Unexpected Worker Absences as Labor Supply Shocks: Evidence from Ambulance Services

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Abstract

We estimate the short-run marginal product of ambulance labour in emergency care. Using comprehensive administrative data on hospitals and ambulance stations, we exploit quasi-random variation in staffing shortages generated by unexpected sickness absences across ambulance stations serving the same emergency department. We find that a one-standard-deviation increase in ambulance staff sickness absences raises patient mortality within 24 hours of emergency department arrival by 0.78%. The effects are concentrated among high-risk patients and during periods of peak demand, highlighting the critical role of ambulance labour in the production of emergency care.

Keywords: SICKNESS ABSENCES, STAFF SHORTAGES, AMBULANCE SERVICES, PATIENT MORTALITY.
JEL Codes: J45, J22, I11, C23.

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1 Introduction

Ambulance services constitute the first stage of emergency care, providing rapid transport and pre-hospital treatment that can be critical for patient survival. In many countries, demand for ambulance services has increased substantially in recent years, placing growing pressure on ambulance systems and their workforce and raising concerns about the capacity of emergency medical systems to deliver timely care (Lowthian et al., 2011; Pittet et al., 2014; Andrew et al., 2020; Khan, 2022).

As demand for emergency care increasingly outpaces the availability of ambulance staff, concerns about workforce shortages have become central to the performance of emergency medical care. When ambulance staffing is insufficient, delays in response or transport may affect the timeliness of emergency care and quality of pre-hospital treatment and ultimately patient outcomes. These pressures raise a fundamental economic question: what is the short-run marginal product of frontline emergency care labour? Answering this question is key to understanding both the emergency care production function and the welfare costs of labour shortages in high-stakes public services.

Despite the central role of ambulance services in emergency care, there is limited evidence on their contribution to patient health outcomes. Existing studies show that response times, demand congestion, and shift-induced fatigue affect emergency care performance (Brachet et al., 2012; Wilde, 2013; Lucchese, 2024; Asheim et al., 2025), but do not directly estimate the marginal product of ambulance labour. We provide the first evidence on the effect of ambulance staff shortages on patient mortality, which can be interpreted as the short-run marginal product of ambulance labour.

Our main outcome is mortality within one day of arrival at the emergency department by ambulance, which reflects a multi-stage and state-dependent health production process involving both pre-hospital and in-hospital inputs. Patient survival depends on the sequential provision of care: ambulance staff provide on-scene stabilisation and rapid transport, while hospital clinicians deliver definitive treatment, so delays or constraints at any stage can affect outcomes. The impact of staff shortages varies with patients' clinical severity and system pressure, making delays especially consequential for severe conditions and during periods of high demand (Liu et al., 2017; Lucchese, 2024).

To isolate the effect of ambulance labour shortages separately from hospital inputs

on patient mortality, we compare patients arriving at the same emergency department but residing in areas served by different ambulance stations, and thus exposed to different levels of staffing shortages. By conditioning on hospital fixed effects, our empirical design holds constant the hospital environment and treatment inputs available upon arrival, allowing us to isolate variation in the pre-hospital component of emergency care. This approach builds on Doyle et al. (2015), but in reverse. While they use ambulance assignment to identify the causal effect of hospital Medicare reimbursement separately from pre-hospital care, we exploit geographic dispatch rules to identify the effect of exogenous variation in ambulance staff shortages, holding hospital inputs fixed.

We measure ambulance staff shortages using sickness absence rates and isolate plausibly exogenous variation by constructing a measure of unexpected absence rate purged of workforce composition, ambulance-station fixed effects, and time effects. This approach is related in spirit to high-dimensional fixed-effects strategies used to isolate unanticipated shocks in other settings (Francetic et al., 2024; Gazze et al., 2024; Ireland et al., 2024; Escobar Carias et al., 2024).

We apply this identification strategy to England, a setting where ambulance assignment is determined by geographic proximity rather than patient choice, implying that—conditional on hospital fixed effects—patients are as good as randomly assigned to ambulances with different levels of unexpected sickness absence rate. A similar identification strategy is used by Knutsson and Tyrefors (2022) to study the effect of ambulance ownership (private versus public) on patient mortality in Stockholm, Sweden.

Ultimately, our main empirical specification regresses patient mortality within one day of arrival at the emergency department on the unexpected staff absence rate, while controlling for hospital fixed effects. This specification exploits plausibly exogenous variation in staffing shortages across ambulance stations serving the same hospital.

Using linked administrative data on over 11 million ambulance-delivered ED attendances between 2013 and 2018, we find that unexpected ambulance staff shortages increase patient mortality within 24 hours of ED arrival. A one-standard-deviation increase in UASA raises 24-hour mortality by 0.78 percent relative to a baseline mortality rate of 1.1 percent. The effect is economically meaningful and precisely estimated. Notably, we find no statistically significant impact on mortality beyond the first 24 hours after hospital arrival, consistent with a mechanism operating through

time-sensitive pre-hospital care and delays in patient transport to the ED.

We find heterogeneity patterns consistent with a state-dependent production function. The mortality effect is concentrated among patients aged 75 and above and those with high-severity diagnoses, and is substantially larger during winter months, when emergency systems face peak demand. These findings underscore the importance of workforce resilience in emergency services and the potential social returns to policies that improve retention, reduce burnout, and strengthen surge capacity during peak periods.

Our confidence in a causal interpretation of the effects of staff shortages is supported by the quasi-experimental design and a comprehensive set of robustness and falsification exercises. In particular, the results remain stable when including hospital-by-month and hospital-by-month-by-year fixed effects, which absorb time-varying hospital inputs and shocks, and when using alternative constructions of unexpected sickness absence based on ambulance-station-by-month fixed effects that capture station-specific seasonal patterns.

This work contributes to several distinct but related strands of the economic literature. First, we add to the research that quantifies the economic impact of work absenteeism (Hansen, 2000; Pauly et al., 2002; Ichino and Moretti, 2009; Herrmann and Rockoff, 2012; Markussen, 2012; Grinza and Rycx, 2020). While absenteeism is known to generate substantial productivity losses (Stewart et al., 2003; Eurofound, 2010), credible evidence on its causal effects remains limited due to identification challenges. Existing studies in healthcare primarily rely on planned absences, such as those caused by strikes or parental leave reforms (Gruber and Kleiner, 2012; Costa, 2022; Stoye and Warner, 2023; Friedrich and Hackmann, 2021). We instead consider unexpected sickness absences, which generate short-run shocks that are difficult to anticipate or mitigate, and study their impact in a high-stakes setting.

Second, we contribute to the literature on healthcare labour productivity and staffing and patient outcomes (Lin, 2014; Bartel et al., 2014; Chen and Grabowski, 2015; Shen et al., 2022; Winter et al., 2020; Chan Jr and Chen, 2022; Grabowski et al., 2023; Zaranko et al., 2023; Moscelli et al., 2024; Kelly et al., 2025). While this literature has focused primarily on in-hospital inputs, we provide the first evidence on the short-run marginal product of ambulance labour, a critical but understudied component of health production. In doing that our paper also contributes to the growing but still very limited literature on the economics of emergency ambulance

services (Brachet et al., 2012; Knutsson and Tyrefors, 2022; Wilde, 2013; Lucchese, 2024; Asheim et al., 2025).

Finally, we contribute to the literature on the organisation and congestion of emergency care systems (Anselmi et al., 2017; Turner et al., 2020; Gruber et al., 2023; Francetic et al., 2024). While prior work has focused on the effects of demand surges and overcrowding on patient outcomes (Hoe, 2022; Francetic et al., 2024), we instead isolate the impact of a labour supply shock in ambulance services on patient survival.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting of ambulance and emergency department services in the English NHS. Section 3 presents the data and sample construction. Section 4 outlines the empirical strategy. Section 5 reports the main results and robustness analyses. Section 6 provides an economic evaluation of the welfare costs of ambulance staff shortages. Section 7 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 above 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 acute medical conditions. Because all NHS urgent and emergency care services are free at the point of care, access to these care services is independent on any financial consideration with respect to the treatment expensiveness.

2.1 Hospital-Based Emergency Departments (EDs)

Emergency Departments (also known as Accident&Emergency) provide free-of-charge, urgent medical care to 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 growing 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

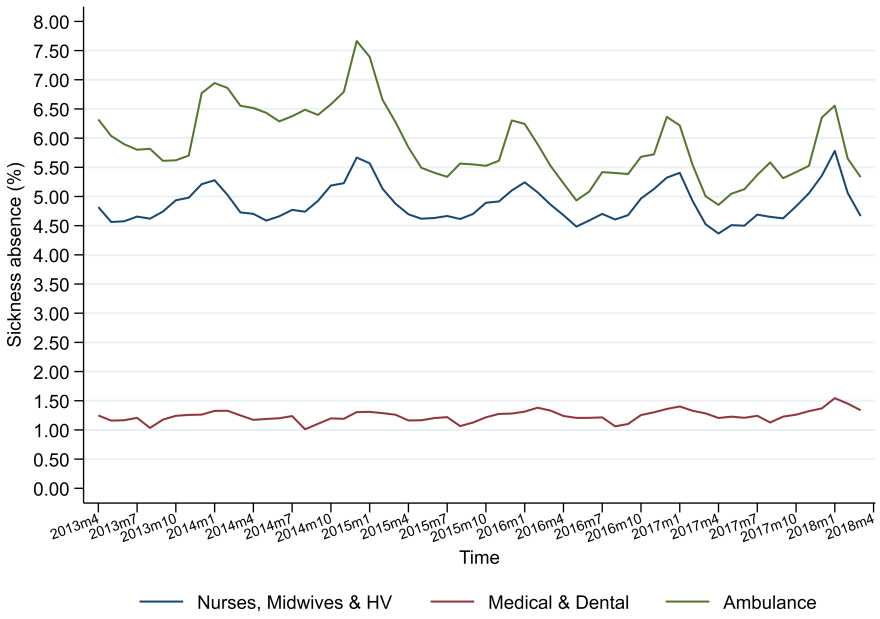
Ambulance services in England are organised into 10 large organizations called NHS Ambulance Trusts (ATs), each covering a large geographical region, except for London, and serving over 55 million people in mainland England. These publicly funded services operate 24/7 and are free at the point of use. The core function of NHS Ambulance Trusts 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, 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 (Carter of Coles, 2018), the ambulance workforce comprises a variety of roles from different professional groups. This includes paramedics, ambulance technicians, and support staff—such as clerical and administrative personnel—who respectively make up 37.8%, 16%, and 15.5% of the entire ambulance staff.

2.3 Workforce Pressures and Sickness Absences

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

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.

Negative experiences in the workplace also remain a serious factor for Ambulance Trust staff: one in three ambulance staff reported experiencing physical violence from

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

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.

3 Data

For our empirical analysis, we construct a multi-level panel dataset using high-quality administrative data from different data sources in England. Figure A1 provides an overview of the construction of this unique dataset, including its sources and linkages. The backbone of this novel dataset are the universe of records of NHS hospital Emergency Department (ED) attendances for patients arriving at a major hospital ED by ambulance, linked to the geographically nearest ambulance stations of each ED patient, and detailed monthly payroll records for the core staff employed at NHS ambulance stations, including rich demographics and their work absences due to sickness and non-sickness reasons.

Our analysis focuses on the five financial years from April 2013 to March 2018 for main three reasons. First, as shown in Section 2, these years were rife with deteriorations in ambulance staff working conditions, driven by increasing demand pressures on ED services. Second, after 2018 there was a structural change in the collection and reporting of administrative data for patients attending English NHS EDs; due to this change, the data quality in the first years of the new dataset (Emergency Care DataSet, ECDS) varies across NHS hospital organizations. Third, the onset of the COVID-19 pandemic from March 2020 until the end of 2021 constitute an intense and abnormal shock to ambulance and hospital ED services, which would not be representative of their normal functioning.

ED attendances and patient mortality

Our data are based on daily ED attendances and are derived from the patient-level **Hospital Episode Statistics Accidents & Emergency (HES A&E)** data (dataset (I) in Figure A1). HES A&E is an administrative dataset that contains detailed records of patients' visits to EDs in England, including information on the timing, location and the nature of the emergency visits with diagnoses, treatment and discharge information, along with basic demographic characteristics of patients (age, gender, ethnicity). As most ED patients are discharged without admission and

may die out of hospital, we match ED visits with **ONS Civil Registration of Deaths** (dataset (I.b) in Figure A1) to capture mortality risk—both in-hospital and out-of-hospital—within one, two and seven days following the ED attendance. An important feature of our study is that patient mortality after ambulance transport to the ED is registered by clinicians in the hospital ED and recorded in the HES A&E dataset, and not by ambulance workers. As these two groups of emergency care workers are employed by different organizations—Hospital Trusts and Ambulance Trusts, respectively—this feature of our data prevents the possibility of gaming by staff in the ambulance services to understate mortality levels, i.e. declaring a patient as alive when they instead died during the ambulance transportation to ED.

Ambulance Station Workforce Panel

There are no readily available datasets on ambulance stations and their workforce. Thus, we construct a novel dataset, the Ambulance Station Workforce panel, based on employee-level **Electronic Staff Records (ESR)** for the years 2013 - 2018 (dataset (II.a) in Figure A1). The ESR is an administrative database containing monthly payroll records, along with basic demographic information on staff (age, gender, ethnicity, nationality) and their sites of employment within NHS organisations in England, such as site name and postcode, which we also combine with staff absences data for the same period. We define an ambulance station as a local physical site that serves as an operational base to station and dispatch NHS ambulance vehicles, and where the majority of employees, henceforth *core staff*, are directly involved in delivering emergency patient care.[2] Ambulance stations are nested within regional NHS organisations known as Ambulance Trusts. To determine the location of each ambulance station, we cross-check and verify ambulance station postcodes recorded in ESR against the yearly reference location data from the NHS Organisational Data Service (ODS)[3] (dataset (II.b) in Figure A1), and repeat the process for each Ambulance Trust separately; we then link geographic coordinates to ambulance station postcodes using the **ONS Postcode Directory** (2020).

[2]In the definition of ambulance *core staff* we include call operators, paramedics, ambulance drivers, and emergency medical dispatchers. Core staff make 76% of all employees across the 10 NHS Ambulance Trusts.

[3]While the ESR contains site names for Ambulance Trusts, the information on the geographical location of these sites is limited, thus cross-checking with NHS ODS data improves data quality. We exclude ambulance stations for which we cannot verify their location, which is less than 1% of all ambulance stations in England.

Our Ambulance Station Workforce panel contains monthly information on staff composition at the ambulance station level, including the share of core staff by age group, gender, ethnicity, nationality, and contract type (full-time, permanent). The panel also contains non-sickness related absences measured as the share of days taken off in a month due to reasons such as annual, study or parental leave, which are generally planned, and ambulance staff turnover rate measured as the ratio of the number of staff leaving their ambulance station between month t and $t+1$ over the number of staff employed in the ambulance station at t. Finally, the Ambulance Station Workforce Panel provides our main variable of interest: the monthly ambulance staff sickness absence rate (ASA), defined as the share of days lost to illness in a given month. To isolate variation in sickness absence from confounding ambulance-station characteristics, we also construct a measure net of ambulance station staff composition, time-invariant station factors, and common time patterns. This derived variable captures unexpected ambulance staff absences (UASA; see Section 4 for details).

Linkage across different datasets

The administrative HES A&E data contain realised emergency visits to hospital EDs[4] and lack information on the specific ambulance station used for patient transport. We use the nearest ambulance station to the patient's home as a proxy for the one actually used. This assumption is based on the operational practice of dispatching ambulances from the nearest available station to an emergency, minimizing response time.[5] Using truncated patient postcodes,[6] we link ED patients' residences to ambulance station locations to generate monthly "patient–ambulance station" pairs. We compute Pythagorean distances and retain the nearest ambulance station for each patient.

Our final panel dataset is constructed by linking multiple administrative sources. First, we match emergency department (ED) attendances (Dataset I) to the nearest ambulance station (Dataset III) using patients' truncated postcodes. Second, we link each physical ambulance station establishment to station-level workforce measures

[4]It does not include pre-hospital care (e.g. 999 or NHS 111 triage) of patients who were treated on site and not transported to an ED.

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

[6]The truncated postcode contains the sector, area, and the district of the geographical location, for which we assign geographical coordinates using average northing and eastings derived from the ONS Postcode Directory (2020) (dataset (I.a) in Figure A1).

from the Ambulance Workforce Panel (Dataset II). This yields a unique dataset of ED attendances enriched with information on the workforce characteristics of the nearest ambulance station.

We further augment the dataset with hospital ED staffing information. Using the Electronic Staff Record (ESR), we link each patient to measures of sickness and non-sickness absences among nurses and doctors working in the attended ED. Finally, we assign each patient to their Lower Super Output Area (LSOA)[7] of residence and merge in area-level socioeconomic characteristics at LSOA level, in particular the income deprivation domain of the 2015 **English Index of Multiple Deprivation (IMD)**.[8]

Sample restrictions

Our main sample consists of patient attendances at EDs in mainland England who were transported by ambulance from home between 1st April 2013 and 31st March 2018. We apply the following sample restrictions: (i) patients must have been alive upon arrival at the ED; (ii) patients must be younger than 97 years and residing in a non-rural area; (iii) for each patient, we retain all unplanned ED attendances, but if multiple attendances occur on the same day, we keep only the first; (iv) observations exclude patients whose travel distance to the ED was 57.7 km or more.[9]

The initial sample selection results in 11,217,507 attendances, representing 831 ambulance stations, 186 EDs and 5,922,957 unique patients (see the overall sample in Table A1, Column 1). Figure A2 illustrates the geographical locations of ambulance stations (panel (a) and EDs (panel (b)) in England based on the Ambulance Workforce Panel and ED attendances, respectively.

We further refine our sample by retaining only patients with at least one ambulance station located within 15 km of their residence. This restriction helps to

[7]LSOAs are small, standardised geographical units with populations typically ranging from 1,000 to 3,000 residents.

[8]The English Index of Multiple Deprivation (IMD) is the official government measure used to identify pockets of relative deprivation across England. It is published by the UK Ministry of Housing, Communities & Local Government and provides a way to compare small geographical areas (LSOAs) based on a variety of social and economic factors.

[9]Only 0.017% of ED patients transported by an ambulance were recorded as deceased before arrival to ED. Non-rural area is defined as an urban settlement, town and fringe or village with wider surrounding area that is less sparsely populated, which is based on the rural-urban indicator available in the HES A&E data. Long-distance transports often involve air ambulances or pre-arranged transfers to highly specialised hospitals (e.g., major trauma centres).

maintain the validity of using the closest ambulance station 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 less than 2% of the total ED attendances (see Table A1, Column 2), while still including the same number of ambulance stations and hospital EDs as in the overall sample (831 and 186, respectively).

We retain observations linked to measures of unexpected ambulance station sickness absences (UASA) at the nearest ambulance station to the patient. Because UASA is undefined for stations observed at fewer than two time points, this restriction slightly reduces the sample size by less than 0.1% (Table A1, Column 3). Thus, the final estimation sample consists of 11,018,201 ED visits from 5,834,187 patients who travelled to 186 EDs, transported by 818 closest ambulance stations.

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% (corresponding to 124 thousand patients), rising slightly within 2 days to 1.5% and nearly tripling within 7 days (2.7%). Table A3 displays the survival rate and short-term mortality rates by ED diagnoses. As expected, most serious conditions, such as cardiac conditions and vascular injuries, have lower survival rates.

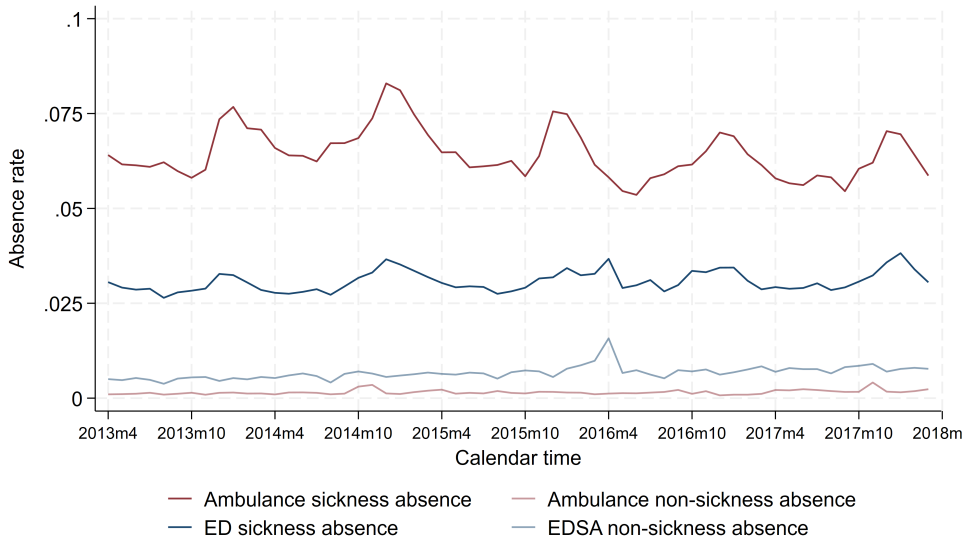
Table 1. Summary statistics, selected variables

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% for all ambulance staff (i.e., including core ambulance staff and support workers) for the same period.[10] 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 are consistently higher, more than twice those of the ED nurses and doctors. In contrast, non-sickness absences among core ambulance staff are lower than those observed in EDs. These non-sickness absences are small in magnitude, averaging 0.2% at ambulance stations and 0.7% in EDs per month.

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.

Table 1 shows that 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 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, including flu and pneumonia, with around one-fifth of cases occurring in December and January, i.e., the winter

[10]The sickness absence rate is similar in the Ambulance Station Workforce panel, presented in Table A4, along with other ambulance station workforce characteristics.

pressure months.

Mortality is closely linked to patients' emergency conditions and may be affected by ambulance prioritisation during periods of high demand or reduced ambulance station labour supply. In our sample, we find no statistical evidence that ambulance stations selectively transported patients to EDs during high-pressure periods, defined as months with above-median core ambulance staff sickness absences. Table A5 reports ED patient characteristics and diagnoses in low- ($ASA < median(ASA)$) and high-pressure ($ASA \geqslant median(ASA)$) periods, along with the standardized differences in means tests (Imai et al., 2008). Patient composition was largely similar across low-ASA and high-ASA periods, as the absolute value of the standardized difference in means for each variable is smaller than 0.1 (Austin, 2011).

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 patient mortality by exploiting 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

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

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 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 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. To avoid confounding the effect of the ambulance sickness absence rate with the effect of the 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 (1) 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 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 (1) 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 ambulance station 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 ambulance station characteristics, we consider the *unexpected ambulance staff absence (UASA)*, which is the ASA net of the observed ambulance station characteristics, as well as ambulance station, calendar month and calendar year fixed effects.

Using the ambulance station workforce panel as described in Section 3, 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 $\boldsymbol{Z_{at}}$ 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 specification is then Equation (5) below, that is, Equation (1) in which ASA is replaced with UASA:[11]

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

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 ambulance station, ED and patient characteristics and year fixed effects, 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 ambulance station sickness absences, which is uncorrelated with patients' characteristics and with observed and unobserved ED factors. The results from our preferred specification are reported in the last column of Table 2, which includes the full set of controls and emergency department fixed effects. We refer to this specification as our benchmark and focus the subsequent

[11] To avoid introducing new symbols, we use the same notation as in model 1, despite the change in the key variable of interest.

discussion and analysis on these estimates.

Standard errors are reported in parentheses and are clustered at the ED level to account for correlation in errors among patients arriving at the same ED.[12]. For the benchmark specification, we also report bootstrapped standard errors (500 replications) in brackets, which are nearly identical. Although bootstrapping is standard in two-step estimation to account for first-stage uncertainty arising from the construction of UASA, its effect is limited in our setting due to the large sample size.

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.[13] In our benchmark specification, 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. The mortality rate we analyse excludes patients who were already deceased upon the ambulance's arrival. Therefore, our estimated effect should be interpreted as a lower bound of the true impact of UASA on mortality, which would include these unobserved cases.

Turning to the other control variables, the log of the average number of core ambulance staff is negatively associated with mortality in Column II. However, in the benchmark specification that includes ED fixed effects, this association attenuates to zero and is no longer statistically significant (Column III).

[12]Clustering the standard errors at the ED-by-ambulance station level leaves the precision of the estimate essentially unchanged, with the standard error moving only slightly from 0.00051 to 0.00049.

[13]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 patient mortality, Θ			
$\Theta(UASA)$	0.61298*	0.66314**	0.78110**
$\Theta(EDSA)$		3.64468**	0.38078
Observations	11,018,201	11,018,201	11,018,201

Notes. Linear probability model with (I) no control variables other than UASA;;(II) with income deprivation, ambulance station and ED variables shown in the Table, plus dummies for patients' age categories, gender, and ethnic minority status, time of day, day of week, month, and year fixed effects, and (III) with ED fixed effects (FE). 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(UASA) and Θ(EDSA) represent the percentage change in the average ED mortality rate (mean = 0.011) associated with a one–standard-deviation increase in UASA (SD = 0.067) or EDSA (SD = 0.015). Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Our next control variable, ED sickness absences (EDSA), is included because its exclusion may introduce omitted variable bias in the measurement of the effect of unplanned ambulance staff absences (UASA): ED staff are front-line emergency healthcare workers who are subject to the same sources and timings of transmissible health diseases of core ambulance staff, and thus their sickness absences patterns may also be correlated with ED patient mortality. While higher EDSA is associated with increased mortality in the specifications reported in Columns (I) and (II), which do not control for ED fixed effects, this association attenuates to zero in our benchmark specification. This pattern is consistent with staff shortages constituting a persistent, system-wide feature of NHS hospitals. Accordingly, once unobserved time-invariant ED characteristics are accounted for, the estimated impact of EDSA on ED patient mortality is substantially reduced and remains markedly smaller than that of UASA.

With respect to the distance between the patient's home and the ED, a negative effect on mortality would be expected, as medical emergencies requiring urgent response due to higher mortality risk are likely to be more sensitive to increases in travel time (Nicholl et al., 2007). However, once ED fixed effects are included, we find no statistically significant effect of distance on mortality.

Turning to the dummy variables for income deprivation quintiles, we obtain the apparently counterintuitive result that patients residing in the most income-deprived areas (the top 20% of the income deprivation index distribution) exhibit lower mortality. However, this pattern is likely driven by demand-side factors associated with low socioeconomic status, such as lack of access to private transport (O'Cathain et al., 2022), limited access to primary care (Turner et al., 2022), and lower confidence in general practitioners (GPs) (Kraaijvanger et al., 2016; Coster et al., 2017). These factors may lead patients from more income-deprived neighbourhoods to attend EDs for relatively less severe conditions, and hence with a lower underlying risk of mortality.

Table A7 reports the estimated effects for the remaining control variables from our benchmark specification. We find higher mortality risk among male patients, patients from ethnic minority groups, and older patients. Mortality risk is also higher during the winter months and for patients arriving at the ED on Sundays, while we observe a declining trend in mortality over time.

To summarise, our findings demonstrate a significant negative effect of unexpected ambulance staff sickness absences on 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, and 12% of the effect of arriving on a Sunday compared to a Friday.

Because sickness absences are not the only form of staff absence that may affect ambulance service quality and, ultimately, patient outcomes, we assess whether our focus on unexpected sickness absences as a source of exogenous variation in ambulance staffing is warranted. To this end, we replicate our benchmark estimation of the effect of staff absence rates on mortality, replacing UASA with unexpected ambulance non-sickness absences (UANSA).[14]

[14] We compute UANSA as the residual from a regression of the observed non-sickness absence rate of core ambulance staff on the same set of predictors used to construct UASA in equation 4.

We find no statistically significant effect of UANSA on 1-day ED patient mortality (see Table 3). This evidence supports our choice of UASA as the relevant measure of unexpected, short-term staffing shocks. Unlike non-sickness absences—such as parental, annual, or study leave—sickness absences arise unpredictably and limit managers' ability to adjust staffing levels in the short run. As a result, UASA is more likely to generate binding staffing constraints with implications for patient outcomes that cannot be readily mitigated by ambulance service managers.

Table 3. Effect on ED patient mortality within 1 day due to unexpected ambulance non-sickness absence rate

	Coefficient
Unexpected monthly ambulance non-sickness absences, UANSA	-0.00309
	(0.00401)
Percentage change in patient mortality, Θ	
$\Theta(UANSA)$	-0.21769
Observations	11,018,201

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). Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.2 Threats to identification

To ensure that the observed effect of UASA on patient mortality is not spurious, we conduct several falsification and sensitivity checks.

Falsification test using lead and lag values of UASA

If the estimated effect of UASA were driven by unobserved factors affecting ambulance staff absence—such as local seasonal patterns in epidemics or illness—rather than by a causal mechanism, the estimated relationship could be spurious. To assess this potential source of endogeneity, we conduct a falsification test by re-estimating the benchmark specification in Equation (5), replacing $UASA_t$ with either (i) $UASA_{t-12}$, defined as the UASA of the same ambulance station and calendar month in the previous year, or (ii) $UASA_{t+12}$, defined as the UASA of the same ambulance station and calendar month in the subsequent year.

The estimated effects of $UASA_{t-12}$ and $UASA_{t+12}$ on ED patient mortality, reported in Columns (II) and (IV) of Table 4, are substantially smaller than the baseline estimates, negative in sign, and statistically insignificant. These findings are consistent with the absence of a spurious correlation driven by semi-persistent[15] or seasonal unobserved factors, and therefore support the interpretation of a genuine causal effect of contemporaneous UASA on the mortality of ambulance patients transported to EDs.

Because the sample size differs when estimating models with $UASA_{t-12}$ and $UASA_{t+12}$ instead of $UASA_t$, we additionally re-estimate the benchmark effect of ASA_t on the corresponding restricted samples. The results reported in Columns (III) and (V) confirm that the estimated effect of ASA_t remains positive and statistically significant in our benchmark specification.[16]

Table 4. Falsification test using UASA values from the same calendar month but different calendar years

	Benchmark specification with $UASA_t$	**Benchmark specification with $UASA_{t-12}$**	**Benchmark specification with $UASA_t$ using column (II) sample**	**Benchmark specification with $\mathbf{UASA}_{t+12}$**	**Benchmark specification with $\mathbf{UASA}_t$ using column (IV) sample**
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**
Unexpected monthly ambulance sickness absence, UASA	0.00131**	-0.00023	0.00170***	0.00004	0.00134**
	(0.00051)	(0.00048)	(0.00053)	(0.00060)	(0.00055)
Percentage change in patient mortality, Θ					
$\Theta(UASA)$	0.78110**	-0.14980	1.04692***	0.01996	0.78331**
Observations	11,018,201	8,344,385	8,344,385	10,017,448	10,017,448

Notes. Standard errors are clustered at the ED level and reported in parentheses. Other variables included in the model specification, but not presented in the table, are patients' age categories, gender, and ethnic minority status. The lag and lead UASA are calculated using the extended version of the ambulance-station workforce panel, which includes an additional year (2019) of data. In contrast, all benchmark estimation results, including those estimated on restricted samples, use the original time period. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Confounding from seasonal epidemics

Ambulance staff sickness absences might rise simultaneously with seasonal epidemics (e.g. influenza) periods, during which there may also be surges in patients with respiratory diseases transported to hospital EDs by ambulance. In our benchmark regression specification, we include month fixed effects to control for the confounding

[15] Note that our benchmark specification controls for any persistent unobserved ambulance characteristics, as UASA is defined net of ambulance fixed effects.

[16] Controlling for UASA_{t-12} results in the loss of one year of observations, leading to a considerable reduction in sample size. By contrast, when we control for UASA_{t+12} we extend the sample to include an additional year of data (2019), rather than ending in 2018. Further changes across samples are caused by cases where UASA is observed for only two consecutive years.

influence of seasonal epidemics. However, this approach may be insufficient to assure that the impact of UASA on 1-day ED patient mortality is not mechanical and simply due to the clogging of ambulance and hospital ED services during seasonal influenza periods.

Therefore, to rule out this identification threat, we adopt two alternative strategies: i) we exclude patients diagnosed with a respiratory illness at their ED admission; ii) we include the month-by-year fixed effects. The estimates, reported in the second and third rows of Table 5 show that, in both cases, the effect of UASA on 1-day ED patient mortality is very similar to our benchmark estimate.

Table 5. UASA effect on patient mortality: Controlling for potential confounders

	Coefficient	S.E.	Θ(UASA)	Observations
(1) Benchmark specification	0.00131**	(0.00051)	0.78110**	11,018,201
(2) Benchmark, excluding respiratory patients	0.00118**	(0.00055)	0.72597**	10,113,867
(3) Benchmark, adding month-by-year fixed effects	0.00130***	(0.00047)	0.77276***	11,018,201
(4) Benchmark, adding ED diagnoses dummies	0.00130**	(0.00055)	0.77462**	11,018,201
(5) Benchmark, adding out of hours (OOH) dummy	0.00131**	(0.00051)	0.78014**	11,018,198
(6) Benchmark, adding ED-by-year fixed effects	0.00121**	(0.00052)	0.71822**	11,018,198
(7) Benchmark, adding ED-by-month fixed effects	0.00154***	(0.00050)	0.91846***	11,018,193
(8) Benchmark, adding ED-by-year-by-month fixed effects	0.00128***	(0.00056)	0.76250**	11,018,103
(9) Benchmark, adding AS turnover (lagged)	0.00134***	(0.00051)	0.80179***	10,712,685
(10) Benchmark, adding AS turnover (contemporaneous)	0.00131**	(0.00051)	0.78115**	11,018,201

Notes. The first row reports the estimated effect of UASA from the benchmark specification (Table 2, Column III). The remaining Columns report estimates obtained by restricting the sample or adding extra control variables to the benchmark specification. Standard errors are clustered at the ED level and reported in parentheses. Θ(UASA) denotes the percentage change in the average ED mortality rate associated with a one–standard-deviation increase in UASA. Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Changes in patient composition during ambulance staff shortages

The estimated effect of UASA on mortality may be confounded by shifts in the composition of patient health conditions. Specifically, if an increase in UASA correlates with a higher volume of patients with high-severe health conditions, the observed effect of UASA may be driven by the patient composition and might disappear once patient health conditions are controlled for. To account for potential confounding by specific health conditions, we augment our benchmark specification of Equation (5) by including dummy variables for patient diagnoses, as recorded by ED staff and defined in Table A3.

The estimated effect of UASA, once controlling for patient diagnosis, is reported in row (4) in Table 5 and remains very similar to our benchmark estimate. Specifically, a one standard deviation increase in UASA corresponds to a 0.77% increase in ED mortality within one day, compared to 0.78% in the benchmark specification. This result indicates that the effect of UASA is not driven by changes in the composition of patients' health conditions.[17]

Emergency care in the English NHS, as in other healthcare systems, results from a complex interaction among multiple services, including general practitioners (GPs), ambulance services, and hospital emergency departments (EDs). This interaction is particularly important during GP out-of-hours (OOH) periods—that is, times when GPs are unavailable to provide or be consulted for urgent patient care.

During GP OOH periods, limited GP availability often leads patients to contact ambulance services (for example, via NHS 111), which may advise ED attendance and, in some cases, dispatch ambulances to provide initial care and transport patients to hospital EDs.

If, in periods of higher sickness absence, ambulance stations reduce ambulance dispatches more during OOH than during normal hours, this could alter the composition of patients by time of ED attendance. Because mortality risk may differ between OOH and normal hours, such compositional changes could bias our estimation of the effect of UASA.

To understand whether ED attendances during GP OOH times is a confounder for our effect of interest, we re-estimate the benchmark specification by including the GP OOH indicator, defined as a binary variable equal to one when the ambulance patient ED attendance occurs either during weekends or during weekdays from 6.30pm to 8am of the next day, that is when most of GPs do not operate. The estimates, displayed in Table 5 row 5, show that the effect of UASA on 1-day patient mortality is significant and almost identical to the benchmark estimate (see Table 5 row 1).

Based on the evidence reported in rows 4 and 5 of Table 5, we can reasonably conclude that the estimated effect of UASA on patient mortality is not confounded by changes in patient composition—either by ED attendance time or by diagnostic severity—during periods of high staff absence.

[17] Figure A3 plots the coefficient estimates for ED diagnoses with 95% confidence intervals. 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).

Confounding from time-varying covariates

In our benchmark estimation, the hospital 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. The sixth row of Table 5 shows that the impact of UASA remains similar to our benchmark estimation, suggesting that our benchmark estimate is not biased by hospital unobserved variables that vary by year.

We further show that our results are unchanged when including hospital-by-month fixed effects or by hospital-by-month-by-year fixed effects, thereby controlling for all time-varying hospital inputs and shocks (see rows 7 and 8 in Table 5).

When evaluating the effect of ambulance staff sickness, we focus on UASA, which is net of time-invariant ambulance station characteristics. However, unobserved time-varying ambulance station characteristics may still affect UASA and could also have a direct impact on patient mortality. A particularly relevant time-varying ambulance station characteristic that could confound the estimated effect of UASA is the monthly ambulance station's staff turnover rate.

High turnover rates may place additional pressure on remaining staff, potentially increasing sickness absence among ambulance station personnel. Moreover, elevated turnover may reflect a poor working environment, which could directly impair service quality and adversely affect patient outcomes, including mortality. To rule out the possibility that the effect of UASA is driven by turnover, we check whether adding either the monthly ambulance station turnover measured in t (same month as the UASA) or the monthly ambulance station turnover measured in $t-1$ among the control variables alters the effect of the UASA. The estimates of UASA obtained when including lagged and contemporaneous turnover rates are reported in rows 9 and 10 of Table 5 and remain largely unchanged.

Falsification test using ED waiting times

Once a patient arrives at the ED by ambulance, the waiting time until initial medical assessment or treatment should depend on the labour supply of ED staff, rather than on the availability of ambulance staff. Consequently, finding a statis-

tically significant effect of UASA on ED waiting times would suggest the presence of unobserved factors that are correlated with both UASA and ED characteristics, raising concerns about endogeneity.

To assess this possibility, we re-estimate the benchmark specification in Equation (5), replacing patient mortality with ED waiting times as the dependent variable. Specifically, we consider two patient-level measures: the (natural logarithm of) the time between arrival at the ED and initial assessment, and the (natural logarithm of) the time between arrival at the ED and receipt of treatment.

As shown in Table 6, UASA has no statistically significant effect on either measure of ED waiting times, providing reassurance that our main results are unlikely to be driven by unobserved confounding factors affecting ED performance.

Table 6. Falsification test: Effect of UASA on the ED waiting times

Outcomes:	**Waiting time to initial assessment**	**Waiting time to treatment**
Unexpected monthly ambulance sickness absence, UASA	11.92847	-6.81902
	(10.12176)	(4.32007)
Percentage change in patient waiting time, Θ		
$\Theta(UASA)$	2.33436	-1.31271
Observations	10,380,574	10,618,902
Mean ED waiting time	34.745	35.143

Notes. Marginal effects from high-dimensional fixed-effects Poisson Pseudo-Maximum Likelihood regressions on ED waiting times, including the same set of control covariates as in Table 2 Column III. Standard errors are clustered at the ED level and reported in parentheses. The outcomes are the 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: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.3 Heterogeneity of UASA effects

Impact of ambulance staff sickness absence by age groups

To explore whether UASA have different ED mortality impacts by patient age, we separately estimate Equation (5) specification for three age groups: under 65 (0 to 64 years), 65 to 74 years, and 75 years and above.[18]

[18]More than half of our sample consists of patients 65 and above; patients between 65 and 74 are considered as the amenable mortality category, that is patients whose death could be avoided through timely and effective healthcare interventions (Office for National Statistics, 2025); patients 75 years and older are instead those in the geriatric category potentially with more complex needs and more severe conditions and comorbidities.

Panel B of Table 7 reports the estimated effects separately for each age group. The effect of UASA on 1-day ED mortality seems driven by aged 75+, for whom the effect is significant at 1% level and larger in magnitude than the benchmark estimate: a one standard deviation (0.066) increase in UASA raises the average mortality of ED patients aged 75+ by 1.05%. The effects of UASA are not statistically significant for patients younger than 75 years, although still positively associated with higher 1-day ED mortality risk.

Impact of ambulance staff sickness absence by patient severity

We also examine whether the effect of UASA on ED mortality varies with the severity of patients' diagnoses. High-risk patients may be more sensitive to marginal shortages of ambulance staff; accordingly, we construct a high-severity indicator that equals one for ED diagnoses associated with the twelve highest mortality risks, based on the estimates reported in Figure A3. Including interactions between UASA and the binary indicator for high-risk, we find that UASA increases the 1-day ED mortality risk disproportionately for patients with high-severity diagnoses: a one standard deviation increase in UASA raises mortality of high-risk patients by 1.78% (Table 7), which is 1 percentage point larger than our baseline estimate. Instead, the impact of UASA on the mortality of low-severity patients is not statistically significant and is less than half the magnitude of the benchmark effect (0.78).

Variation in the impact of UASA by season

Winter (demand) pressures are a seasonal phenomenon that recurrently strains the capacity of NHS emergency care services. These strains have affected the NHS with particular intensity during the winter seasons between 2012 and 2019 (Fisher and Dorning, 2016; House of Commons Health Committee, 2016; Baker, 2018; British Medical Association, 2019), a period that overlaps closely with our study window of 2013–2018.

As the impact of UASA on patient mortality may vary sensibly according to seasonal patterns of patient demand, we estimate our benchmark model (Equation 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 emer-

Table 7. UASA effect on patient mortality: Heterogeneity analyses

	Coefficient	S.E.	Θ(UASA)	Observations
Panel A: Benchmark estimate				
UASA	0.00131**	(0.00051)	0.78110**	11,018,201
Panel B: Heterogeneity by age group				
Patients younger than 65	0.00068	(0.00056)	1.07607	5,180,984
Patients aged 65–74	0.00022	(0.00165)	0.09831	1,500,413
Patients aged 75 or older	0.00288***	(0.00102)	1.04549***	4,336,801
Panel C: Heterogeneity by diagnosis				
High-risk ED diagnoses	0.00299**	(0.00147)	1.78131**	11,018,201
Low-risk ED diagnoses	0.00060	(0.00066)	0.36044	11,018,201
Panel D: Seasonality				
Full sample				
October–March	0.00214***	(0.00078)	1.21109***	5,457,795
April–September	0.00028	(0.00065)	0.17856	5,560,406
Panel E: Seasonality				
Excluding respiratory conditions				
October–March	0.00201**	(0.00090)	1.16982**	4,960,055
April–September	0.00020	(0.00066)	0.12858	5,153,812
Panel F: Heterogeneity by day time				
Morning [8am-12pm)	0.00280**	(0.00118)	1.20970**	1,920,558
Afternoon [12pm-6.30pm)	0.00117	(0.00082)	0.71939	3,619,667
Evening [6.30pm-12am)	0.00024	(0.00079)	0.18866	3,017,882
Night [12am-8am)	0.00176*	(0.00096)	0.97678*	2,448,081
Panel E: Heterogeneity by AS size				
Small ambulance stations	0.00110*	(0.00056)	1.08791*	2,877,100
Medium ambulance stations	0.00195	(0.00140)	0.81212	2,736,675
Large ambulance stations	0.00224	(0.00187)	0.54844	5,404,426

Notes. The top panel reports the estimated effect of UASA from the benchmark specification (Table 2, Column III). The remaining panels present heterogeneity analyses of the UASA effect across different variables. The Standard errors are clustered at the ED level and reported in parentheses. Θ(UASA) denotes the percentage change in the average ED mortality rate associated with a one–standard-deviation increase in UASA. Significance levels are denoted as follows: *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

gency care services, we find that UASA increase ED patients' mortality risk by 1.2% (Panel D of Table 7): this estimate is 50% higher than our baseline estimate, and it is robust to the exclusion ED patients diagnosed with a respiratory health condition (Panel E of Table 7), confirming that the increase in patient mortality associated with UASA is not related to a mechanical correlation between the higher likelihood of respiratory diseases affecting both ambulance station staff and ambulance patients. Instead, the UASA impact during months from April to September is much smaller in magnitude and never statistically significant, although still positive.

These estimates suggest that UASA has the greatest impact during periods of high seasonal demand, when winter pressures strain emergency care services and unexpected ambulance staff shortages can increase patient mortality risk. These findings highlight the importance of integrated, data-driven planning across ambulance and ED services (Lewis et al., 2023) to manage the complexity of seasonal demand for urgent secondary care.

Impact of ambulance staff sickness absence by timing of the ED attendances

We investigate the impact of UASA on ED patient mortality across different times of the day by splitting our sample into four time periods, based on the HES A&E records of the initial time of patient ED attendance: 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).

UASA increases the mortality risk of ED patients during morning and night attendances (first and last rows in Panel F of Table 7). A one standard deviation increase in UASA (0.066) leads to a 1.2% increase in patient mortality in a morning ED visit ($p < 0.05$). The impact of UASA on ED mortality during night attendances is slightly smaller than during morning hours: a one standard deviation (0.068) increase in UASA leads to a 0.98% higher ED mortality risk ($p < 0.10$).

These findings have intuitive and complementary explanations, which strengthen the credibility of our analysis. Severe health events—such as heart attacks (Pierce-Hayes, 2009) and strokes (Denny et al., 2014)—are more likely to occur during the early morning hours. At the same time, morning shifts are precisely when staff shortages due to sickness absence are most likely to materialise, as ambulance staff who wake up unwell may report sick shortly before their shift begins.

As a result, unexpected staff shortages are likely to be most difficult for ambulance station managers and remaining staff to absorb during morning hours. In contrast, shortages arising later in the day—such as during afternoon or evening shifts—may be easier to mitigate through internal reallocation or by drawing on staff from nearby ambulance stations. Similarly, night shifts are typically characterised by lower baseline staffing levels, making them another period in which the impact of UASA on patient mortality is likely to be particularly pronounced.

Impact of UASA by ambulance station staff levels

Finally, we examine whether the impact of UASA on ED mortality varies with core staffing levels by splitting ambulance stations into three groups—small, medium, and large—defined by terciles of core staff size computed over the full sample of ambulance stations. In our estimation sample, more than half of patients are transported to EDs by large ambulance stations, with the remaining patients split roughly evenly between small and medium stations.

The estimates reported in Panel E of Table 7 show that a one standard deviation increase in UASA leads to a 1.09% increase in ED patient mortality in small ambulance stations, which employs on average six core staff. In contrast, we find no supporting evidence that sickness absences in medium and large ambulance stations significantly affect ED patient survival. Moreover, the percentage change in ED mortality declines with station size from 1.1% in small ambulance stations to 0.81% in medium ambulance stations and to 0.55% in large ambulance stations.

In conclusion, we find that the estimated effect of ambulance staff sickness absences on one-day patient mortality is statistically significant only for low-staffed ambulance stations, and only at the 10% level. While the confidence intervals across ambulance station size groups overlap, the pattern of point estimates is consistent with smaller stations being more vulnerable to sudden reductions in staff availability. By contrast, larger stations appear better able to absorb short-term staffing shocks, potentially due to greater baseline staffing capacity.

Heterogenous effects by mortality horizon time

We extend our benchmark analysis by examining the effect of UASA on patient mortality within two days and within seven days of ED arrival. While the quality

of (pre-hospital) ambulance care and the timeliness of the initial transfer to the ED hospital services are critical determinants of survival in the first 24 hours, they are unlikely to be the primary drivers of mortality beyond that window. After the first day, mortality risk is more plausibly driven mostly by hospital-level factors, including the quality of care provided by, and the labor supply of, hospital ED staff rather than by ambulance staff.[19]

Table 8 reports the estimation results. Column (I) presents the benchmark estimate for mortality within one day of ED arrival, Column (II) reports estimates for mortality within two days, and Column (IV) for mortality within seven days.

Table 8. UASA effect on ED patient mortality at different time horizons

	(I)	(II)	(III)	(IV)	(V)
	ED patient mortality within				
	1 day	2 days	2nd day only	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)
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 patient waiting time, 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	11,018,201	11,018,201	10,893,963	11,018,201	10,854,313

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. In Column (II), the ED patient mortality is defined as taking the value 1 if the patient died within 2 days of ED attendance, i.e., including the first day, and zero otherwise. In Column (III), only deaths occurring on the second day following the ED visit take the value 1. Likewise, the outcome variable for the model in Column (IV), patient mortality, is defined as a patient dying within 7 days of the patient's ED attendance, and Column (V) includes only deaths between the third and seventh days following the ED visit. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results are consistent with the hypothesis that the effect of UASA on mortality is confined to the first 24 hours following ED attendance. The estimated effects for two-day and seven-day mortality are substantially smaller in magnitude and not statistically significant (Columns (II) and (IV)). Similar conclusions emerge when we condition on short-term survival: Column (III) reports estimates for mortality on the second day conditional on surviving the first day, and Column (V) for mortality between days three and seven conditional on survival to day two. In both cases, the estimated effects of UASA are close to zero and statistically insignificant. Fur-

[19]The intuition behind this conjecture is that, on the first day under the care of emergency services, patient survival depends on labor inputs from both ambulance and hospital ED workers. However, beyond the first day, the labor inputs from ambulance workers remains constant—as they are not involved anymore in caring for the patients after the trasfer to ED services—whereas the labor inputs from hospital ED workers can still vary over time and be correlated with patients' survival.

thermore, our conjecture appears to be supported also by the association of patient mortality with ED staff monthly sickness absence (EDSA), reported on the second row of Table 8. The estimate of the EDSA coefficient is always positive and increasing in magnitude over time—signalling an increase in the importance of ED staff absences for patient mortality beyond the first 24 hours—although never statistically significant.

Policy Implications

Drawing on the heterogeneity analyses, we suggest some targeted interventions to mitigate the adverse effects of unexpected ambulance staff absences (UASA) on patient mortality. Our findings indicate that the mortality burden of staffing shocks is non-uniformly distributed across demographics and clinical conditions, suggesting that uniform resource management may be suboptimal. While current triage systems, such as NHS Pathways and the Advanced Medical Priority Dispatch System (AMPDS), prioritize patients based on clinical acuity, they do not explicitly account for the heightened marginal mortality risk we identify among the elderly (aged 75+) and those with high-severity diagnoses during periods of ambulance stations staff shortages.

Given the logistical complexity of recalibrating real-time triage algorithms during idiosyncratic staffing shocks, we propose two primary structural levers to enhance system resilience. irst, as the adverse effects of UASA are heavily concentrated in the winter months (October–March), the NHS should implement seasonal surge capacity to buffer the emergency care system against the heightened marginal sensitivity to labor supply shocks observed during peak demand periods.

Second, as our findings suggest that smaller ambulance stations lack the operational scale to effectively absorb unexpected absences, strengthening their resilience to within-day and short-term staffing shortages may be particularly valuable. While our evidence on higher mortality caused by UASA in small ambulance stations should be interpreted with caution, given the limited precision of the estimates, it suggests that targeted measures—such as greater staffing flexibility or improved contingency arrangements—may help mitigate the risks associated with unexpected staff absences in smaller stations.

Ultimately, while targeted resilience measures can mitigate the immediate risks to patient health, long-term stabilization of the emergency workforce requires addressing

the underlying drivers of staff absences, such as occupational burnout and stress.

5.4 Robustness checks

Complementary log-log model

As death after an ED attendance is a rather rare event, we are concerned that the linear probability model may not be appropriate; thus, we estimate a complementary log–log (cloglog) model. The second Rowin Table 9 presents the marginal effects from the cloglog model, which are similar to the baseline estimate of the impact of UASA on 1-day patient mortality.

Table 9. UASA effect on patient mortality: Robustness checks

	Coefficient	S.E.	Θ(UASA)	Observations
(1) Benchmark estimate of UASA	0.00131**	(0.00051)	0.78110**	11,018,201
(2) Complementary log-log (average marginal effect)	0.00124***	(0.00046)	0.73606***	11,016,311
(3) Adding UASA for the 2nd nearest AS	0.00130**	(0.00051)	0.77161**	11,011,173
(4) Computing UASA net of AS-by-month FE	0.00131**	(0.00059)	0.71152**	10,750,502
(5) UASA net of only the AS fixed effect	0.00121**	(0.00051)	0.72357**	11,018,201
(6) UASA net of only the month and year fixed effects and time-varying AS characteristics	0.00091*	(0.00047)	0.58802*	11,018,201
(7) Subsample of AS observed for at least 20 months	0.00140***	(0.00052)	0.83230***	10,691,081
(8) Subsample of AS observed for at least 30 months	0.00132**	(0.00053)	0.78792**	10,347,120
(9) Subsample of AS observed for at least 40 months	0.00140**	(0.00058)	0.82412**	9,459,167

Notes. The top row reports the estimated effect of UASA from the benchmark specification (Table 2, Column III). The remaining rows present the effect of the UASA for a set of robustness checks. The Standard errors are clustered at the ED level and reported in parentheses. Θ(UASA) denotes the percentage change in the average ED mortality rate associated with a one–standard-deviation increase in UASA. Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Controlling for UASA in the second nearest ambulance station

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 robustness of our results to the inclusion in the benchmark model specification of the UASA for the second nearest station.[20] As shown in row 3 in Table 9 the effect of UASA for the nearest ambulance station remains almost

[20]Similarly to what was done for the closest ambulance station, we identify the second nearest ambulance station to the patient and link its UASA accordingly.

unaltered by the inclusion of the UASA for the second nearest ambulance station. In Table A8 we also show the effect of UASA for the second-closest station, which has the expected positive sign, but is not statistically significant and is much smaller (0.097%) than the estimated effect of UASA for the nearest station (0.77%).

Robustness to different computation of UASA

We construct UASA, the measure of unexpected ambulance staff absences, by purging observed sickness rates of ambulance station fixed effects and a set of time-varying ambulance station observable characteristics, thereby removing all time-invariant differences across stations. However, if sickness follows station-specific seasonal patterns—for example, if better-managed stations are more effective at mitigating predictable seasonal fluctuations—then the remaining variation in UASA could still reflect endogenous station characteristics. To address this concern, we implement a more demanding specification in which UASA is defined net of ambulance station-by-month fixed effects, absorbing all persistent station-specific seasonal patterns in sickness. As shown in row 4 of Table 9, the estimates are virtually unchanged relative to the baseline specification, indicating that our results are not driven by differential seasonal patterns across ambulance stations.

We also examine whether our estimates are sensitive to defining UASA using fewer controls—specifically, by purging either only station fixed effects or only time-varying observables. We find that these alternative definitions yield slightly attenuated coefficients compared to our benchmark model (see rows (5) and (6) of Table 9). This suggests that our primary definition of UASA more precisely isolates idiosyncratic labor supply shocks by purging variations driven by predictable characteristics. Insofar as station management anticipates and adjusts staffing levels based on these observable factors, our benchmark approach correctly identifies the unexpected portion of the sickness absences rate that precludes such as ex-ante managerial mitigation.

Finally, we assess the robustness of our findings to the sample selection and specification used in the auxiliary model (3) employed to construct UASA. Our benchmark results rely on UASA computed from estimating model (3) using the full Ambulance Station Workforce panel, which includes all ambulance stations observed for at least two months.[21]

[21] As described in Section 3, the Ambulance Station Workforce panel spans April 2013 to March 2018, implying a maximum of 60 monthly observations per ambulance station.

To examine sensitivity to panel length, we re-estimate model (3) using 3 restricted panel samples that include only ambulance stations observed for at least 20, 30, and 40 months, respectively. Across these alternative restricted panel samples, we find no meaningful differences in the estimated effect of UASA on patient mortality (see rows (7)-(9) of Table 9).

Bias due to unobservables and coefficient stability

Finally, we employ the coefficient stability method proposed by Oster (2019) to test for the direction of potential omitted variable bias in ambulance sickness absences.[22] We assume that the magnitude of the selection on unobservables is perfectly proportional to the magnitude of the selection on observables, and test the coefficient stability of our effect of interest by employing four different comparisons between uncontrolled (or partially controlled) regressions and controlled regressions. Table A9 presents the results, including the Oster (2019) bounds for the projected bias-corrected estimates in the last columns, based on the recommended R^2_{max} equal to 1.3 times the R^2 achieved by the fully specified model. Regardless of the specifications of the uncontrolled and controlled regressions, the bias-corrected Oster (2019) estimates of the UASA effect on patient mortality are always very close to the estimate from our baseline specification, thus suggesting that the potential selection bias due to omitted variables in our UASA effect estimate on patient mortality is minimal.

6 Valuing the Mortality Consequences of Ambulance Staff Absences

This section quantifies the welfare implications of ambulance staff shortages by (i) computing the number of excess deaths implied by a one–standard-deviation increase in the unexpected ambulance staff sickness absence rate (UASA), and (ii) assigning a monetary value to these losses using the UK Treasury *Green Book* framework for Quality-Adjusted Life Years (QALYs).

[22] Under a strict set of assumptions, the coefficient estimated through the Oster (2019) method converges asymptotically to the true parameter of interest. 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; and a stable relationship between covariates and treatment assignment.

Excess Deaths from a One-Standard-Deviation Increase in UASA

Let M_{iht} denote a one-day mortality indicator for patient i attending emergency department (ED) h at time t. The baseline linear probability specification estimates that unexpected ambulance staff absences increase the probability of one-day mortality with marginal effect $\rho = 0.00131$ (SE $= 0.00051$). Given a standard deviation of UASA equal to 0.06707, the per-visit increase in one-day mortality risk induced by a one-standard-deviation increase in UASA is

$$\Delta Pr(M_i) = \rho \times \text{SD(UASA)} = 0.00131 \times 0.06707 = 8.78617 \times 10^{-5}. \tag{6}$$

For interpretability, the effect corresponds to approximately 8.79 excess deaths per 100,000 ambulance-delivered ED visits. The estimation sample contains $N =$ 11,018,201 ambulance-delivered first daily ED visits during the period 2013–2018. Multiplying the value of Equation (6) by N yields the implied number of excess deaths:

$$\Delta Deaths = \Delta Pr(M_i) \times N = \frac{8.78617}{10^5} \times 11{,}018{,}201 \approx 968 \text{ [95\% C.I.: } 229; 1707], \tag{7}$$

or roughly $\frac{968}{5} \approx 193$ annual excess deaths over the five-year sample.

QALY-Valued Monetisation

To translate the mortality impact in Equation (7) into economic terms, we adopt the valuation framework recommended in HM Treasury (2020)'s *Green Book*, which assigns a monetary value to changes in health through Quality-Adjusted Life Years (QALYs). According to the HM Treasury (2020)'s *Green Book*, the value of a QALY is $v =$ £70,000. The median age of death of the ED patients in our main sample is 67 years; for English residents aged 67, the average remaining life expectancy (RLE) in 2015 (the mid-year of our sample) was 18 years; throughout this period, we assume an average health-related quality weight $u = 0.8$.[23] The QALY loss per death is therefore equal to RLE $\times\, u = 18 \times 0.8 = 14.4$, which multiplied by the total number of excess deaths, Equation (7), yields QALY $= 968 \times 14.4 = 13{,}939.2$. The monetary valuation under the Green Book is then ΔQALY $\times\, v = 13{,}939.2 \times$ £70,000 = £975.744 million. A one–standard-deviation increase in unexpected ambulance staff absences entails a

[23] The RLE at 67 years in 2015 in England was estimated to be 17 (19.2) years for male (female) residents by the UK Office for National Statistics (2024).

welfare loss approaching £1 billion over the five-year period.

These figures highlight the substantial welfare cost associated with fluctuations in the availability of ambulance personnel, and underscore the centrality of pre-hospital staffing conditions in the production of emergency care outcomes.

7 Conclusions

This paper provides the first empirical evidence on the effect of unexpected ambulance staff shortages on patient mortality. To address the endogeneity of healthcare labor supply, we exploit idiosyncratic variation in unexpected ambulance staff absences (UASA). By purging ambulance staff sickness rates of the ambulance station fixed effect, month and year effects and observable time-varying ambulance station characteristics, we isolate quasi-random shocks to ambulance station labour supply. Furthermore, by using variation in UASA across different ambulance station serving the same ED, we control for any confounding time-invariant factor related to ED characteristics. The credibility of this strategy is supported by a range of falsification tests and robustness checks, including tests for seasonal illness patterns, changes in patient composition during periods of high absences, and confounding from time-varying emergency department characteristics.

We find that these labor supply shocks have a statistically significant and economically meaningful effect on patient survival. The mechanisms through which UASA affects patient mortality are direct and highly time-sensitive. Reductions in available ambulance staff increase response and waiting times, worsening outcomes in acute emergencies such as heart attacks, strokes, and severe trauma. Inadequate staffing also limits the ability to monitor and treat patients during transport, raising the risk of clinical deterioration and medical errors. Consistent with these mechanisms, we find that ambulance staff shortages affect mortality only on the day of emergency department arrival, with no detectable effects at 2 or 7 days. This sharp temporal pattern indicates that the impact operates through delays in early emergency treatment and deficiencies in pre-hospital care. Our results thus provide direct empirical evidence that minimizing delays in pre-hospital and early emergency care can save lives, particularly for time-critical conditions such as sepsis, severe respiratory illnesses, and acute cardiac and vascular events.

Importantly, the mortality impact of UASA is highly heterogeneous. The effect

is largest for elderly patients (aged 75 and older) and for patients with high-severity diagnoses. We also identify operational contexts in which the effect is amplified, that is, morning and night shifts and the winter months (October–March). In addition, smaller ambulance stations appear disproportionately vulnerable, consistent with limited capacity to absorb unexpected staffing shortfalls relative to larger stations. Finally, based on our estimates we quantify a considerable welfare loss (about £1 billion over a five-year period) related to increases in ambulance staff absences.

These results have direct policy implications. Rather than uniform staffing increases, our findings suggest that welfare gains may be achieved through targeted interventions, such as a winter surge in labour supply and state-contingent overtime arrangements, particularly for smaller stations. While such resilience measures can mitigate short run risks caused by staff sicknesses, long-run workforce stability may require addressing the underlying drivers of staff absences, including occupational stress and burnout.

Overall, our study's findings underscore the centrality of pre-hospital staffing conditions in the production of emergency care outcomes and reinforce the broader policy relevance of labour supply constraints in critical public services.

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Appendix A. Additional Tables & Figures

Figure A1. Data linkages for the sample construction

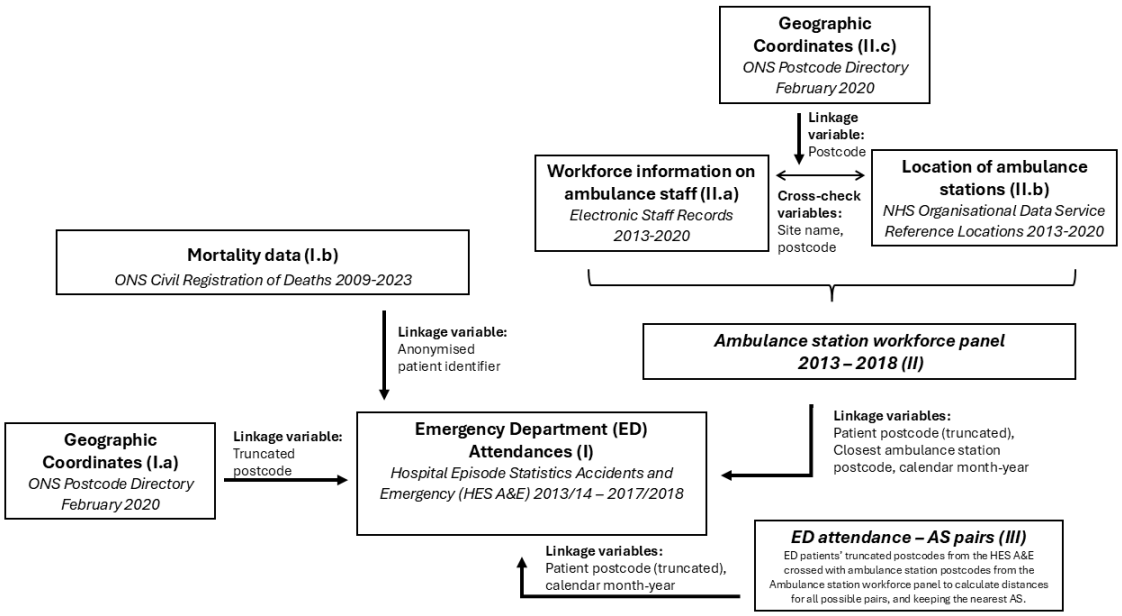
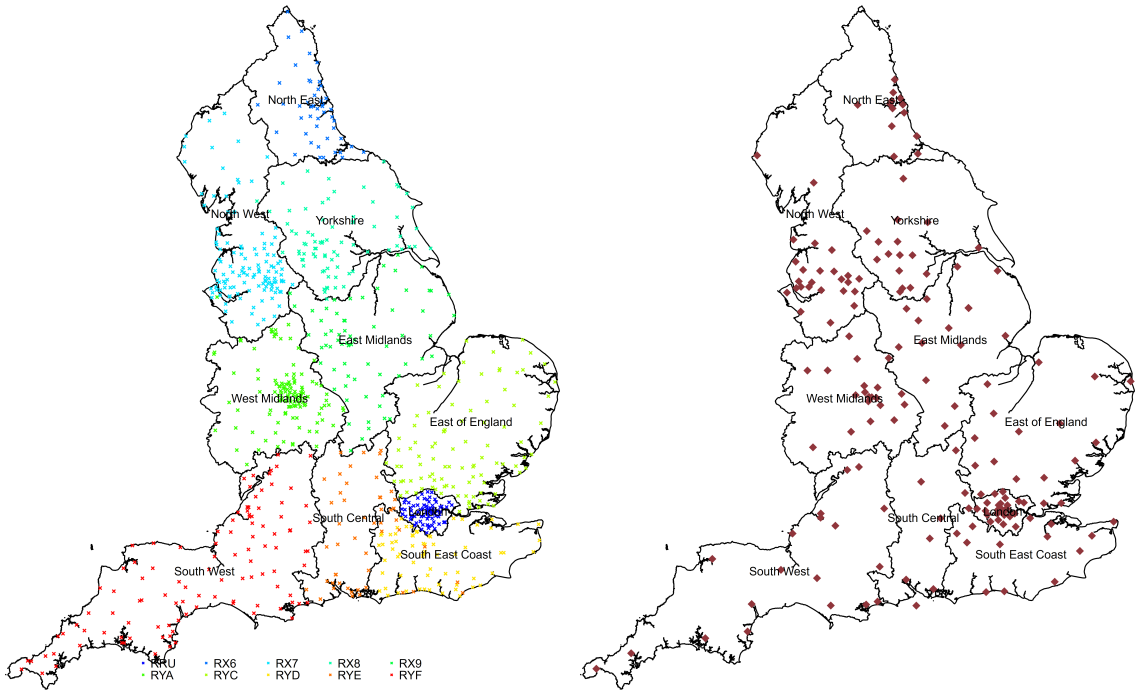


Figure A2. NHS Ambulance Stations and Emergency Departments across mainland England, 2013-2018

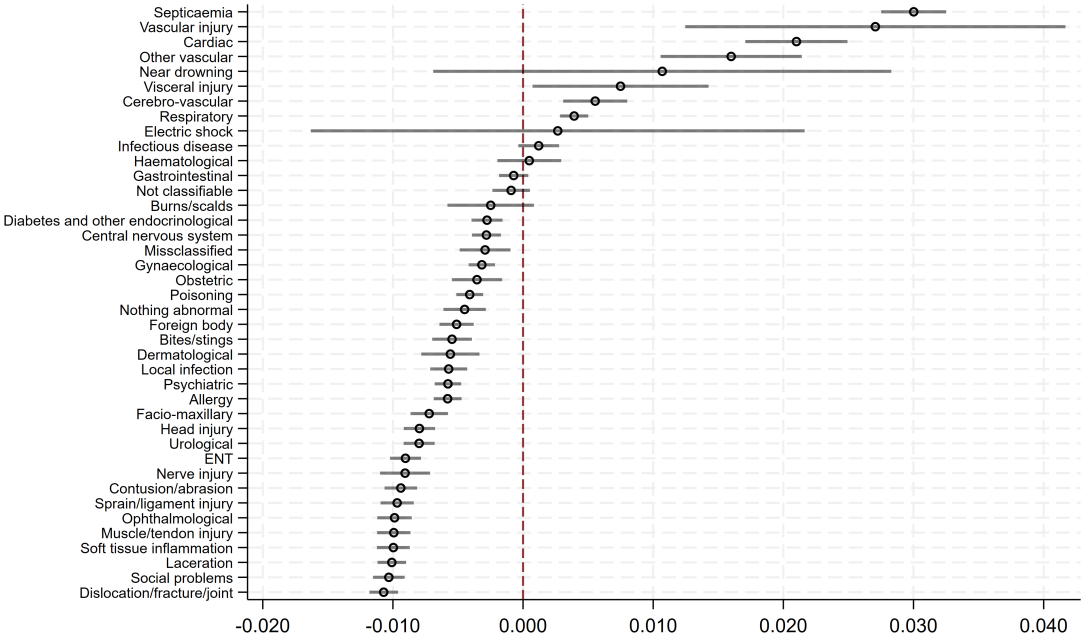
(a) Ambulance Stations

(b) Emergency Departments



Notes. Panel (a) is based on the ambulance stations included in the Ambulance Station Workforce panel as described in Section 3. Panel (b) is based on hospital EDs in the analysis sample.

Figure A3. 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 a missing diagnosis code. 95% confidence intervals are based on standard errors are clustered at the ED level.

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 the estimation sample using ICD codes for diagnoses. † Central nervous system conditions exclude stroke. ‡ Social problems include chronic alcoholism and homelessness.

Table A4. Summary statistics based on ambulance station workforce 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 the ambulance station workforce panel. The unit of observation is an ambulance station-month where the majority of staff are responsible for delivering emergency patient care.

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

	ASA < median ASA		**ASA ⩾ median ASA**		**Normalised Δ(Mean)**
	Mean	**Std**	**Mean**	**Std**	
Patient characteristics					
Age [0–17]	0.087	0.282	0.088	0.283	-0.00354
Age [18–34]	0.125	0.331	0.123	0.329	0.00606
Age [35–49]	0.117	0.321	0.116	0.320	0.00312
Age [50–64]	0.142	0.349	0.143	0.350	-0.00286
Age 65 and above	0.529	0.499	0.531	0.499	-0.00401
Female	0.543	0.498	0.545	0.498	-0.00402
Black – Asian ethnic minority	0.108	0.311	0.102	0.303	0.01954
Unknown ethnic minority status	0.078	0.268	0.072	0.259	0.02277
Share of patients in income deprivation					
Least deprived 20%	0.138	0.345	0.134	0.341	0.01166
Quintile 2	0.168	0.374	0.162	0.369	0.01615
Quintile 3	0.195	0.396	0.192	0.394	0.00759
Quintile 4	0.221	0.415	0.229	0.420	-0.01916
Most deprived 20%	0.278	0.448	0.283	0.451	-0.01112
Diagnoses					
Laceration	0.012	0.109	0.013	0.112	-0.00905
Contusion/abrasion	0.009	0.093	0.010	0.098	-0.01047
Soft tissue inflammation	0.011	0.105	0.011	0.103	0.00000
Head injury	0.022	0.146	0.022	0.145	0.00000
Sprain/ligament injury	0.007	0.082	0.008	0.087	-0.01183
Muscle/tendon injury	0.006	0.079	0.006	0.078	0.00000
Nerve injury	0.001	0.029	0.001	0.030	0.00000
Vascular injury	0.001	0.023	0.001	0.025	0.00000
Burns and scalds	0.002	0.041	0.002	0.046	0.00000
Electric shock	0.000	0.011	0.000	0.014	0.00000
Foreign body	0.001	0.033	0.001	0.035	0.00000
Bites/stings	0.000	0.017	0.000	0.018	0.00000
Poisoning (inc overdose)	0.022	0.147	0.021	0.144	0.00687
Near drowning	0.000	0.005	0.000	0.005	0.00000
Visceral injury	0.000	0.016	0.000	0.016	0.00000
Infectious disease	0.014	0.117	0.015	0.122	-0.00837
Local infection	0.008	0.087	0.007	0.083	0.01176
Septicaemia	0.013	0.112	0.012	0.109	0.00905
Cardiac conditions	0.067	0.251	0.069	0.254	-0.00792
Cerebro-vascular conditions	0.016	0.125	0.017	0.130	-0.00784
Other vascular conditions	0.005	0.070	0.005	0.071	0.00000
Haematological conditions	0.004	0.061	0.004	0.060	0.00000
Central nervous system conditions	0.035	0.185	0.036	0.186	-0.00539
Respiratory conditions	0.082	0.274	0.082	0.275	0.00000
Gastrointestinal conditions	0.071	0.256	0.070	0.255	0.00391
Urological conditions	0.032	0.177	0.033	0.178	-0.00563
Obstetric conditions	0.001	0.038	0.002	0.042	-0.02500
Gynaecological conditions	0.006	0.076	0.005	0.072	0.01351
Diabetes/endocrine	0.009	0.095	0.010	0.098	-0.01036
Dermatological conditions	0.003	0.051	0.003	0.050	0.00000
Allergy	0.003	0.057	0.003	0.056	0.00000
Facio-maxillary	0.001	0.025	0.001	0.025	0.00000
ENT conditions	0.008	0.090	0.008	0.090	0.00000
Psychiatric conditions	0.018	0.132	0.017	0.128	0.00769
Ophthalmological conditions	0.001	0.027	0.001	0.027	0.00000
Social problems	0.006	0.080	0.007	0.081	-0.01242
Diagnosis not classifiable	0.171	0.376	0.183	0.387	-0.03145
Nothing abnormal detected	0.022	0.146	0.023	0.150	-0.00676
Missclassified	0.034	0.182	0.029	0.167	0.02865
No/missing diagnosis	0.245	0.430	0.232	0.422	0.03052

Notes. Based on patients in the 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 $(X_{low} - X_{high})/\sqrt{\frac{\sigma^2_{low} + \sigma^2_{high}}{2}}$ 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. Column 5 reports the balance test suggested by Imai et al. (2008).

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 ambulance station 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. Effect of other covariates not presented in Table 2 Column (III)

	Coefficient	**Std 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. Robusteness 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	11,011,173	

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, the 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 A9. Bias-corrected Oster estimates for the unexpected ambulance sickness absences

	Uncontrolled regression (U)		**Controlled regression (C)**			**Oster (2019) projection**	
Contrast	**Estimate (Standard Error)**	R^2	**Estimate (Standard Error)**	R^2	R^2_{max}	**Estimate**	**95% CI**
1. no controls, no ED fixed effects (U) *vs.* baseline specification (C)	0.00103* (0.00061)	0.00000	0.00131** (0.00051)	0.00566	0.00736	0.00140***	[0.00051, 0.00228]
2. no controls, no ED fixed effects (U) *vs.* baseline specification w/o ED fixed effects (C)	0.00103* (0.00061)	0.00000	0.00111** (0.00056)	0.00511	0.00664	0.00114**	[0.00016, 0.00212]
3. with ED fixed effects, w/o other controls (U) *vs.* baseline specification (C)	0.00123** (0.00054)	0.00069	0.00131** (0.00051)	0.00566	0.00736	0.00140***	[0.00047, 0.00232]
4. with all controls, w/o ED fixed effects (U) *vs.* baseline specification (C)	0.00111** (0.00056)	0.00511	0.00131** (0.00051)	0.00566	0.00736	0.00194***	[0.00102, 0.00286]

Notes. For the bias-adjusted Oster estimates, the assumption is that the degree of selection on unobservables is the same as the observables and $R^2_{max} = 1.3 \times R^2$ The 95% confidence intervals based on bootstrapped standard errors (300 replications) are in brackets, and those from clustered standard errors are in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.