months.

Mortality is closely related to patients' emergency conditions and likely to be influenced by prioritisation by ambulance services during periods of high pressure due to rising demand or low AS labour supply. In our sample, we do not find statistical evidence that ambulance stations selected patients during periods of high pressure, measured as above-median core ambulance staff sickness absences, to transport to ED.[18] Table A5 presents ED patient characteristics and diagnoses in low- ($ASA < median(ASA)$) and high-pressure ($ASA \geqslant median(ASA)$) periods and their differences with p-values. Patient compositions, except for ethnic minority status, were similar in both low and high-pressure periods.

4 Empirical strategy

We are interested in evaluating the effect of ambulance understaffing caused by staff sickness absences on patient mortality. Staff sickness absences are difficult to predict and are likely to worsen the already existing pressures on emergency services due to high demand.

We estimate the effect of ambulance staff sickness absences on the mortality of patients by exploiting the quasi-random variation across patients who arrive at the same ED but whose homes are located in different areas with different closest ambulance stations.

We estimate the following linear probability model

$$M_{i,h,t} = \rho ASA_{i,t} + \gamma EDSA_{i,t,h} + \phi ln(Asize)_{i,t,h} + \boldsymbol{\beta}\mathbf{X}_{i,h,t} + \tau_t + \mu_h + \epsilon_{i,h,t}, \qquad (1)$$

where the subscripts are used to denote the patient attendance i to ED h in month t, $M_{i,h,t}$ is a dummy variable taking the value 1 if the patient died within 1 day

[18] Our analysis does not rule out potential selection by ambulance services' response to emergency patients in general. Due to data limitations, we cannot account for patients who were not transported to EDs.

of the ED attendance i. $ASA_{i,t}$ measures the ambulance staff sickness absences by considering the staff sickness absence rate in month t in the closest ambulance station to the patient's home. To isolate the variation in the ambulance sickness absence rate unrelated to characteristics of the ED and hospital where the patient was brought, we control for the ED fixed effect, μ_h, which is equivalent to a hospital fixed effect because there is only one ED for each NHS hospital. To avoid confounding the effect of the ambulance sickness absence rate with the effect of ED staff sickness absence rate (EDSA), we control for the latter by including the covariate $EDSA_{i,t,h}$, which measures the share of staff in sickness absences in ED h in month t. We also control for the effect of the ambulance station size, measured as the average number of core ambulance workers averaged across the patient's nearby ambulance stations and expressed in natural log, $ln(ASize_{i,t,h})$. Additionally, we include a set of control variables, $X_{i,t,h}$, that capture the characteristics of ED patients that could affect their mortality. These are the natural log distance in kilometres (km) between the patient's home and the ED, a set of dummy variables for the age groups 0-17, 18-34, 35-49, 50-64 and 65 and over (baseline group), dummy for male, dummy for Black or Asian ethnic minority background, dummy for missing ethnicity information, and income deprivation quintiles.

Finally, we control for a set of time and seasonality fixed effects, τ_t, including time of day τ_p, day of week τ_d, month τ_m, and year τ_y fixed effects.

$$\tau_t = \tau_p + \tau_d + \tau_m + \tau_y \tag{2}$$

The final addend in equation (5) is the idiosyncratic error term $\epsilon_{i,h,t}$.

Even with the inclusion of time and ED fixed effects, we may still have endogeneity in ASA, which might bias our estimation. The variation in ASA can be driven by (i) station-level heterogeneity in observable or unobservable characteristics, such as station size and workforce composition (by age, gender, ethnicity and types of contract) and unobserved quality of the job environment in the ambulance station; and (ii) time-varying factors such as seasonal illnesses (e.g., influenza outbreaks) and temperature variations, which can affect staff health and, consequently, (sickness) absence rates.

While our regression model (5) controls for systematic temporal patterns through

the inclusion of month and year fixed effects, it does not fully address the potential endogeneity arising from the correlation between ASA and station characteristics. Specifically, unobserved AS factors that influence ASA, e.g. a poor work environment, which can lead to higher stress and sickness leaves, may also be correlated with patient mortality. This can lead to an omitted variable bias.

To isolate the idiosyncratic variation in sickness absences net of these AS characteristics, we consider the *unexpected ambulance staff absence (UASA)* which is the ASA net of the observed AS characteristics and AS, month and year fixed effects.

Using the auxiliary data on ambulance stations as described in Section 3.1, we estimate the following regression:

$$ASA_{at} = \boldsymbol{\alpha Z_{at}} + \lambda ln(Asize)_{at} + \phi_m + \phi_y + \eta_a + \varepsilon_{at} \tag{3}$$

where Z_{at} are characteristics of ambulance station a in month t and includes the share of staff by age groups (under 35, 35-44, 45-54, 55-64 and 65+), gender, nationality, ethnicity, type of contract (permanent versus temporary and full-time versus part-time), and the natural logarithm of the core staff level; ϕ_m and ϕ_y are the month and year fixed effects, η_a is the ambulance station fixed effects, and ε_{at} is the idiosyncratic error term.

We compute the expected ambulance staff absence rate $\widehat{ASA_{at}}$ using the prediction from Equation (3) and then the unexpected ambulance staff absence rate as

$$UASA_{at} = ASA_{at} - \widehat{ASA_{at}}. \tag{4}$$

Our preferred estimation model is then model (5), but with the ASA replaced by the UASA:[19]

$$M_{i,h,t} = \rho UASA_{i,t} + \gamma EDSA_{i,t,h} + \phi ln(Asize)_{i,t,h} + \boldsymbol{\beta X}_{i,h,t} + \tau_t + \mu_h + \epsilon_{i,h,t}. \tag{5}$$

[19] To avoid introducing new symbols, we use the same notation as in model 5, despite the change in the key variable of interest.

5 Results

5.1 Main Results

Table 2 presents the estimates for the effect of the unexpected ambulance staff sickness rate (UASA), which is the our key parameter of interest, along with parameters of secondary importance.

We find that the impact of UASA on ED mortality within one day of attendance is remarkably stable across various model specifications: whether the model omits all control variables, includes observed ED and patient characteristics, or additionally controls for ED fixed effects (see first row, columns I-III). These results are reassuring and support our causal claim that UASA captures exogenous variation in AS sickness absences, which is uncorrelated with patients' characteristics and with observed and unobserved ED factors. Our preferred model is presented in the last column of Table 2 with the full set of controls and fixed effects. We will focus our subsequent discussion and further analysis on this specific model.

To facilitate the interpretation of our estimates, we report the percentage change in ED mortality from its mean of 0.011 caused by one standard deviation increase in UASA (std dev: 0.067) at the bottom of Table 2.[20] We find that a one-standard-deviation increase in UASA raises the probability of death within one day of an ED visit by 0.78%, which is significant at the 5% level.

[20]The percentage increase in the mortality rate is computed as $\Theta(\text{UASA}) = \frac{\hat{\rho} \cdot SD(UASA)}{\overline{M}}$, where $\hat{\rho}$ and $SD(UASA)$ are the estimated coefficient and standard deviation of $UASA$ and $\overline{M}$ is the average ED mortality rate.

Table 2. Effect on ED patient mortality within 1 day due to unexpected ambulance sickness absences (UASA)

	(I) No controls	(II) With controls	(III) With ED FE
Unexpected monthly ambulance sickness absence, UASA	0.00103*	0.00111**	0.00131**
	(0.00061)	(0.00056)	(0.00051) [0.00053]
ln(average number of core ambulance staff), ln(ASize)		-0.00020**	0.00000
		(0.00009)	(0.00004) [0.00004]
ED staff monthly sickness absence, EDSA		0.02728**	0.00285
		(0.01324)	(0.00219) [0.00385]
ln(patient-hospital distance in km)		0.00023**	0.00003
		(0.00011)	(0.00008) [0.00007]
Income deprivation (ref: Least deprived 20%)			
Quintile 2		0.00030**	0.00015
		(0.00014)	(0.00011) [0.00009]
Quintile 3		-0.00000	-0.00016
		(0.00020)	(0.00014) [0.00014]
Quintile 4		-0.00002	-0.00014
		(0.00021)	(0.00014) [0.00015]
Quintile 5 (Most deprived 20%)		0.00018	-0.00042***
		(0.00026)	(0.00015) [0.00016]
Percentage change in ED mortality, Θ			
$\Theta(UASA)$	0.61298*	0.66314**	0.78110**
$\Theta(EDSA)$		3.64468**	0.38078
Observations	11018201	11018201	11018201

Notes: Linear probability model with (I) no control variables other than UASA, (II) with controls and time of day, day of week, month, and year fixed effects (FE), and (III) with ED fixed effects. Other controls, not shown in the table, include patients' age categories, gender, and ethnic minority status for columns (II) and (III). Standard errors are clustered at the ED level and reported in parentheses. The last column also reports bootstrapped standard errors (500 replications) in brackets. Θ is the percentage change in average ED mortality rate (mean: 0.011) by one standard deviation increase in UASA (std dev: 0.067), and in EDSA (std. dev: 0.015). Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

ED staff work closely with ambulance services, which increases the chances of spreading illnesses across care settings, increasing ASA and confounding our parameter of interest. Unlike UASA, the effect of ED sickness absences (EDSA) is more sensitive to the inclusion of ED fixed effects in the model specification. This is not surprising as staff shortages have become a part of a systemic structural pressure point in NHS hospitals. Thus, once controlled for unobserved time-invariant ED factors, the impact of EDSA on ED patient mortality reduces significantly and becomes much smaller than that of UASA.

Some medical emergencies require urgent response due to higher mortality risk, such as septicemia, cardiac conditions and respiratory problems[21] and are likely to

[21]Table A3 shows the percentage of patients died with an ED diagnoses within 1, 2 and 7 days

be more sensitive to increased travel time (Nicholl et al., 2007); however, we find no significant effect of the distance between the patient's home and the ED, once controlled for the ED fixed effect. Similarly, the inclusion of the ED fixed effect eliminates the statistical significance of the average number of core ambulance staff (in logs).

A counterintuitive result is the finding that patients living in the most deprived areas (top 20% of the distribution of the income deprivation index) have a lower mortality. The lack of own transport (O'Cathain et al., 2022), limited access to primary care (Turner et al., 2022), and lack of confidence in primary care physicians (GPs) (Kraaijvanger et al., 2016; Coster et al., 2017) may result in patients from deprived areas attending EDs with less severe conditions and therefore with a lower risk of mortality. We will revisit this potential explanation, examining low-priority (avoidable) ED visits in Section 5.3.

Table A7 reports the remainder of the estimated effects for our preferred model.

Our findings show a higher mortality risk for male, ethnic minority, and older patients. As expected, we also find a higher risk of mortality in winter months and for patients arriving at the ED on Sunday. There also appears to be a decline in mortality over the years.

To summarise, our findings demonstrate a significant negative effect of unforeseen ambulance staff sickness absences and patient survival within the first day following ED attendance. A one standard deviation increase in the UASA (0.067) resulted in an increase in mortality comparable to about 17% of the effect of an ED attendance in December with respect to April, 16% of the effect of arriving at the ED in the night rather than in the afternoon, 12% of the effect of arriving on a Sunday compared to a Friday, and 17% of the differential effect of belonging to a minority group.

We argue that UASA captures an unexpected short-term staff shortages, unlike other types of (non-sickness) absences such as parental, annual and study leaves. These absences, by nature, are anticipated and accommodated by managers through workforce planning to maintain safe staffing levels. We find no significant effect of unexpected non-sickness absences (UNSA) on ED patient mortality (see Table A8), supporting our hypothesis that UASA is the best way to predict the effect of short-

following ED visit.

term unpredicted AS staff shortages.

5.2 Threats to identification

In this section, we address potential concerns related to our identification strategy, which may arise from the prevalence of seasonal epidemics, variations in patients' health conditions, and AS turnover rates.

Accounting for seasonal epidemics

Ambulance staff sickness absences are likely to rise with seasonal epidemics (influenza), which may also lead to an increase in patients with respiratory diseases brought to the ED by ambulance and ultimately to a possible worsening of patients' mortality. To net out the effect of unexpected ambulance staff sickness of these confounding seasonal factors, our benchmark model controls for month-fixed effects. However, seasonal weather and epidemics may vary from year to year, so there could still be some confounding. We address this issue by adopting two different strategies: excluding from the sample patients with respiratory diagnoses in the ED and controlling for month-by-year fixed effects, i.e. for year-specific month fixed effects. Results reported in the first and second columns of Table 3, respectively, and show that the effect of unexpected ambulance sickness absences hardly changes with respect to the benchmark estimated effect in Table 2 Column (III).

Accounting for patient diagnoses

While our baseline model controls for patient characteristics, some correlation between residual sickness absences and the types of patients arriving at the ED may still exist. For instance, patients with more severe conditions that may be more susceptible to increased AS staff shortages are also likely to have higher mortality. We control for the variation in patient severity by including ED diagnoses dummies to model (5), which enables us to isolate the effect of UASA on ED mortality by holding patient diagnoses constant. The last column in Table 3 shows that the impact of UASA remains unchanged, with a standard deviation increase in UASA leading to a

Table 3. Checks for identification: Seasonal epidemics and ED diagnoses

	No respiratory patients	**Calendar time FE**	**ED diagnoses**
Unexpected monthly ambulance sickness absence, UASA	0.00118**	0.00130***	0.00130**
	(0.00055)	(0.00047)	(0.00055)
ln(average number of core ambulance staff), ln(ASize)	0.00001	-0.00000	0.00130**
	(0.00004)	(0.00004)	(0.00055)
ED staff monthly sickness absence, EDSA	0.00138	0.00153	0.00183
	(0.00233)	(0.00225)	(0.00247)
ln(patient-hospital distance in km)	0.00002	0.00003	0.00002
	(0.00008)	(0.00008)	(0.00007)
Income deprivation (ref: Least deprived 20%)			
Quintile 2	0.00008	0.00015	0.00014
	(0.00012)	(0.00011)	(0.00011)
Quintile 3	-0.00022	-0.00016	-0.00015
	(0.00014)	(0.00014)	(0.00014)
Quintile 4	-0.00016	-0.00014	-0.00010
	(0.00014)	(0.00014)	(0.00014)
Quintile 5 (Most deprived 20%)	-0.00035**	-0.00042***	-0.00039***
	(0.00016)	(0.00015)	(0.00015)
Percentage change in ED mortality, Θ			
$\Theta(UASA)$	0.72597**	0.77276***	0.77462**
$\Theta(EDSA)$	0.19154	0.20447	0.24397
Mean(M)	0.01086	0.01128	0.01128
Number of clusters (ED hospitals)	185	186	186
Observations	10113867	11018201	11018201

Notes: Standard errors are clustered at the ED level and are reported in parentheses. The first column excludes patients diagnosed with a respiratory disease in the ED. The second column changes the FE structure in Eq. (5) and uses calendar time FE instead of separate month and financial year FEs. The third column includes dummies for diagnoses patients received at their ED attendance. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

0.78% increase in ED mortality within one day, indicating that UASA is not driven by patients' health conditions.[22]

Accounting for Ambulance Staff turnover rates

We are also concerned that ambulance staff turnover rates might confound the effect of UASA. High turnover rates may put additional pressure on existing staff and lead to a rise in sickness absences. We assess this by modifying the baseline model

[22]Figure A1 presents the coefficient estimates for ED diagnoses with 95% confidence intervals from the model specification shown in the last column in Table 3. Compared to the reference category (missing or no ED diagnosis), septicemia has the largest effect on patient mortality within one day of the ED visit, increasing the risk 2.7 times, which is significantly higher than the 1.8-fold increase with the cardiac conditions (e.g., heart attack).

(5) in three steps: first, we control for AS and ED turnover rates as key staff shortage measures; second, we add AS turnover to Eq. (5); and third, we add ED turnover to the model. The estimation results for both lagged and contemporaneous turnover rates are reported in Table 4 . We find no significant effect of AS core staff turnover on ED patient mortality across model specifications and time lags. Our results are encouraging as the effect of UASA remains unchanged when we control for core staff turnover rates, both in ambulance stations and EDs, as shown in Columns (II), (IV), (III) and (V), respectively.

Table 4. Checks for identification: Controlling for AS core staff turnover rate

	Lagged Turnover, t-1			**Turnover, t**	
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**
Unexpected monthly ambulance sickness absence, UASA		0.00134***	0.00133**	0.00131**	0.00128**
		(0.00051)	(0.00051)	(0.00051)	(0.00051)
Ambulance staff monthly turnover	-0.00052	-0.00054	-0.00054	-0.00002	0.00001
	(0.00042)	(0.00042)	(0.00042)	(0.00032)	(0.00032)
ln(average number of core ambulance staff), lnASize	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
ED staff monthly sickness absence, EDSA		0.00326	0.00400	0.00285	0.00385
		(0.00220)	(0.00532)	(0.00219)	(0.00526)
ED nurses' turnover	0.00124		0.00118		-0.00042
	(0.00265)		(0.00265)		(0.00245)
ED consultants' turnover	0.00031		0.00032		-0.00009
	(0.00071)		(0.00071)		(0.00081)
Percentage change in ED mortality, Θ					
$\Theta(UASA)$		0.80179***	0.79844**	0.78115**	0.76918**
$\Theta(EDSA)$		0.43922	0.40002	0.38081	0.38402
Θ(Amb turnover)	-0.28703	-0.29079	-0.29617	-0.01325	0.00710
Θ(ED nurse turnover)	0.16245		0.15400		-0.05410
Θ(ED consultant turnover)	0.15007		0.15414		-0.04362
Mean(M)	0.01123	0.01124	0.01123	0.01128	0.01127
Observations	10478843	10712685	10478843	11018201	10787423

Notes: In the first three columns, turnover rates enter as a lagged term at $t-1$, and in the last two columns they enter as a contemporaneous measure at t. Standard errors are clustered at the ED level and are reported in parentheses. Other controls included in the model specifications, but not shown in the table, are income deprivation quintiles, distance between patients and EDs, patients' age categories, gender, ethnic minority status, time of day, day of week, and month and year of ED attendance, as well as ED FEs. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.3 Heterogeneity analyses

In this section, we examine the heterogeneity of patient mortality resulting from various factors. First, we conduct a split-sample analysis by age to understand whether our results vary by age group, as they have different healthcare needs and frailties. Second, we control for out-of-hours periods to assess whether and how the

availability of primary care affects the relationship between ambulance staff sickness absences and patient mortality. Third, we examine avoidable ED attendances, an important consideration from the ambulance services' perspective, as reducing unnecessary ED visits could alleviate strain on emergency resources and improve response times for critical cases.

Differences across age groups

We estimate the baseline model in Eq. (5) to explore whether unexpected ambulance staff sickness absences have a differential impact on the mortality of patients across three age groups: those under 65 (0 to 64 years), 65 to 74 years, and 75 years and above. More than half of our sample consists of patients 65 and above, with patients between 65 and 74 are considered within the amenable mortality[23] range, and patients 75 years and older can be considered as having potentially more complex needs and comorbidities.

Table 5 presents the estimated effects for each age group in columns. Patients aged 75 and above suffer the most from higher UASA. A one standard deviation (0.066) increase in UASA raises the average mortality of ED patients aged 75+ by 1.05%. Unlike the eldest group of patients, the effect of ambulance sickness absences is less precise on the younger patients' mortality. For patients below 65, however, care provided by the ED staff carries more weight. A one standard deviation (0.015) increase in ED staff sickness absence rate contributes to a 3% increase in their mortality within one day following their ED visit. We find that while younger patients may rely on ambulance transport, their conditions are often less severe compared to higher-risk elderly groups and can be effectively managed by ED staff, whereas older patients are seriously affected by AS staff shortages.

[23] Amenable mortality is defined defined as deaths that could potentially be avoided through timely and effective healthcare interventions (Office for National Statistics, 2025).

Table 5. Differential effects on ED mortality within 1 day across age groups

	Below 65	**65-74**	**75+**
Unexpected monthly ambulance sickness absence, UASA	0.00068	0.00022	0.00288***
	(0.00056)	(0.00165)	(0.00102)
ln(average number of core ambulance staff), lnASize	0.00004	0.00020**	-0.00009
	(0.00004)	(0.00009)	(0.00007)
ED staff monthly sickness absence, EDSA	0.00867***	0.00126	-0.00077
	(0.00329)	(0.00672)	(0.00391)
ln(patient-hospital distance in km)	0.00010	-0.00009	-0.00003
	(0.00008)	(0.00015)	(0.00012)
Income deprivation (ref: Least deprived 20%)			
Quintile 2	0.00027	0.00013	0.00019
	(0.00019)	(0.00030)	(0.00021)
Quintile 3	0.00024	-0.00050	-0.00002
	(0.00016)	(0.00033)	(0.00022)
Quintile 4	0.00038**	-0.00002	-0.00008
	(0.00017)	(0.00034)	(0.00024)
Quintile 5 (Most deprived 20%)	0.00026	-0.00042	-0.00047*
	(0.00017)	(0.00035)	(0.00026)
Percentage change in ED mortality, Θ			
$\Theta(UASA)$	1.07607	0.09831	1.04549***
$\Theta(EDSA)$	3.00759***	0.12655	-0.06460
Mean(M)	0.00429	0.01519	0.01827
Observations	5180984	1500413	4336801

Notes: Linear probability model with time of day, day of week, month, financial year and ED fixed effects (FE). Standard errors are clustered at the ED level and in parentheses. Other variables included in the model specification but not presented in the table are patients' age categories (for those below 65), gender, ethnic minority status, ED attendance month, day of attendance, and time of attendance. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Differences in timing of the ED attendances

Emergency care in the English NHS is a complex interplay of services within and between GPs, ED, and ambulance services, particularly during out-of-hours (OOH) when GPs are not available to provide urgent care. During OOH, patients often contact ambulance services (such as NHS 111), which may direct them to ED depending on the severity of the issue, and sometimes dispatch ambulances.

To understand whether OOH visits play a confounding role in ED patient mortality in our setting, we re-estimate our baseline model (5) by including the OOH indicator, defined as ED visits during weekends and weekdays from 6.30 pm to 8 am the next day, which aligns with most GPs' operating hours.

We find that patients visiting the ED during OOH have 4.6% higher risk of mor-

tality within one day (first column in Table A9), whereas we do not find significant differences between weekday OOH and weekends (second column in Table A9).

Next, we investigate the differential impact of UASA on ED patient mortality across different times of the day by splitting our sample into four periods: morning (8 am to 12 pm), afternoon (12 pm to 6:30 pm), evening (6.:30 pm to 12 am) and night (12 am to 8 am).

Table 6. Differential effect on ED patient mortality over time of day of ED attendance

	Morning [8am-12pm)	**Afternoon [12pm-6.30pm)**	**Evening [6.30pm-12am)**	**Night [12am-8am)**
Unexpected monthly ambulance sickness absence, UASA	0.00280**	0.00117	0.00024	0.00176*
	(0.00118)	(0.00082)	(0.00079)	(0.00096)
ln(average number of core ambulance staff), lnASize	-0.00005	-0.00012**	0.00003	0.00020***
	(0.00009)	(0.00006)	(0.00005)	(0.00007)
ED staff monthly sickness absence, EDSA	0.00283	0.00564	0.00216	-0.00081
	(0.00462)	(0.00389)	(0.00405)	(0.00325)
ln(patient-hospital distance in km)	0.00025**	-0.00013	0.00002	0.00010
	(0.00012)	(0.00009)	(0.00008)	(0.00011)
Income deprivation (ref: Least deprived 20%)				
Quintile 2	-0.00020	0.00039*	-0.00011	0.00039
	(0.00034)	(0.00021)	(0.00021)	(0.00028)
Quintile 3	-0.00056*	0.00016	-0.00054**	0.00007
	(0.00031)	(0.00022)	(0.00025)	(0.00029)
Quintile 4	-0.00017	0.00024	-0.00063***	-0.00010
	(0.00030)	(0.00024)	(0.00021)	(0.00030)
Quintile 5 (Most deprived 20%)	-0.00039	0.00008	-0.00098***	-0.00051*
	(0.00032)	(0.00024)	(0.00020)	(0.00028)
Percentage change in ED mortality, Θ				
$\Theta(UASA)$	1.20970**	0.71939	0.18866	0.97678*
$\Theta(EDSA)$	0.28649	0.76922	0.37889	-0.10159
Mean(M)	0.01528	0.01088	0.00850	0.01215
Stdev UASA	0.06602	0.06713	0.06765	0.06762
Stdev EDSA	0.01550	0.01483	0.01491	0.01526
Observations	1920558	3619667	3017882	2448081

Notes: Standard errors are clustered at the ED level and are reported in parentheses. Other controls included in the model specifications, but not shown in the table, are patients' age categories, gender, ethnic minority status, time of day, day of week, and month and year of ED attendance, as well as ED FEs. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We find that unforeseen AS sickness absences increase the mortality risk of ED patients during morning and night attendances, as shown in the first and last columns of Table 6. A one standard deviation increase in UASA (0.066) leads to a 1.2% increase in patient mortality in a morning ED visit, which is significant at the 5% level. Mornings are also the only time of day when patient-ED distances significantly increase patient mortality, with a 1% increase in patient-to-ED distance increasing patient mortality on average by 0.025%. A potential explanation for this is the higher probability of severe conditions such as heart attacks (Pierce-Hayes, 2009) and stroke (Denny et al., 2014) being experienced in the early hours of the day, i.e. mornings.

The impact of UASA on ED mortality during night visits is comparable to that of morning hours; a one standard deviation (0.068) increase in UASA leads to a 0.98% higher ED mortality risk, although less precisely estimated.

Accounting for NHS Winter pressures to hospital Emergency Departments

Winter pressures have consistently strained the capacity of NHS Emergency Departments (EDs) and ambulance services, particularly during the 2012–2019 seasons. Increased incidence of seasonal illnesses, such as influenza and respiratory infections leads to surges in emergency demand, often overwhelming EDs and delaying ambulance handovers (Pearce et al., 2023; Ahsan et al., 2019). These pressures exacerbate crowding, reduce throughput, and increase waiting times, with downstream effects on patient outcomes and staff workload (Atkin et al., 2022; Paling et al., 2020; Grant et al., 2020; Samadbeik et al., 2024).

Most importantly, the existence of Winter demand pressures in the NHS means that our effects may be sensibly different depending on seasonal patterns of patient demand. To this extent, we estimate our benchmark model in Eq. 5 by splitting the sample between ED attendances in two semesters: the Fall/Winter one (October to March) and the Spring/Summer one (April to September).

During months from October to March, when there is higher demand for emergency health services due to increased seasonal illnesses or accidents due to colder weather, we find that the unexpected ambulance staff sickness absences increase ED patients' mortality risk by 1.2% as presented in the first column of Table 7. Compared to our benchmark estimate, the impact is 50% higher, and persists when we exclude ED patients who were diagnosed with a respiratory illness. On the other hand, as expected, we do not find any significant impact of ambulance sickness absences during quieter summer months from April to September. Instead, there is a significant, albeit weak, impact of ED staff sickness absences that contribute to higher mortality risk for ED patients, which disappears when we exclude respiratory patients.

These findings, underscore the need for integrated data-driven planning across ambulance and ED services (Lewis et al., 2023), to cope with the complexity of seasonal demand for urgent secondary care.

Table 7. The impact of UASA on ED patient mortality accounting for seasonality in ED demand pressures

	All sample		Excluding respiratory patients	
	Oct-March	**Apr-Sept**	**Oct-March**	**Apr-Sept**
Deviation from expected monthly sickness absence, UASA	0.00214***	0.00028	0.00201**	0.00020
	(0.00078)	(0.00065)	(0.00090)	(0.00066)
ln(average number of core ambulance staff), ln(Asize)	0.00002	-0.00002	0.00003	-0.00001
	(0.00005)	(0.00004)	(0.00006)	(0.00004)
ED staff monthly sickness absence, EDSA	0.00200	0.00340*	0.00082	0.00205
	(0.00686)	(0.00186)	(0.00681)	(0.00204)
ln(patient-hospital distance in km)	0.00008	-0.00003	0.00009	-0.00005
	(0.00009)	(0.00008)	(0.00009)	(0.00009)
Income deprivation (ref: Least deprived 20%)				
Quintile 2	0.00015	0.00015	0.00002	0.00013
	(0.00020)	(0.00015)	(0.00020)	(0.00016)
Quintile 3	-0.00012	-0.00021	-0.00022	-0.00022
	(0.00020)	(0.00018)	(0.00020)	(0.00017)
Quintile 4	-0.00010	-0.00017	-0.00016	-0.00017
	(0.00020)	(0.00018)	(0.00022)	(0.00018)
Quintile 5 (most deprived 20%)	-0.00023	-0.00060***	-0.00022	-0.00048**
	(0.00022)	(0.00019)	(0.00023)	(0.00019)
Percentage change in ED mortality, Theta				
Theta(UASA)	1.21109***	0.17856	1.16982**	0.12858
Theta(EDSA)	0.19835	0.56056*	0.08405	0.35268
Mean(M)	0.01193	0.01064	0.01154	0.01020
Observations	5457795	5560406	4960055	5153812

Notes: Linear probability model with time of day, day of week, month, year, and ED FEs. Other controls, not shown in the table, include the distance between patients' residences and EDs, income deprivation quintiles, patients' age categories, gender, and ethnic minority status. Standard errors are clustered at the ED level and reported in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Differential impact of avoidable ED attendances

Overcrowding of ED services could lead to adverse patient outcomes through increased waiting times (Gruber et al., 2023), delaying patient handovers, which could further affect ED patient mortality by reducing the availability of ambulances for new emergencies. The high demand in hospital ED services may be due to increases in unplanned attendances (Turner et al., 2020) or due to unnecessary (low-priority) attendances (Francetic et al., 2024). Following Parkinson et al. (2021), we define unnecessary, i.e. avoidable, attendances in two ways: (1) *GP treatable attendances* (AA_{GP}) include patients' first attendance with some recorded treatment or investigation, which may have been provided by a GP, followed by discharge to home or GP care. (2) *No treatment and discharge attendances* (AA_{NTD}) consists of self-referred patients with initial (not follow-up) attendance, who received no investigation and either no treatment or guidance/advice only; and were discharged with either no follow-

up or follow-up with primary care, which is the definition borrowed from McHale et al. (2013). On average 22.6% of ED attendances in a day are potentially GP-treatable visits, and 14.5% end with no treatment and discharge. We then define an ED as unnecessarily crowded if the share of avoidable attendances on a given day (among all ED visits,i.e. including patients who do not arrive by ambulance) is higher than the monthly median share of avoidable attendances within the ED.

Table 8. Differential effects of avoidable attendances on ED patient mortality

	GP treatable		**No treatment & discharged**	
	Below median	**Above median**	**Below median**	**Above median**
Unexpected monthly ambulance sickness absence, UASA	0.00123	0.00140**	0.00125	0.00145**
	(0.00089)	(0.00065)	(0.00079)	(0.00068)
ln(average number of core ambulance staff), lnaASize	-0.00001	0.00001	-0.00004	0.00005
	(0.00005)	(0.00005)	(0.00005)	(0.00005)
ED staff monthly sickness absence, EDSA	0.00127	0.00503*	-0.00019	0.00730**
	(0.00296)	(0.00280)	(0.00342)	(0.00303)
ln(patient-hospital distance in km)	-0.00001	0.00006	-0.00003	0.00007
	(0.00008)	(0.00009)	(0.00008)	(0.00010)
Income deprivation (ref: Least deprived 20%)				
Quintile 2	0.00017	0.00014	0.00031**	0.00001
	(0.00016)	(0.00019)	(0.00015)	(0.00019)
Quintile 3	-0.00026	-0.00006	-0.00007	-0.00026
	(0.00018)	(0.00020)	(0.00019)	(0.00020)
Quintile 4	-0.00014	-0.00014	-0.00001	-0.00025
	(0.00020)	(0.00019)	(0.00020)	(0.00018)
Quintile 5 (Most deprived 20%)	-0.00038**	-0.00046**	-0.00018	-0.00069***
	(0.00018)	(0.00020)	(0.00019)	(0.00020)
Percentage change in ED mortality, Θ				
$\Theta(UASA)$	0.73662	0.82870**	0.72061	0.85282**
$\Theta(EDSA)$	0.17026	0.66873*	-0.02320	0.92015**
Mean(M)	0.01116	0.01140	0.01160	0.01156
Stdev UASA	0.06696	0.06742	0.06689	0.06810
Stdev EDSA	0.01498	0.01516	0.01411	0.01457
Mean AA share per day	0.19963	0.25575	0.11692	0.17178
Observations	5779289	5238907	5771527	4947931

Notes: Linear probability model with time of day, day of week, month, financial year and ED fixed effects (FE). Standard errors are clustered at the ED level and in parentheses. Other variables included in the model specification but not presented in the table are patients' age categories, gender, ethnic minority status, month of ED attendance, day of attendance, and time of attendance. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

On average, a one standard deviation increase in UASA leads to a 0.83% higher mortality risk for patients attending EDs with above-median GP-treatable attendances and by 0.85% in EDs with above-median NTD attendances as presented in Columns 2 and 4 of Table 8. In contrast to our baseline model in Table 2 Column (III), EDs overcrowded by avoidable attendances (above the median), EDSA becomes a contributing risk factor increasing patient mortality. While the effect sizes for EDSA and UASA are comparable for a standard deviation increase in EDs where most of the avoidable visits could be treated by a GP (0.67% and 0.82%, respectively), we

find a slightly larger and stronger effect of EDSA on patient mortality when the ED services were overcrowded by patients receiving no treatment and were discharged.

The impact of UASA on ED mortality at different horizons

Our analysis thus far has focused on mortality within one day of ED attendance, a period marked by higher acute vulnerability for patients with time-sensitive conditions, when unexpected AS shortages may directly influence the survival probability of emergency patients. We hypothesise that beyond the first day of ED visit, particularly following hospital admission, the effect of UASA to dissipate, as patient outcomes, including mortality, are more likely to be influenced by the care provided by the ED and hospital staff.

To examine whether unexpected ambulance staff absences have longer-term effects, we extend the time window used to measure mortality within 2 days and within 7 days of ED visit and by conditioning on survival on previous days. Table 9 presents the estimation results and includes the benchmark estimates for mortality within one day in Column (I) for comparison.

Table 9. The impact of UASA on ED patient mortality at different time horizons

	(I)	**(II)**	**(III)**	**(IV)**	**(V)**
	ED patient mortality within				
	1 day	**2 days**	**2nd day**	**7 days**	**3 to 7 days**
Unexpected monthly ambulance sickness absence, UASA	0.00131**	0.00094	-0.00037	0.00079	-0.00012
	(0.00051)	(0.00059)	(0.00027)	(0.00078)	(0.00050)
ln(average number of core ambulance staff), lnASize	0.00000	0.00001	0.00001	0.00001	0.00000
	(0.00004)	(0.00005)	(0.00002)	(0.00006)	(0.00004)
ED staff monthly sickness absence, EDSA	0.00285	0.00320	0.00037	0.00470	0.00156
	(0.00219)	(0.00286)	(0.00130)	(0.00410)	(0.00209)
Percentage change in ED mortality, Θ					
$\Theta(UASA)$	0.78110**	0.42304	-0.68329	0.19467	-0.06369
$\Theta(EDSA)$	0.38078	0.32454	0.15159	0.25828	0.18416
Mean(M)	0.01128	0.01487	0.00364	0.02741	0.01272
Observations	11018201	11018201	10893963	11018201	10854313

Notes: Linear probability model with time of day, day of week, month, year, and ED FEs. Other controls, not shown in the table, include the distance between patients' residences and EDs, income deprivation quintiles, patients' age categories, gender, and ethnic minority status. Standard errors are clustered at the ED level and reported in parentheses. Columns (II) and (IV) are nested in time, whereas columns (III) and (V) exclude the preceding time periods from the analysis. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Our estimation results support our hypothesis as the effect of UASA does not extend beyond the initial 24 hours after ED attendance (Columns (II) and (IV)).

We find similar results when we condition ED patients' mortality on their survival in the first day (Column (II)) and from the third day onwards (Column (V)) with the estimated effect of UASA turns negative and remains insignificant. This result can be partially explained by fewer deaths on the second day (2.7% of all deaths), as well as factors such as patient co-morbidities, hospital-based care and treatment quality affecting patients' mortality risk.

5.4 Sensitivity and additional checks

Alternative model specifications

In our baseline model, the ED fixed effects capture only time-invariant characteristics; thus, hospital characteristics that are time-varying and correlated with both patients' mortality and UASA could bias our results. To check if this is an issue, we run a sensitivity analysis with ED-by-year fixed effects, which controls for any unobserved hospital or ED characteristics that are time varying across years. Results in the third column of Table 3 show that the effect of UASA remains similar to the one in Table 2 Column (III), suggesting that our benchmark results are not biased by hospital unobserved variables that are varying across years. As death is a rare event, we are also concerned that the linear probability model may not be appropriate; thus, we estimate a complementary log–log (cloglog) model. The second column in Table A10 presents the marginal effects from the cloglog model, which are comparable to the benchmark effect of UASA on ED mortality.

Next, we address the sensitivity of our results to the specifications used to compute UASA based on the model (3). We do this in two ways: first by estimating Equation (3) based on subsample of auxiliary AS panel by months T over which we observe ambulance stations[24], and secondly by changing model specifications and applying different methods for computing the standard errors. Table A11 presents the estimation results. We do not find any significant differences when UASA is computed from different subsamples of the auxiliary AS panel, regardless of whether AS were observed for at least 20, 30 or 40 months. The effect of UASA derived from these subsamples is highly consistent with the benchmark estimate of 0.78%. Table A11

[24]The auxiliary panel on ambulance stations covers the period from April 2013 to March 2018, and as such the maximum value T can attain is 60 months.

panel (b) Columns (IV) and (V) presents results from deriving UASA from alternative model specifications of Equation (3): by excluding AS workforce covariates, $\boldsymbol{X_{at}}$ and $ln(Asize)$, and by excluding AS fixed effects, η_a, respectively. We find that our results on ED mortality are not sensitive to the exclusion of AS workforce covariates when estimating unexpected AS sickness absences, but they are sensitive to the exclusion of AS fixed effects, which we find reduces the impact of UASA on ED mortality on average by 0.20 percentage points.

Although it is unlikely to pose a significant concern in our contextual setting, we check the robustness of our results to autocorrelation within ambulance stations.[25] We estimate Eq. (3) using Driscoll-Kraay standard errors, allowing for adjustments for 2 lags. We find that the significant positive impact of the UASA remains; however the percentage change in ED mortality is reduced by one-fifth of the baseline UASA estimate to 0.60% (Column (IV) in Table A11).

Adding UASA from the second nearest AS as a control

In our baseline model, we make the implicit assumption that the closest ambulance station would respond to the patient. However, it is possible that other closer ambulance stations could be called upon if the station were busy or had unexpected staff absences. We test the sensitivity of our results to the availability of a second closest ambulance station by re-estimating the model (5) and including UASA for the second closest station in the model specification.[26] While the effect of UASA in the second closest station on ED mortality has the expected sign, it is weaker, with almost one-tenth of the effect estimated for the nearest station. UASA in the closest AS retained its significant effect on ED mortality (Table A12).

[25] In contrast to vacancies, which allow for planned hiring decisions, ambulance managers do not have neither the time nor resources to adjust for shortages due to sickness absences in advance. Instead, their response to ASA is potentially limited to extending the shifts of existing staff or temporarily borrowing staff from other ambulance stations.

[26] The first-step model is based on all available stations in mainland England. This enables us to compute UASA for all ambulance stations in the auxiliary dataset described in Section 3.1. We identify the second nearest AS to the patient, and link their UASA accordingly.

Bias due to unobservables and coefficient stability

We also test for the direction of the potential omitted variable bias in ambulance sickness absences, using the method proposed in Oster (2019) based on coefficient stability. The coefficient estimated through the Oster (2019) method converges asymptotically to the true parameter of interest, under a set of assumptions[27] Table A13 presents the estimation results from the linear regression using alternative model specifications with R_{max} set to 1.3 times the R-squared achievable from the fully specified model. These results are consistent with the estimates reported in Table 2.

Placebo test using ED waiting times

Since the unexpected ambulance sickness absences should not explain waiting times at the ED, finding a statistically significant effect of UASA on ED waiting times would suggest the presence of unobserved variables that are correlated with both UASA and unobserved ED characteristics, which could bias our benchmark estimation. In Table A14, we show that there is no statistically significant effect of UASA on two measures of (natural logarithm of) waiting times at the ED, which are the time between arrival at the ED and the initial assessment and between arrival at the ED and receiving treatment. As expected, we do not find any significant impact of the UASA. On the other hand, we find that a rise in ED sickness absences significantly increases the waiting time for treatment among ED patients.

6 Conclusions

This paper investigates the impact of ambulance staff sickness absences on patient mortality in English NHS hospital emergency departments. The central research question is whether unforeseen sickness absences negatively affect the survival rate of patients transported to hospital emergency departments by ambulance. To address this, we constructed an ED-visit and ambulance station data leveraging rich adminis-

[27]The necessary conditions are: linear model specification; proportionality between selection on unobservables and selection on observables; no measurement error and sufficient variation in covariates; large sample size; no endogeneity among controls; a stable relationship between covariates and treatment assignment.

trative datasets and patient mortality records. We exploited quasi-random variation in unforeseen sickness absence rates across ambulance stations serving the same ED.

Our key finding is that unexpected sickness absences in ambulance stations (UASA) closest to the patient's home reduce their survival significantly, with a one standard deviation increase in UASA resulting in 0.78% higher mortality risk.

We further showed that the impact of ambulance staff absences on mortality was particularly pronounced for patients aged 75 and older. Patients in this age group were significantly more susceptible to increased mortality due to ambulance staff absences than younger age groups. This aligns with expectation,s given the higher vulnerability of this population to severe health conditions. Similar to previous research on out-of-hours ED attendances, we found that patient mortality increases during times when GPs are often unavailable. Specifically, UASA significantly reduces patients' survival probabilities during morning and night ED visits. This highlights the critical role of timely access to emergency care. We showed that unexpected sickness absences among ambulance station staff increase patient mortality significantly in EDs with above-median avoidable attendances, where sickness absences among ED staff also become a significant factor reducing patients' survival probability. This demonstrates the importance of addressing overcrowding of hospital emergency departments.

Our core finding on the impact of UASA on ED patient mortality within one day remained consistent even after controlling for seasonal influenza, patients' health conditions diagnosed at ED, and attrition behaviour among ambulance staff, demonstrating the robustness of the results.

With this research, we provide robust evidence of a critical link between ambulance staff sickness absences and patient mortality in English NHS hospital emergency departments. The findings strongly suggest that addressing ambulance staff shortages through improved workforce management strategies, including proactive mitigation of sickness absences, is vital to improving emergency care quality and reducing preventable deaths. Further research into potential policy implications and addressing emergency department overcrowding is warranted.

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Appendix A. Additional Tables & Figures

Table A1. Number of observations across different samples

	Overall sample	**15 KM**	**Estimation sample**
No observations	11,217,507	11,022,408	11,018,201
Unique patients	5,922,957	5,835,605	5,834,187
Unique closest ambulance station	831	831	818
Unique ED	186	186	186
Mean distance of closest ambulance station	3.69	3.424	3.425
Std. dev distance of closest ambulance station	3.438	2.797	2.798

Table A2. Definitions of variables

Variable name	**Definition**
Patient mortality	
within ω day	Takes the value of 1 if the patient died within time, ω, following ED arrival, 0 otherwise. ω element 1,2,7 .
Ambulance station characteristics	
Sickness absence rate	The share of days lost to sickness absences in a month for core ambulance staff. Core ambulance staff are those who are directly involved in delivering care to emergency patients, working in ambulance stations. We also include call operators, ambulance drivers and emergency medical dispatchers to our core ambulance staff definition.
Non-sickness (other) absence rate	The share of days lost due to non-sickness-related reasons in a month for core ambulance staff.
Number of core staff	Number of core staff working in an ambulance station.
Churn rate	Monthly share of ambulance core staff who switch jobs from one ambulance station to another, but remain in the NHS Ambulance sector.
NHS leavers' rate	Monthly share of ambulance core staff who have left their job and have not appeared in any Ambulance Trusts' payroll in the following six months.
Leaver rate	Monthly share of ambulance core staff who left their job in their ambulance station. It is the sum of churn and NHS leavers' rate.
ED characteristics	
ED staff sickness absence	Monthly share of days lost to sickness absences of nurses and doctors who worked in acute care NHS hospitals Trusts, whose secondary area of work is listed as Accident and Emergency.
GP-treatable attendances (AA_{GP})	The GP-treatable attendances are defined as the first attendance with some recorded treatment or investigation, which may have been provided by a GP, followed by discharge to home or GP care. The share of GP treatable avoidable attendances in ED in a day is calculated as the ratio of GP avoidable attendances over all ED attendances in an ED hospital at time t.
Share of ED with above median AA_{GP}	The share of EDs that have above-(monthly) median AA_{GP} in a day
No-treatment and discharge attendances (AA_{NTD})	No treatment and discharge(NTD) ED attendances consist of self-referred patients with an initial attendance, who received no investigation and either no treatment or guidance/advice only; and were discharged with either no follow-up or follow-up with primary care (McHale et al., 2013). The share of AA_{NTD} attendances is the ratio of the number of AA_{NTD} over all ED within ED-hospital at time t.
Share of ED with above median AA_{NTD}	The share of EDs that have above-(monthly) median AA_{NTD} in a day
Patients arriving ED with a respiratory diagnosis	Dummy variable which takes the value of 1 if the patient arriving at an ED by an ambulance was diagnosed with a respiratory condition. Respiratory conditions are derived from the first diagnosis using ICD-10 codes.
Patient characteristics	
Age	Patients' age bracket when they arrive at the ED. Separate age dummy variables taking the value of 1 if the age category their age falls under (0-17, 18-34, 35-49, 50-64 and 65 and above), and 0 otherwise.
Female	Takes the value 1 if patient is female, 0 if male.
Black - Asian ethnic minority	Takes the value 1 if patient is from a Black, Asian or mixed ethnic minority background, 0 otherwise.
Unknown ethnic minority status	Takes the value 1 if patient's ethnicity is unknown or missing, 0 otherwise.
Income deprivation quintiles	Income deprivation measures the share of the population in the LSOA who receive income-tested benefits, or cannot afford basic necessities. A higher score means higher deprivation, and we use dummy variables for each quintile. Thus, the bottom quintile is the least deprived (bottom 20%), and the top quintile (top 20%) is the most income-deprived.
Patient-ED distance in km	The Pythagorean distance between patient's residence and ED in kilometres.
Waiting time in ED to initial assessment	Patients waiting time to initial assessment in minutes at the ED after arriving by an ambulance.
Waiting time in ED to treatment	Patients waiting time to treatment in minutes at the ED after arriving by an ambulance.
Share of out-of-hours visits	Share of out-of-hour visits among ED patients delivered by the hospital on weekends or between 6.30 pm and 8 am on weekdays.

Table A3. ED patient mortality and ED diagnoses

Diagnosis	% Alive	% ED patient mortality within Day 1	Day 2	Days 3 to 7	Total
Respiratory conditions	95.193	1.596	0.733	2.478	904,333
Gastrointestinal conditions	97.545	0.949	0.386	1.12	776,060
Cardiac conditions	95.035	3.439	0.384	1.142	752,555
Central nervous system conditions†	98.12	0.697	0.271	0.912	392,889
Dislocation/fracture/joint	98.576	0.245	0.218	0.961	364,491
Urological conditions (inc cystitis)	97.934	0.56	0.288	1.218	357,773
Missclassified	97.563	0.965	0.323	1.149	347,215
Nothing abnormal detected	97.976	0.736	0.253	1.035	246,520
Head injury	98.992	0.345	0.134	0.53	238,897
Poisoning (inc overdose)	99.675	0.114	0.048	0.162	237,826
Psychiatric conditions	99.686	0.066	0.048	0.2	189,707
Cerebro-vascular conditions	94.812	2.001	0.722	2.465	181,464
Infectious disease	96.743	1.06	0.479	1.718	159,479
Septicaemia	89.275	4.425	1.531	4.77	135,967
Laceration	99.558	0.078	0.052	0.313	135,670
Soft tissue inflammation	99.315	0.142	0.107	0.437	120,825
Diabetes and other endocrin	97.199	0.856	0.404	1.541	103,179
Contusion/abrasion	99.149	0.207	0.114	0.529	100,752
ENT conditions	99.661	0.098	0.04	0.201	89,997
Local infection	97.433	0.663	0.396	1.508	80,550
Sprain/ligament injury	99.704	0.032	0.037	0.227	79,153
Social problems‡	98.737	0.208	0.159	0.896	71,171
Muscle/tendon injury	99.718	0.045	0.035	0.202	68,389
Gynaecological conditions	99.783	0.047	0.045	0.125	59,994
Other vascular conditions	94.713	2.886	0.703	1.698	55,366
Haematological conditions	95.848	1.23	0.524	2.398	40,652
Allergy (inc anaphylaxis)	99.826	0.045	0.025	0.104	35,668
Dermatological conditions	98.171	0.49	0.299	1.039	28,383
Burns and scalds	98.704	0.572	0.148	0.576	20,991
Obstetric conditions	99.768	0.051	0.04	0.141	17,674
Foreign body	98.933	0.294	0.162	0.611	12,930
Nerve injury	99.328	0.166	0.103	0.403	9,666
Ophthalmological conditions	99.657	0.086	0.037	0.221	8,153
Facio-maxillary conditions	99.334	0.148	0.044	0.474	6,755
Vascular injury	92.421	4.091	1.158	2.331	6,478
Bites/stings	99.854	0.117	0.029	0	3,432
Visceral injury	95.575	1.812	0.767	1.847	2,870
Electric shock	98.926	0.961	0.057	0.057	1,769
Near drowning	98.276	1.724	0	0	290
No/missing diagnosis	97.359	1.056	0.348	1.237	2,621,755
Diagnosis not classifiable	97.385	1.05	0.336	1.229	1,950,513
Total	97.259	1.128	0.36	1.253	11,018,201

Notes: Based on estimation sample using ICD codes for diagnoses. † Central nervous system conditions excludes stroke. ‡ Social problems include chronic alcholism and homelessness.

Table A4. Summary statistics on AS workforce from auxiliary panel

Variable name	**Mean**	**Std. dev.**
Sickness absence rate, ASA	0.064	0.069
Non-sickness (other) absence rate	0.002	0.009
Number of core AS staff	32.385	35.571
Share of staff		
Aged under 35	0.227	0.175
Aged 35-44	0.314	0.159
Aged 45-54	0.308	0.162
Aged 55-64	0.140	0.138
Aged 65 and above	0.011	0.039
Female	0.367	0.174
EU-EEA national	0.011	0.029
Overseas national	0.016	0.048
Black and ethnic minority	0.022	0.057
On permanent contract	0.986	0.066
On full-time contract	0.864	0.134
Observations (AS-month)	40,168	

Notes: Based on auxiliary AS panel.

Table A5. Comparing patients delivered to ED during high/low ASA

	ASA < median ASA		ASA ⩾ median ASA			
	Mean	**Std**	**Mean**	**Std**	**Normalised Δ(Mean)**	**p-value**
Patient characteristics						
Age [0-17]	0.087	0.282	0.088	0.283	-0.001	0.847
Age [18-34]	0.125	0.331	0.123	0.329	0.004	0.306
Age [35-49]	0.117	0.321	0.116	0.320	0.001	0.761
Age [50-64]	0.142	0.349	0.143	0.350	-0.001	0.604
Age 65 and above	0.529	0.499	0.531	0.499	-0.002	0.719
Female	0.543	0.498	0.545	0.498	-0.0026**	0.031
Black - Asian ethnic minority	0.108	0.311	0.102	0.303	0.014	0.475
Unknown ethnic minority status	0.078	0.268	0.072	0.259	0.016	0.184
Share of patients in income deprivation						
Least deprived 20%	0.138	0.345	0.134	0.341	0.0072	0.465
Quintile 2	0.168	0.374	0.162	0.369	0.0115	0.176
Quintile 3	0.195	0.396	0.192	0.394	0.0061	0.348
Quintile 4	0.221	0.415	0.229	0.420	-0.0136	0.109
Most deprived 20%	0.278	0.448	0.283	0.451	-0.0078	0.663
Diagnoses						
Laceration	0.012	0.109	0.013	0.112	-0.0041	0.142
Contusion/abrasion	0.009	0.093	0.010	0.098	-0.0070**	0.029
Soft tissue inflammation	0.011	0.105	0.011	0.103	0.0021	0.753
Head injury	0.022	0.146	0.022	0.145	0.0014	0.674
Sprain/ligament injury	0.007	0.082	0.008	0.087	-0.0071**	0.041
Muscle/tendon injury	0.006	0.079	0.006	0.078	0.0009	0.839
Nerve injury	0.001	0.029	0.001	0.030	-0.0012	0.759
Vascular injury	0.001	0.023	0.001	0.025	-0.0028*	0.097
Burns and scalds	0.002	0.041	0.002	0.046	-0.0069	0.318
Electric shock	0.000	0.011	0.000	0.014	-0.0044	0.193
Foreign body	0.001	0.033	0.001	0.035	-0.0031	0.141
Bites/stings	0.000	0.017	0.000	0.018	-0.0005	0.564
Poisoning (inc overdose)	0.022	0.147	0.021	0.144	0.0042	0.248
Near drowning	0.000	0.005	0.000	0.005	-0.0010	0.441
Visceral injury	0.000	0.016	0.000	0.016	0.0000	0.989
Infectious disease	0.014	0.117	0.015	0.122	-0.0077	0.128
Local infection	0.008	0.087	0.007	0.083	0.0057	0.356
Septicaemia	0.013	0.112	0.012	0.109	0.0055	0.283
Cardiac conditions	0.067	0.251	0.069	0.254	-0.0050	0.509
Cerebro-vascular conditions	0.016	0.125	0.017	0.130	-0.0073	0.104
Other vascular conditions	0.005	0.070	0.005	0.071	-0.0006	0.821
Haematological conditions	0.004	0.061	0.004	0.060	0.0015	0.452
Central nervous system conditions (exc stroke)	0.035	0.185	0.036	0.186	-0.0013	0.815
Respiratory conditions	0.082	0.274	0.082	0.275	-0.0019	0.815
Gastrointestinal conditions	0.071	0.256	0.070	0.255	0.0015	0.809
Urological conditions (inc cystitis)	0.032	0.177	0.033	0.178	-0.0008	0.867
Obstetric conditions	0.001	0.038	0.002	0.042	-0.0053	0.189
Gynaecological conditions	0.006	0.076	0.005	0.072	0.0055	0.152
Diabetes and other endocrinological conditions	0.009	0.095	0.010	0.098	-0.0045	0.217
Dermatological conditions	0.003	0.051	0.003	0.050	0.0012	0.719
Allergy (inc anaphylaxis)	0.003	0.057	0.003	0.056	0.0014	0.430
Facio-maxillary conditions	0.001	0.025	0.001	0.025	-0.0005	0.665
ENT conditions	0.008	0.090	0.008	0.090	-0.0012	0.634
Psychiatric conditions	0.018	0.132	0.017	0.128	0.0055	0.111
Ophthalmological conditions	0.001	0.027	0.001	0.027	0.0000	0.983
Social problems (inc chronic alcoholism and homelessness)	0.006	0.080	0.007	0.081	-0.0017	0.657
Diagnosis not classifiable	0.171	0.376	0.183	0.387	-0.0222	0.183
Nothing abnormal detected	0.022	0.146	0.023	0.150	-0.0056	0.572
Missclassified	0.034	0.182	0.029	0.167	0.0224	0.349
No/missing diagnosis	0.245	0.430	0.232	0.422	0.0214	0.485

Notes: Based on patients in estimation sample. The median ASA is computed from a pooled sample of all ambulance stations in mainland England from April 2013 to March 2018. Normalised Δ(Mean) is $^{(X_{low}-X_{high})}/\sqrt{\sigma^2_{low}+\sigma^2_{high}}$ where X_{low} and X_{high} are the sample mean for below and above median ASA samples for patient characteristic X, and $sigma^2$s are the sample variance of the variable X. Significance levels: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A6. Predictors of ambulance sickness absence rate (ASA)

	Coefficient	**Standard error**
Age groups (share of staff)		
Under 35	-0.02324	(0.04606)
35-44	0.00915	(0.04550)
45-54	0.02611	(0.04541)
55-64	0.03282	(0.04758)
Share of female staff	0.04240***	(0.01530)
Nationality (share of staff, ref: British)		
EU-EEA	0.00116	(0.03685)
Overseas	-0.01739	(0.02373)
Unknown	0.00584	(0.02799)
Share of ethnic minority	0.03415*	(0.01749)
Share of staff on permanent contract	0.00776	(0.01595)
Share of staff on full-time contract	0.00969	(0.01148)
ln(ambulance station core staff size)	0.00497*	(0.00276)
Month FE (ref:April)		
January	0.01165***	(0.00149)
February	0.00605***	(0.00146)
March	0.00214*	(0.00118)
May	-0.00180*	(0.00101)
June	-0.00321**	(0.00148)
July	-0.00224	(0.00150)
August	-0.00078	(0.00144)
September	-0.00152	(0.00147)
October	-0.00086	(0.00147)
November	0.00242*	(0.00141)
December	0.01148***	(0.00141)
Year FE (ref 2013/14)		
2014/15	0.00507***	(0.00188)
2015/16	-0.00029	(0.00199)
2016/17	-0.00431**	(0.00200)
2017/18	-0.00452**	(0.00219)
Constant	0.00619	(0.04648)
Observations	40,168	

Notes: Equation 3 is estimated using month, year and ambulance station FEs and controlling for the proportion of AS staff by age, gender, nationality, ethnic minority and type of contract. Standard errors are clustered at the ambulance station level and reported in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A7. Effects of other covariates not presented in Table 2 Column (III)

	Coefficient	**Standard error**
Patient age group (ref: 65+)		
0-17	-0.01583***	(0.00032)
18-34	-0.01638***	(0.00031)
35-49	-0.01384***	(0.00025)
50-64	-0.00850***	(0.00017)
Male	0.00260***	(0.00011)
Ethnic minority	0.00051***	(0.00013)
Ethnicity not known	0.00694***	(0.00032)
Time of day (ref: Afternoon)		
Morning	0.00352***	(0.00014)
Evening	-0.00124***	(0.00010)
Night	0.00054***	(0.00011)
Day of week (ref: Friday)		
Monday	0.00017	(0.00011)
Tuesday	0.00005	(0.00011)
Wednesday	0.00007	(0.00011)
Thursday	0.00006	(0.00013)
Saturday	0.00019	(0.00012)
Sunday	0.00069***	(0.00011)
Month FE (ref:April)		
January	0.00089***	(0.00016)
February	0.00032*	(0.00018)
March	-0.00035**	(0.00016)
May	-0.00076***	(0.00017)
June	-0.00119***	(0.00016)
July	-0.00171***	(0.00015)
August	-0.00144***	(0.00016)
September	-0.00117***	(0.00017)
October	-0.00063***	(0.00016)
November	-0.00027*	(0.00015)
December	0.00050***	(0.00017)
Year FE (ref: 2013/14)		
2014/15	-0.00019	(0.00016)
2015/16	-0.00076***	(0.00018)
2016/17	-0.00132***	(0.00020)
2017/18	-0.00165***	(0.00022)
Observations	11,018,201	

Notes: Linear probability model with all observed controls and time of day, day of week, month, year and ED fixed effects (see Equation 5). Standard errors are clustered at the ED level and reported in parentheses. Significance levels: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A8. Effect on ED patient mortality within 1 day due to unpredicted ambulance non-sickness absence rate

	Coefficient	**Std error**
Unexpected monthly ambulance non-sickness absences, UANSA	-0.00309	(0.00401)
ln(average number of core ambulance staff), lnASize	0.00000	(0.00004)
ED staff monthly non-sickness absences, EDNSA	-0.00579	(0.00888)
Percentage change in ED mortality, Θ		
$\Theta(UOTHA)$	-0.21769	
$\Theta(EDOTHA)$	-0.40472	
Observations	11018201	

Notes: Linear probability model (5) with UASA replaced with the deviation of the ambulance non-sickness absence rate from its expected value using the same variables as in model (3). Θ is the percentage change in average ED mortality rate (mean: 0.011) by one standard deviation increase in UANSA (std dev: 0.00006), and in EDNSA (std. dev: 0.008). Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A9. Effect on ED mortality controlling for out-of-(GP)hours

	OOH	**OOH breakdown**
Unexpected monthly ambulance sickness absence, UASA	0.00131**	0.00131**
	(0.00051)	(0.00051)
Out of (GP) hours, OOH	0.00051***	
	(0.00012)	
OOH, 6.30 pm - 8.00 am weekday		0.00051***
		(0.00012)
OOH, weekend		0.00045***
		(0.00014)
ln(average number of core ambulance staff), lnASize	0.00000	0.00000
	(0.00004)	(0.00004)
ED staff monthly sickness absence, EDSA	0.00286	0.00286
	(0.00219)	(0.00219)
Percentage change, Θ		
$\Theta(UASA)$	0.78014**	0.78014**
$\Theta(OOH)$	4.56702***	
$\Theta(OOH_{weekday})$		4.56702***
$\Theta(OOH_{weekend})$		3.95996***
$\Theta(EDSA)$	0.38152	0.38152
Mean(M)	0.01128	
Observations	11018201	

Notes: Linear probability model with time of day, day of week, month, financial year and ED fixed effects (FE). Standard errors are clustered at the ED level and in parentheses. OOH takes the value of 1 if the attendance occurs on a weekday between 6:30 pm and 8:00 am, or on a weekend. Other variables included in the model specification but not presented in the table are the distance between patients and ED, income deprivation quintiles, patients' age categories, gender, ethnic minority status, ED attendance month, day of attendance, and time of attendance. Significance levels: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table A10. Robustness check: Alternative specifications of baseline model

	ED x fin.year FE	**Cloglog ME**
Unexpected monthly ambulance sickness absence, UASA	0.00121**	0.00124***
	(0.00052)	(0.00046)
ln(average number of core ambulance staff), ln(ASize)	0.00002	0.00001
	(0.00004)	(0.00004)
ED staff monthly sickness absence, EDSA	0.00399*	0.00278
	(0.00206)	(0.00188)
ln(patient-hospital distance in km)	0.00003	-0.00001
	(0.00008)	(0.00008)
Income deprivation (ref: Least deprived 20%)		
Quintile 2	0.00015	0.00011
	(0.00011)	(0.00010)
Quintile 3	-0.00016	-0.00015
	(0.00014)	(0.00013)
Quintile 4	-0.00014	-0.00011
	(0.00014)	(0.00013)
Quintile 5 (Most deprived 20%)	-0.00042***	-0.00037***
	(0.00015)	(0.00014)
Percentage change in ED mortality, Θ		
$\Theta(UASA)$	0.71822**	0.73606***
$\Theta(EDSA)$	0.53324*	0.37160
Mean(M)	0.01128	0.01128
Number of clusters (ED hospitals)	185	173
Observations	11018198	11016311

Notes: Standard errors are clustered at the ED level and are reported in parentheses. The first column uses interacted ED and financial year FE, which entered separately in Eq. (5). The second column presents marginal effects from the complementary log-log model. Other variables included in the model specification but not presented in the table are patients' age categories, gender, ethnic minority status, time of day, day of the week, and month and year of ED attendance, as well as ED FEs. Significance levels: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A11. Effect on ED due to UASA based on alternative first-stage specifications to compute UASA

(a) Time restriction to auxiliary AS panel	**(I)** T**=20**	**(II)** T**=30**	**(III)** T**=40**
Unexpected monthly ambulance sickness absence, UASA	0.00140***	0.00132**	0.00140**
	(0.00052)	(0.00053)	(0.00058)
ln(average number of core ambulance staff), lnASize	-0.00000	0.00002	0.00003
	(0.00004)	(0.00004)	(0.00005)
ED staff monthly sickness absence, EDSA	0.00297	0.00310	0.00383*
	(0.00217)	(0.00215)	(0.00219)
Percentage change in ED mortality, Θ			
$\Theta(UASA)$	0.83230***	0.78792**	0.82412**
$\Theta(EDSA)$	0.39919	0.42094	0.53285*
Mean(M)	0.01126	0.01125	0.01123
Observations	10691081	10347120	9459167

(b) Alternative model specifications	**(IV) Only FEs**	**(V) No Amb Station FE**	**(VI) DK standard errors**
Unexpected monthly ambulance sickness absence, UASA	0.00121**	0.00091*	0.00093**
	(0.00051)	(0.00047)	(0.00046)
ln(average number of core ambulance staff), lnASize	0.00000	0.00000	0.00001
	(0.00004)	(0.00004)	(0.00004)
ED staff monthly sickness absence, EDSA	0.00285	0.00282	0.00282
	(0.00219)	(0.00219)	(0.00219)
Percentage change in ED mortality, Θ			
$\Theta(UASA)$	0.72357**	0.58769*	0.60180**
$\Theta(EDSA)$	0.38116	0.37673	0.37677
Mean(M)	0.01128	0.01128	0.01128
Observations	11018201	11022408	11022408

Notes: Linear probability model with time of day, day of week, month, year, and ED FEs. Other controls, not shown in the table, include the natural logarithm of patient-ED distances, income deprivation quintiles, patients' age categories, gender, and ethnic minority status. Panel (a) presents results, where the UASA is the residuals from Eq. (3) based on the auxiliary panel restricted to AS with at least T observations. Panel (b) presents estimates where the UASA represents the residuals from alternative specifications of Eq. (3). The last column in panel (b) uses Driscoll-Kraay standard errors with 2 lags instead of cluster robust standard errors at ED level. Significance levels: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A12. Sensitivity check: Effect on ED patient mortality due to UASA in the two closest ambulance stations

	Coefficient	**Std error**
Unexpected monthly ambulance absences in the closest station, UASA1	0.00130**	(0.00051)
ln(average number of core ambulance staff in the closest station) , lnASize1	-0.00001	(0.00004)
Unexpected monthly ambulance absences in the 2nd closest station, UASA2	0.00016	(0.00047)
ln(average number of core ambulance staff in the 2nd closest station), lnASize2	-0.00003	(0.00005)
ED staff monthly sickness absence, EDSA	0.00286	(0.00220)
Percentage change in ED mortality, Θ		
$\Theta(UASA1)$	0.77161**	
$\Theta(UASA2)$	0.09674	
$\Theta(EDSA)$	0.38187	
Observations	11011173	

Notes: Standard errors are clustered at the ED level and are reported in parentheses. Other controls included in the model specifications, but not shown in the table, are income deprivation quintiles, distance between patients and EDs, patients' age categories, gender, ethnic minority status, time of day, day of week, and month and year of ED attendance, as well as ED FEs. Average ED mortality within 1 day is 0.01128, standard deviation of UASA1 is 0.06707, of UASA2 is 0.06779, and of EDSA is 0.01507. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A13. Bias-corrected Oster estimates for the unexpected ambulance sickness absences

	Uncontrolled regression		**Controlled regression**		**Oster (2019)**	
	Estimate	**Standard error**	**Estimate**	**Standard error**	**Estimate**	**95% CI**
No controls and FEs *vs.* baseline specification	0.00103*	(0.00061)	0.00131**	(0.00051)	0.00137***	[0.00049, 0.00225]
No controls and FEs *vs.* baseline specification no ED FE	0.00099*	(0.00059)	0.00107*	(0.00055)	0.00111**	[0.00019, 0.00203]
No controls with ED FE *vs.* baseline specification	0.00120**	(0.00052)	0.00128**	(0.00049)	0.00137***	[0.00035, 0.00239]
All controls without ED FE *vs* baseline specification	0.00111**	(0.00056)	0.00131**	(0.00051)	0.00194***	[0.00098, 0.00291]

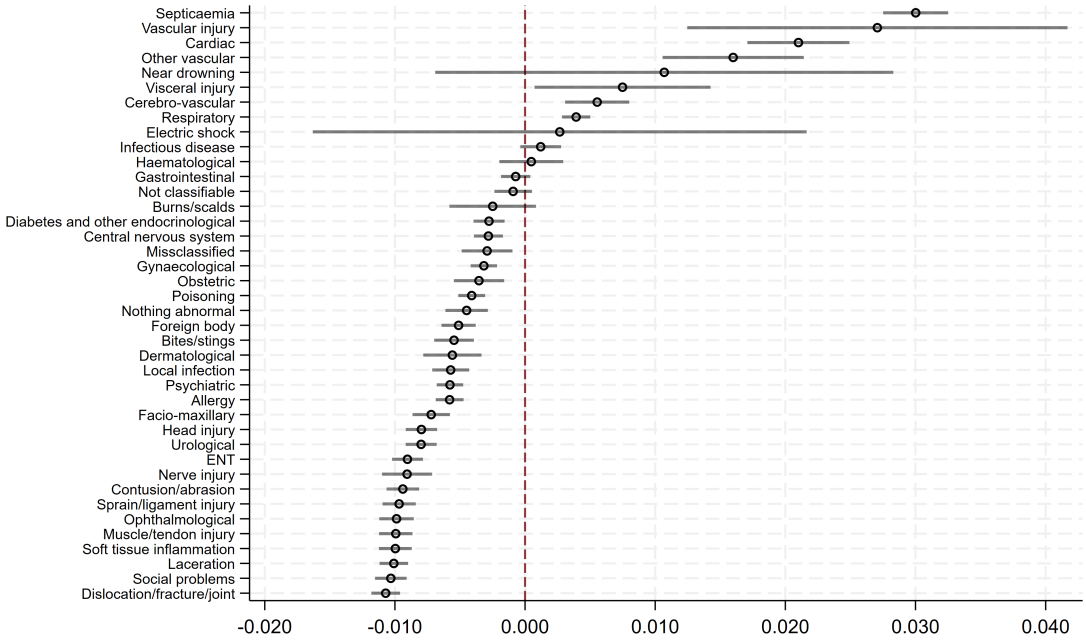
Notes: For the bias-adjusted Oster estimates, the assumption is that the degree of selection on unobservables is the same as the observables and Rmax = 1.3 x R2 (0.007). The 95% confidence intervals based on bootstrapped standard errors (100 reps) are in brackets, and those from clustered standard errors are in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A14. Placebo test: Effect on the ED waiting times due to UASA

	Waiting time to initial assessment	**Waiting time to treatment**
Unexpected monthly ambulance sickness absence, UASA	-0.02354	-0.04038
	(0.08565)	(0.02608)
ln(average number of core ambulance staff), lnASize	-0.01247	0.00168
	(0.00863)	(0.00569)
ED staff monthly sickness absence, EDSA	-0.00070	0.67973*
	(0.77832)	(0.40404)
ln(patient-hospital distance in km)	0.02147	0.00363
	(0.02464)	(0.01204)
Income deprivation (ref: Least depriveed 20%)		
Quintile 2	0.01201*	0.00909***
	(0.00708)	(0.00228)
Quintile 3	0.02953**	0.01427***
	(0.01142)	(0.00300)
Quintile 4	0.02687*	0.02091***
	(0.01437)	(0.00540)
Quintile 5 (Most deprived 20%)	0.02327	0.01536**
	(0.01758)	(0.00660)
Mean(WT)	2.276	4.014
Observations	8267896	10382446

Notes: Log-Linear probability model with the time of day, day of the week, month, financial year and ED FEs. Standard errors are clustered at the ED level and reported in parentheses. The outcomes are natural logarithms of ED waiting times until initial assessment (first column) and treatment (second column). Other variables included in the model specification, but not presented in the table, are patients' age categories, gender, and ethnic minority status. Significance levels: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Figure A1. Coefficient estimates of ED diagnoses on ED mortality within 1 day



Notes. Estimates are based on Equation 5, with ED diagnosis dummies included in the model specification. The reference category is no or missing diagnosis code. 95% confidence intervals are based on standard errors are clustered at the ED level.