

Sayli, Melisa; Nicoletti, Cheti; Moscelli, Giuseppe

Working Paper

Unexpected worker absences as labor supply shocks: Evidence from ambulance services

CINCH series, No. 2026/06

Provided in Cooperation with:

CINCH – Health Economics Research Center, Universität Duisburg-Essen (UDE)

Suggested Citation: Sayli, Melisa; Nicoletti, Cheti; Moscelli, Giuseppe (2026) : Unexpected worker absences as labor supply shocks: Evidence from ambulance services, CINCH series, No. 2026/06, University of Duisburg-Essen, CINCH - Health Economics Research Center, Essen, <https://doi.org/10.17185/dupublico/86511>

This Version is available at:

<https://hdl.handle.net/10419/342342>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



competence in competition + health

series

#2026/06

Melisa Sayli, Cheti Nicoletti, and Giuseppe Moscelli

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

Imprint

EDITOR-IN-CHIEF

Martin Karlsson, Essen

MANAGING EDITOR

Martin Karlsson, Essen

EDITORIAL BOARD

Boris Augurzky, Essen
Daniel Avdic, Melbourne (AUS)
Jeanette Brosig-Koch, Magdeburg
Stefan Felder, Basel
Annika Herr, Hannover
Nadja Kairies-Schwarz, Düsseldorf
Hendrik Schmitz, Paderborn
Harald Tauchmann, Erlangen-Nürnberg
Jürgen Wasem, Essen
Katharina Blankart, Bern (CHE)
Christoph Kronenberg, Essen

CINCH SERIES

CINCH – Health Economics Research Center
Weststadttürme, Berliner Platz 6-8
45127 Essen

www.cinch.uni-due.de
cinchseries@cinch-essen.de
Phone +49 (0) 201 183 - 3679
Fax +49 (0) 201 183 - 3716

All rights reserved. Essen, Germany, 2026

ISSN 2199-8744 (online)

The working papers published in the Series constitute work in progress circulated to stimulate discussion and critical comments. Views expressed represent exclusively the authors' own opinions and do not necessarily reflect those of the editors.

#2026/06

Melisa Sayli, Cheti Nicoletti, and Giuseppe Moscelli

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

Melisa Sayli[†], Cheti Nicoletti^{‡§}, and Giuseppe Moscelli^{*†§}

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

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.

JEL classification: J45, J2, I11, C23

Keywords: sickness absences, staff shortages, ambulance services, patient mortality, marginal product of labor

[†] Economics Unit, School of Social Sciences, University of Surrey

[‡] Department of Economics and Related Studies, University of York

[§] IZA@LISER

^{*} Corresponding author: g.moscelli@surrey.ac.uk

The authors acknowledge funding for this research by The Health Foundation under the “Efficiency Research Programme – Round 3” grant scheme (Award ID: 1327076). The findings and opinions expressed in this study do not represent any views from The Health Foundation. The research of Cheti Nicoletti was supported by funding from the Department of Economics and Related Studies (DERS), University of York. The authors thank the Department of Health and Social Care for access to NHS Electronic Staff Record (ESR) data. Hospital Episode Statistics are Copyright 2009–2021, re-used with the permission of NHS England Digital; all rights reserved. The authors are grateful for comments and useful suggestions received from Jack Britton, Igor Francetic, Andrew Jones, Martin Koppensteiner, Shirlee Lichtman-Sadot, Sandra McNally, Carol Propper, Luigi Siciliani, Peter Sivey, Jenny Williams, and seminar participants at the Universities of York, Portsmouth, 2025 Royal Economics Society Conference (Birmingham, UK), 5th Arne Ryde Workshop (Lund, Sweden, October 2025), a7th Dondena Workshop on Public Policies (Bocconi University, Milan, Italy, December 2025), Essen Health Conference (Essen, Germany, June 2026). All errors are our own.

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 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 from hospital inputs on pa-

tient 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 to high-dimensional fixed-effects strategies used to isolate unanticipated shocks in other settings ([Escobar Carias et al., 2024](#); [Francetic et al., 2024](#); [Gazze et al., 2024](#); [Ireland 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. Importantly, our unexpected absence measure is purged of systematic differences across stations and over time, ensuring that it is not correlated with persistent local characteristics or predictable demand fluctuations. This approach is similar in spirit to [Knutsson and Tyrefors \(2022\)](#) who exploit similar ambulance assignment rules in Stockholm, Sweden, to study the effect of ambulance ownership on patient mortality.

Ultimately, our main empirical specification regresses patient mortality within one day of arrival at the emergency department on the unexpected ambulance 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 unexpected ambulance station sickness absence rate raises 24-hour mortal-

ity by 0.78% relative to a baseline mortality rate of 1.1%. 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.

Although we do not directly observe response times, on-scene care, or transport delays, the absence of effects beyond the first 24 hours after hospital arrival—together with their concentration among clinically vulnerable patients—strongly supports a mechanism operating through time-sensitive pre-hospital care.

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; Friedrich and Hackmann, 2021; Costa, 2022; Stoye and Warner, 2023). 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; Winter et al., 2020; Chan Jr and Chen, 2022; Shen et al., 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 so our paper also contributes to the growing but still very limited literature on the economics of emergency ambulance services (Brachet et al., 2012; Wilde, 2013; Knutsson and Tyrefors, 2022; 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; Hoe, 2022; 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

Urgent and emergency ambulance services in England are provided by the National Health Service (NHS), a publicly funded healthcare system that delivers comprehensive services free at the point of use and financed primarily through general taxation.

Rising demand in emergency care has placed increasing pressure on NHS ambulance services. Between 2011/12 and 2017/18, demand grew at an average annual rate of 5.2%, exacerbating existing strains on emergency care provision and workforce capacity (National Audit Office, 2018). As of March 2018, the ambulance workforce in England comprised 20,552 full-time equivalent staff, representing 1.9% of the NHS

workforce and 3.6% of professionally qualified clinical staff.

NHS ambulance stations are local operational bases from which NHS ambulance vehicles are dispatched and are organised within 10 regional entities known as Ambulance Trusts. Ambulances are dispatched from the nearest available station to minimise response times.¹ When the nearest station is unavailable, the control centre assigns patients to the second nearest available NHS ambulance station.² The use of more distant stations can increase travel and response times. Even when the nearest station ultimately responds, high workload may delay dispatch or reduce the effectiveness of on-scene care due to capacity constraints. In the vast majority of cases, patients are transported to the nearest emergency department. Exceptions arise for specific life-threatening conditions (e.g., major trauma or stroke), for which patients are directed to specialised hospitals (NHS England, 2023).

Taken together, these institutional features generate quasi-random variation in patients’ exposure to short-run fluctuations in ambulance staffing within the same hospital catchment area, which we exploit to identify the causal effect of unexpected ambulance staff absences on patient outcomes.

3 Data

We construct a multi-level panel dataset from high-quality administrative data sources in England. Figure A1 summarises the data sources and their linkage.

At the core of the analysis is a patient-level dataset linking emergency department

¹999 calls are triaged using structured pre-triage questions to determine acuity, after which call handlers assign each incident to one of four categories, ranging from immediately life-threatening (Category 1) to non-urgent (Category 4) (NHS England, 2023). These categories determine both dispatch priority and the type of resource sent. Call handlers prioritise clinical need: Category 1 calls require a response within seven minutes on average, while Category 2 calls (e.g., stroke or chest pain) involve rapid assessment and urgent transport (South East Coast Ambulance Service NHS Foundation Trust, 2026; London Ambulance Service NHS Trust, 2026). For lower-acuity cases (Categories 3 and 4), clinicians may treat patients at home or provide telephone advice, ensuring that ambulances are reserved for those most in need (North East Ambulance Service NHS Foundation Trust, 2026; North West Ambulance Service NHS Trust, 2026).

²During periods of extreme operational pressure—classified as Resource Escalation Action Plan (REAP) Level 4 (often termed “Black Alert”), when ambulance services can no longer effectively deliver normal care—NHS Ambulance Trusts may also rely on private ambulance crews to provide additional 999 cover and help manage lower-acuity demand (Category 3 and Category 4 calls), thereby enabling NHS resources to prioritise life-threatening Category 1 and serious Category 2 emergencies (NursingNotes, 2022; Edwards, 2017; UNISON, 2023; MET Medical, 2024; NHS England, 2023).

(ED) attendances to ambulance station workforce characteristics. Our primary data source is the universe of ED visits in England between 2013 and 2018 for patients transported by ambulance from their residence, drawn from Hospital Episode Statistics (HES A&E). These records provide detailed information on patient demographics, diagnoses, and the timing of care.

We measure mortality using linked Office for National Statistics (ONS) Civil Registration of Deaths data, which capture deaths occurring both within and outside hospital within one day of ED arrival. Importantly, patient outcomes are recorded independently of ambulance services—by hospital clinicians and official death registries—mitigating concerns that measurement error in mortality or other patient characteristics is correlated with ambulance workforce conditions.

We combine these data with a newly constructed panel of ambulance station workforce characteristics derived from the NHS Electronic Staff Records (ESR). We refer to the resulting patient-level linked dataset, in which the unit of observation is the patient visit, as the **Patient-Level Linked Dataset**. We refer to the ambulance station-level panel dataset as the **Ambulance Station Workforce Panel**. The latter contains monthly information on staffing levels, workforce composition, and absences for all ambulance stations in England and is distinct from the patient-level dataset used in the analysis.

We consider only stations where most employees, henceforth *core staff*, are directly involved in delivering emergency patient care.³ Figure A2 describes the distribution of NHS ambulance stations and emergency departments across mainland England.

Because HES data do not record the ambulance station that dispatched the ambulance, we assign each patient to the nearest ambulance station based on residential location.⁴ This proxy aligns with operational practice, under which ambulances are dispatched from the nearest available station to minimise response times.

We further link patients to characteristics of the receiving ED, including staff absence rates, and to area-level socioeconomic conditions using the Index of Multiple

³In 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.

⁴Using truncated patient postcodes, defined as postcode sectors that omit the final unit-level characters, we assign geographic coordinates using average northing and easting values from the ONS Postcode Directory (2020) and link each patient to the nearest ambulance station based on straight-line distance.

Deprivation (IMD) for the patient’s area of residence.⁵

3.1 Variables definitions

Our main outcome, 1-day mortality, is an indicator variable equal to one if the patient dies within 24 hours of ED arrival. We also construct mortality within 2 and 7 days for robustness analysis.

We measure the ambulance staff sickness absence rate (ASA) as the monthly share of working days lost to sickness among core staff at each ambulance station. Building on this measure, our key explanatory variable is the unexpected ambulance staff sickness absence rate (UASA), which captures idiosyncratic variation in ambulance staff sickness absences after removing predictable components related to workforce composition and systematic differences across ambulance stations and over time. The construction of UASA is described in detail in Section 4.⁶

We also construct the emergency department staff sickness absence rate (EDSA), defined as the monthly share of working days lost to sickness among ED staff. We include EDSA as a control variable to account for the possibility that staff shortages within emergency departments may independently affect patient outcomes.

For our main analysis, we use the **Patient-Level Linked Dataset**, in which the unit of observation is the ED attendance and which combines patient records with information on ambulance stations, emergency departments, mortality, and area-level characteristics. The control variables in our main specification, in addition to unexpected ambulance staff sickness absence, include:

- *Patient characteristics*: age, gender, and ethnic minority indicators;
- *Socioeconomic status*: Index of Multiple Deprivation (IMD) quintiles (from least to most deprived);
- *Distance to ED*: distance in kilometres;
- *Ambulance station size*: number of staff;

⁵The IMD is measured at the level of Lower Super Output Areas, small, standardised geographic units with populations of around 1,000 to 3,000 residents.

⁶UASA is constructed using the **Ambulance Station Workforce Panel**. See Section 4 for details of its construction and Table A1 for definitions of the main variables in the Ambulance Station Workforce Panel.

- *ED staffing*: monthly ED staff sickness absence rates;
- *Time controls*: hour-of-day, day-of-week, month, and year fixed effects.

3.2 Estimation sample restrictions

Our **Patient-Level Linked Dataset** includes ED attendances in mainland England for patients transported by ambulance from home between 1st April 2013 and 31st March 2018. We restrict to patients alive at arrival, younger than 97, residing in non-rural areas, and with travel distance to the ED below 57.7 km; for multiple same-day attendances, we retain the first.⁷

We further restrict the sample to patients with at least one ambulance station within 15 km of their residence, ensuring the validity of using the nearest station as a proxy for dispatch. This excludes less than 2% of attendances while preserving the full set of stations and EDs. We retain observations with valid measures of unexpected ambulance staff absence (UASA), which requires stations to be observed in at least two periods and causes a further small reduction.

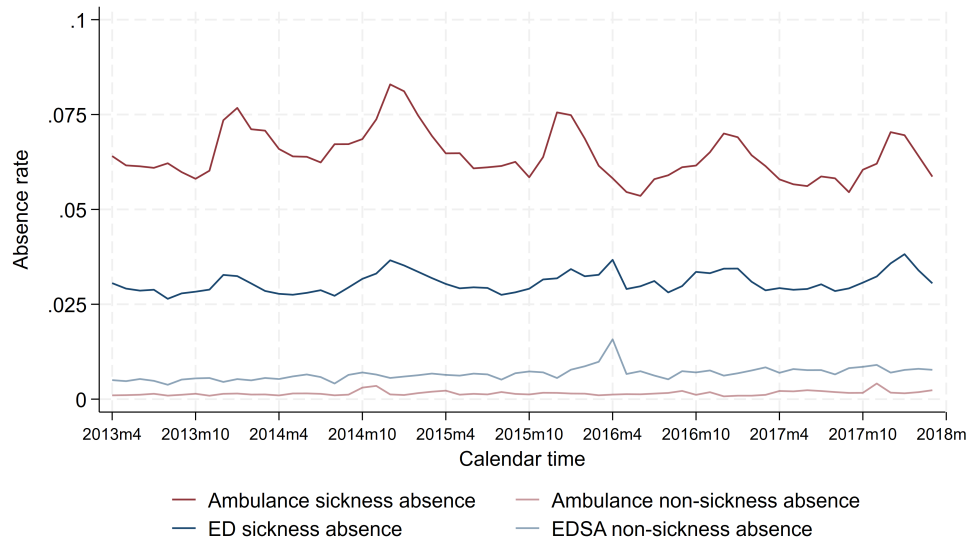
We refer to this final sample as the **Estimation Sample**, which comprises 11,018,201 attendances from 5,834,187 patients across 186 EDs and 818 ambulance stations (see the last column of Table A2).

3.3 Descriptive statistics

Figure 1 plots the monthly average rates of ambulance and ED staff absences (ASA and EDSA) over time. 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 slightly lower than those observed in EDs.

⁷Only 0.017% of patients were recorded as deceased before arrival. Non-rural areas are defined using the HES A&E (Accident & Emergency rural-urban classification. Long-distance transports often involve air ambulances or transfers to specialised hospitals.

Figure 1. Monthly ambulance and ED staff absence rates over time



Notes. Authors' calculations based on the Estimation Sample. Monthly averages are computed across 818 ambulance stations for ASA and 138 NHS Trusts for EDSA. Non-sickness absences include study leave, annual leave, and parental leave.

Table 1. Summary statistics, selected variables

Variable name	Mean	Std. dev
Patient mortality		
within 1 day	0.011	0.106
<i>within 2 days</i>	0.015	0.121
<i>within 7 days</i>	0.027	0.163
Ambulance station characteristics		
Sickness absence rate, ASA	0.064	0.073
Number of core staff	44.185	42.112
<i>Non-sickness (other) absence rate</i>	0.002	0.008
<i>Churn rate (leavers moving within NHS)</i>	0.024	0.090
<i>NHS leaver rate</i>	0.006	0.026
<i>Leaver rate (Churn + NHS leaver rate)</i>	0.030	0.094
ED characteristics		
ED staff sickness absence rate, EDSA	0.030	0.015
<i>ED staff non-sickness (other) absence rate</i>	0.007	0.008
<i>GP-treatable attendances (AA_{GP})</i>	0.226	0.106
<i>Share of ED with above median AA_{GP}</i>	0.475	0.499
<i>No-treatment and discharge attendances (AA_{NTD})</i>	0.145	0.099
<i>Share of ED with above median AA_{NTD}</i>	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
<i>Diagnosed with a respiratory illness</i>	0.082	0.274
<i>ED waiting time to initial assessment, in minutes</i>	34.745	142.467
<i>ED waiting time to treatment, in minutes</i>	88.468	105.530
<i>Share of out-of-hours visits</i>	0.644	0.479

Notes. Variables used in sensitivity and robustness checks are reported in italics. Number of observations: 11,018,201. Estimation Sample. See Table A3 for detailed variable definitions.

Table 1 reports descriptive statistics for the variables in the **Estimation Sample**. Variables used in the main analysis are shown in regular font, whereas variables used in sensitivity and robustness checks are reported in italics. Average mortality within one day of ED attendance is 1.1%, increasing to 1.5% within two days and 2.7% within seven days. As expected, more severe conditions—such as cardiac conditions and vascular injuries—are associated with higher mortality rates (see Table A4 for short-term mortality by ED diagnosis).

The average ambulance staff sickness absence rate (ASA) at the nearest ambulance station is 6.4%, while non-sickness absences are uncommon, averaging 0.2% of working days. Ambulance stations employ, on average, 44 core staff members. Leaving rates are low relative to sickness absence rates, with NHS leavers accounting for only a small fraction of total departures.

Emergency department staff sickness absence rates average 3.0%, approximately half the level observed among ambulance staff. The share of GP-treatable attendances and no-treatment-and-discharge attendances are quite large 22.6% and 14.5% respectively.

The majority of ambulance users are aged 65 years and above, consistent with a higher prevalence of chronic conditions and greater reliance on emergency transport among older populations. Approximately 54% of patients are female, around 10% belong to Black or Asian ethnic minority groups, and 7.5% have missing ethnicity information. Patients are disproportionately drawn from more deprived areas, with 28% residing in the most income-deprived quintile.

Patients travel, on average, 8.7 kilometres to reach the ED. Respiratory illnesses account for approximately 8.2% of ED attendances in the sample. Mean waiting times are around 35 minutes until initial assessment and 88 minutes until treatment, although the large standard deviations indicate substantial variation across attendances. Finally, nearly two-thirds of ambulance-delivered ED attendances occur during GP out-of-hours periods.

3.4 Balance

Patients’ clinical severity, and hence mortality risk, may vary during periods of reduced ambulance staffing if ambulance services prioritise transporting more severe cases. However, we find no evidence of selective transport to EDs during high-pressure

periods, defined as months with above-median ambulance staff sickness absence, suggesting no systematic changes in patient composition. Table A5 compares patient characteristics and diagnoses across low- ($ASA < median(ASA)$) and high-pressure ($ASA \geq median(ASA)$) periods. The distributions are highly similar, with standardized differences in means below 0.1 for all variables (Imai et al., 2008; Austin, 2011), indicating no meaningful changes in patient composition.

4 Empirical strategy

We are interested in evaluating the effect of ambulance understaffing caused by staff sickness absences on patient mortality. Because sickness absences are difficult to predict, they generate short-run staffing shocks that can exacerbate existing capacity constraints in emergency services.

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 nearest ambulance stations.

We estimate the following linear probability model

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

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 absence rate by considering the staff sickness absence rate in month t in the nearest ambulance station to the patient's home. To isolate variation in the ambulance sickness absence rate unrelated to the ED and hospital characteristics 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 number of core ambulance workers and expressed in natural log, $\ln(ASize_{i,t,h})$. Additionally, we include a set of control variables, $\mathbf{X}_{i,t,h}$, that capture characteristics of ED patients that may affect 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.

$$\tau_t = \tau_p + \tau_d + \tau_m + \tau_y \quad (2)$$

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 by including month and year fixed effects, it does not fully address potential endogeneity due to correlations 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 absences, may also be correlated with patient mortality through worse emergency care quality. This can lead to 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:

$$ASA_{at} = \alpha \mathbf{Z}_{at} + \phi_m + \phi_y + \eta_a + \varepsilon_{at} \quad (3)$$

where $\mathbf{Z}_{at}$ 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

$$UASA_{at} = ASA_{at} - \widehat{ASA}_{at}. \quad (4)$$

Our preferred specification is then Equation (5) below, that is, Equation (1) in which ASA is replaced with UASA:⁸

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

5 Results

5.1 Main Results

Table 2 presents the estimates for the effect of the unexpected ambulance staff sickness rate (UASA), which is our key parameter of interest, along with parameters of secondary importance.⁹

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 discussion and analysis on these estimates.

Standard errors are reported in parentheses and are clustered at the ED level to

⁸To avoid introducing new symbols, we use the same notation as in model 1, despite the change in the key variable of interest.

⁹UASA is computed as the residual from equation (3). Table A6 presents the estimated coefficients from the first-stage equation.

account for correlation in errors among patients arriving at the same ED.¹⁰ 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, its impact is limited in our setting given the near-universe 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 2.¹¹ 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 arrival at the ED. 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 and is no longer statistically significant (Column III).

¹⁰Clustering 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.

¹¹The percentage increase in the mortality rate is computed as $\Theta(\text{UASA}) = \frac{\hat{\rho} \cdot SD(\text{UASA})}{\bar{M}}$, where $\hat{\rho}$ and $SD(\text{UASA})$ are the estimated coefficient and standard deviation of UASA and $\bar{M}$ 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* (0.00061)	0.00111** (0.00056)	0.00131** (0.00051) [0.00053]
ln(average number of core ambulance staff), ln(ASize)		-0.00020** (0.00009)	0.00000 (0.00004) [0.00004]
ED staff monthly sickness absence, EDSA		0.02728** (0.01324)	0.00285 (0.00219) [0.00385]
ln(patient-hospital distance in km)		0.00023** (0.00011)	0.00003 (0.00008) [0.00007]
Income deprivation (ref: Least deprived 20%) Quintile 2		0.00030** (0.00014)	0.00015 (0.00011) [0.00009]
Quintile 3		-0.00000 (0.00020)	-0.00016 (0.00014) [0.00014]
Quintile 4		-0.00002 (0.00021)	-0.00014 (0.00014) [0.00015]
Quintile 5 (Most deprived 20%)		0.00018 (0.00026)	-0.00042*** (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. Estimation Sample. 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. $\Theta(UASA)$ and $\Theta(EDSA)$ 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We include ED staff sickness absence (EDSA) to address potential omitted variable bias in estimating the effect of unexpected ambulance staff absences (UASA). Because ED staff are frontline workers exposed to similar demand pressures and to the same sources and timing of infectious diseases as ambulance staff, their absence patterns may be correlated with both UASA and 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).¹²

¹²We 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)
<i>Percentage change in patient mortality, Θ</i> $\Theta(UANSA)$	-0.21769
Observations	11,018,201

Notes. Estimation Sample. 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-persistent¹³ 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.¹⁴

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 $UASA_{t+12}$	Benchmark specification with $UASA_t$ using column (IV) sample
	(I)	(II)	(III)	(IV)	(V)
Unexpected monthly ambulance sickness absence, UASA	0.00131** (0.00051)	-0.00023 (0.00048)	0.00170*** (0.00053)	0.00004 (0.00060)	0.00134** (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. Additional controls, not shown, include patient age categories, gender, and ethnic minority status. Lag and lead UASA are constructed using an extended ambulance-station workforce panel that includes data for 2019. All benchmark estimates, including those based on restricted samples, use the original sample 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 influence of seasonal epidemics. However, this approach may be insufficient to assure

¹³Note that our benchmark specification controls for any persistent unobserved ambulance characteristics, as UASA is defined net of ambulance fixed effects.

¹⁴Controlling 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.

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.	$\Theta(\text{UASA})$	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 rows report estimates obtained by restricting the estimation sample or adding extra control variables to the benchmark specification. Standard errors are clustered at the ED level and reported in parentheses. $\Theta(\text{UASA})$ 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 from underlying health conditions, we augment our benchmark specification in Equation (5) by including diagnoses recorded by ED staff.¹⁵

¹⁵We use a harmonised diagnosis classification that combines ED diagnostic codes with ICD-10 (International Classification of Diseases, Tenth Revision).

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.¹⁶

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.

¹⁶Figure 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 whether this is an issue, we run a sensitivity analysis with ED-by-year fixed effects, which controls for unobserved hospital or ED characteristics that vary 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 staff turnover rate at ambulance stations.

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) with patient mortality replaced by 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 (10.12176)	-6.81902 (4.32007)
<i>Percentage change in patient waiting time, Θ</i> $\Theta(UASA)$	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.¹⁷

¹⁷More 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.

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 greater demand for emer-

Table 7. UASA effect on patient mortality: Heterogeneity analyses

	Coefficient	S.E.	$\Theta(\text{UASA})$	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 G: 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. $\Theta(\text{UASA})$ 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 approximately 50% larger 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 April to September is much smaller in magnitude and never statistically significant, although it remains 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 the risk of patient mortality. 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 time of 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-time 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 G 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 employ, 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 transport to the ED are critical

determinants of survival within 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 by hospital-level factors, including the quality of care and staffing of ED services, as ambulance staff are no longer involved in patient care following transfer.

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** (0.00051)	0.00094 (0.00059)	-0.00037 (0.00027)	0.00079 (0.00078)	-0.00012 (0.00050)
ED staff monthly sickness absence, EDSA	0.00285 (0.00219)	0.00320 (0.00286)	0.00037 (0.00130)	0.00470 (0.00410)	0.00156 (0.00209)
<i>Percentage change in patient waiting time, Θ</i>					
$\Theta(UASA)$	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, 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 0 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. Furthermore, our conjecture appears to be supported also by the association of patient mortality with ED staff monthly sickness absence (EDSA), reported in 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 emergency 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. First, 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.

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 row of Table 9 presents the marginal effects from the cloglog model, which are similar to the baseline estimate of UASA’s impact on 1-day patient mortality.

Table 9. UASA effect on patient mortality: Robustness checks

	Coefficient	S.E.	$\Theta(\text{UASA})$	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. $\Theta(\text{UASA})$ 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 nearest 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.¹⁸ As shown in row 3 in Table 9 the effect of UASA for the nearest ambulance station remains almost 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-nearest 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 pre-

¹⁸Similarly to what was done for the nearest ambulance station, we identify the second nearest ambulance station to the patient and link its UASA accordingly.

dictable 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.¹⁹

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 assess the direction of potential omitted variable bias in the estimated effect of UASA.²⁰

¹⁹As 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.

²⁰Under 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

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 reports the results, including [Oster \(2019\)](#) bounds for the bias-corrected estimates in the final columns. Following [Oster \(2019\)](#), we set the maximum attainable R^2 ($R^2_{\max}$) to 1.3 times the R^2 of the fully specified model, reflecting the assumption that unobservables can increase explanatory power beyond observables. 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 Welfare Costs of Mortality from 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).

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

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

measurement error and sufficient variation in covariates; large sample size; no endogeneity among controls; and a stable relationship between covariates and treatment assignment.

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 ED visits during the period 2013–2018. Multiplying the value of Equation (6) by N yields the implied number of excess deaths:

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

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 $u = 0.8$.²¹ 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 $\Delta QALY \times v = 13,939.2 \times £70,000 = £975,744$ million. A one-standard-deviation increase in unexpected ambulance staff absences entails a 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 ab-

²¹The 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 \(2024\)](#).

sences (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 factors 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, our estimates imply a welfare loss of approximately £1 billion over five years from a one-standard-deviation increase in UASA.

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.

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

References

- Andrew, E., Nehme, Z., Cameron, P. and Smith, K. (2020), ‘Drivers of increasing emergency ambulance demand’, *Prehospital Emergency Care* **24**(3), 385–393.
- Anselmi, L., Meacock, R., Kristensen, S. R., Doran, T. and Sutton, M. (2017), ‘Arrival by ambulance explains variation in mortality by time of admission: retrospective study of admissions to hospital following emergency department attendance in england’, *BMJ quality & safety* **26**(8), 613–621.
- Asheim, A., Næss, L. E., Krüger, A., Uleberg, O., Dale, J., Haugland, H., Ulvin, O. E., Nilsen, S. M., Bjørnelv, G. M. W., Wattø, J.-O. et al. (2025), ‘Does delayed response due to busy ambulances impact risk of death and hospital service use?: A cohort study of 240,000 medical emergencies’, *Epidemiology* **36**(6), 830–840.
- Austin, P. C. (2011), ‘An introduction to propensity score methods for reducing the effects of confounding in observational studies’, *Multivariate Behavioral Research* **46**(3), 399–424.
- Baker, C. (2018), ‘NHS Winter Pressures 2017/18, England’, <https://researchbriefings.files.parliament.uk/documents/CBP-8210/CBP-8210.pdf>.
- Bartel, A. P., Beaulieu, N. D., Phibbs, C. S. and Stone, P. W. (2014), ‘Human capital and productivity in a team environment: evidence from the healthcare sector’, *American Economic Journal: Applied Economics* **6**(2), 231–259.
- Brachet, T., David, G. and Drechsler, A. M. (2012), ‘The effect of shift structure on performance’, *American Economic Journal: Applied Economics* **4**(2), 219–246.
- British Medical Association (2019), ‘NHS Pressures – Winter 2018/19: A hidden crisis’, <https://www.readkong.com/page/nhs-pressures-winter-2018-19-a-hidden-crisis-5178562>.
- Chan Jr, D. C. and Chen, Y. (2022), The productivity of professions: Evidence from the emergency department, NBER Working Paper 30608, National Bureau of Economic Research.

- Chen, M. M. and Grabowski, D. C. (2015), ‘Intended and unintended consequences of minimum staffing standards for nursing homes’, *Health Economics* **24**(7), 822–839.
- Costa, E. (2022), ‘The unintended consequences of hospital strikes on patient outcomes evidence from multiple strikes in the Portuguese National Health Service’, *Health Economics* **31**(11), 2499–2511.
- Coster, J. E., Turner, J. K., Bradbury, D. and Cantrell, A. (2017), ‘Why do people choose emergency and urgent care services? A rapid review utilizing a systematic literature search and narrative synthesis’, *Academic Emergency Medicine* **24**(9), 1137–1149.
- Denny, M., Boehme, A., Dorsey, A., George, A., Yeh, A., Albright, K. and Martin-Schild, S. (2014), ‘Wake-up strokes are similar to known-onset morning strokes in severity and outcome’, *Journal of Neurology and Neurological Disorders* **1**(1).
- Doyle, J. J., Graves, J. A., Gruber, J. and Kleiner, S. A. (2015), ‘Measuring returns to hospital care: Evidence from ambulance referral patterns’, *Journal of Political Economy* **123**(1), 170–214.
- Edwards, N. (2017), ‘Black alert? or many shades of opel’, <https://www.nuffieldtrust.org.uk/news-item/black-alert-or-many-shades-of-opel>. Accessed 31 March 2026.
- Escobar Carias, M., Johnston, D. W., Knott, R. and Sweeney, R. (2024), ‘Temperature’s toll on decision-making’, *The Economic Journal* **134**(663), 2746–2771.
- Eurofound (2010), ‘Absence from work’, https://www.eurofound.europa.eu/sites/default/files/ef_files/docs/ewco/tn0911039s/tn0911039s.pdf.
- Fisher, E. and Dorning, H. (2016), ‘Winter pressures: what’s going on behind the scenes?’, <https://www.nuffieldtrust.org.uk/research/winter-pressure-what-s-going-on-behind-the-scenes>.
- Francetic, I., Meacock, R. and Sutton, M. (2024), ‘Free-for-all: Does crowding impact outcomes because hospital emergency departments do not prioritise effectively?’, *Journal of Health Economics* **95**, 102881.
- Friedrich, B. U. and Hackmann, M. B. (2021), ‘The returns to nursing: Evidence from a parental-leave program’, *The Review of Economic Studies* **88**(5), 2308–2343.
- Gazze, L., Persico, C. and Spirovska, S. (2024), ‘The long-run spillover effects of pollution: How exposure to lead affects everyone in the classroom’, *Journal of Labor Economics* **42**(2), 357–394.
- Grabowski, D. C., Gruber, J. and McGarry, B. (2023), Immigration, the long-term care

- workforce, and elder outcomes in the U.S., NBER Working Paper 30960, National Bureau of Economic Research.
- Grinza, E. and Rycx, F. (2020), ‘The impact of sickness absenteeism on firm productivity: new evidence from Belgian matched employer–employee panel data’, *Industrial Relations: A Journal of Economy and Society* **59**(1), 150–194.
- Gruber, J., Hoe, T. P. and Stoye, G. (2023), ‘Saving lives by tying hands: the unexpected effects of constraining health care providers’, *Review of Economics and Statistics* **105**(1), 1–19.
- Gruber, J. and Kleiner, S. A. (2012), ‘Do strikes kill? Evidence from New York State’, *American Economic Journal: Economic Policy* **4**(1), 127–157.
- Hansen, J. (2000), ‘The effect of work absence on wages and wage gaps in Sweden’, *Journal of Population Economics* **13**(1), 45–55.
- Herrmann, M. A. and Rockoff, J. E. (2012), ‘Worker absence and productivity: Evidence from teaching’, *Journal of Labor Economics* **30**(4), 749–782.
- HM Treasury (2020), *The Green Book: Central Government Guidance on Appraisal and Evaluation*, The Stationery Office / Crown.
URL: <https://www.gov.uk/government/publications/the-green-book-appraisal-and-evaluation-in-central-government/the-green-book-2020#introduction-to-appraisal-and-evaluation>
- Hoe, T. P. (2022), ‘Does hospital crowding matter? Evidence from trauma and orthopedics in England’, *American Economic Journal: Economic Policy* **14**(2), 231–262.
- House of Commons Health Committee (2016), ‘Winter pressure in accident and emergency departments’, <https://publications.parliament.uk/pa/cm201617/cmselect/cmhealth/277/27704.htm>. UK Parliament.
- Ichino, A. and Moretti, E. (2009), ‘Biological gender differences, absenteeism, and the earnings gap’, *American Economic Journal: Applied Economics* **1**(1), 183–218.
- Imai, K., King, G. and Stuart, E. A. (2008), ‘Misunderstandings between experimentalists and observationalists about causal inference’, *Journal of the Royal Statistical Society Series A: Statistics in Society* **171**(2), 481–502.
- Ireland, A., Johnston, D. and Knott, R. (2024), ‘Impacts of extreme heat on labor force dynamics’, *arXiv preprint arXiv:2402.15072*.
- Kelly, E., Propper, C. and Zaranko, B. (2025), ‘Nursing shortages and patient outcomes’, *Journal of Health Economics* **105**, 103082.

- Khan, N. (2022), ‘Ambulance response times: the NHS’s falling house of cards’, *The British Journal of General Practice* **72**(722), 436.
- Knutsson, D. and Tyrefors, B. (2022), ‘The quality and efficiency of public and private firms: evidence from ambulance services’, *The Quarterly Journal of Economics* **137**(4), 2213–2262.
- Kraaijvanger, N., van Leeuwen, H., Rijpsma, D. and Edwards, M. J. R. (2016), ‘Motives for self-referral to the emergency department: A systematic review of the literature’, *BMC Health Services Research* **16**, 685.
- Lewis, J., Jacques, R., Simpson, R., Hasan, M., Croft, S., Croft, S., McMurray, R. and Mason, S. (2023), ‘Understanding seasonal demand for emergency care: aggregating routine data from regional emergency departments and acute hospital admissions’, *Emergency Medicine Journal* **40**(12), 883–889.
- Lin, H. (2014), ‘Revisiting the relationship between nurse staffing and quality of care in nursing homes: An instrumental variables approach’, *Journal of Health Economics* **37**, 13–24.
- Liu, V. X., Fielding-Singh, V., Greene, J. D., Baker, J. M., Iwashyna, T. J., Bhattacharya, J. and Escobar, G. J. (2017), ‘The timing of early antibiotics and hospital mortality in sepsis’, *American Journal of Respiratory and Critical Care Medicine* **196**(7), 856–863.
- London Ambulance Service NHS Trust (2026), ‘Ambulance response categories’, <https://www.londonambulance.nhs.uk/calling-us/ambulance-response-categories/>. Accessed 31 March 2026.
- Lowthian, J. A., Cameron, P. A., Stoelwinder, J. U., Curtis, A., Currell, A., Cooke, M. W. and McNeil, J. J. (2011), ‘Increasing utilisation of emergency ambulances’, *Australian Health Review* **35**(1), 63–69.
- Lucchese, E. (2024), ‘How important are delays in treatment for health outcomes? The case of ambulance response time and cardiovascular events’, *Health Economics* **33**(4), 652–673.
- Markussen, S. (2012), ‘The individual cost of sick leave’, *Journal of Population Economics* **25**(4), 1287–1306.
- McHale, P., Wood, S., Hughes, K., Bellis, M. A., Demnitz, U. and Wyke, S. (2013), ‘Who uses emergency departments inappropriately and when – a national cross-sectional study using a monitoring data system’, *BMC Medicine* **11**, 1–9.
- MET Medical (2024), ‘Do private ambulances attend 999

- emergency calls in the uk? Here's what you need to know', <https://www.met-medical.co.uk/met-medical-news/do-private-ambulances-attend-999-emergency-calls-in-the-uk-heres-what-you-need-to-> Accessed 31 March 2026.
- Moscelli, G., Mello, M., Sayli, M. and Boyle, A. (2024), 'Hospital nurse and doctor turnover and patient outcomes: A retrospective longitudinal study on English NHS acute hospitals', *BMJ* **387**, e079987.
- National Audit Office (2018), 'NHS ambulance services', <https://www.nao.org.uk/wp-content/uploads/2017/01/NHS-Ambulance-Services.pdf>.
- NHS England (2023), 'Ambulance response programme', <https://www.england.nhs.uk/urgent-emergency-care/improving-ambulance-services/arp/>. Accessed 31 March 2026.
- Nicholl, J., West, J., Goodacre, S. and Turner, J. (2007), 'The relationship between distance to hospital and patient mortality in emergencies: An observational study', *Emergency Medicine Journal* **24**(9), 665–668.
- North East Ambulance Service NHS Foundation Trust (2026), 'Ambulance response programme', <https://www.neas.nhs.uk/your-service/999/ambulance-response-programme>. Accessed 31 March 2026.
- North West Ambulance Service NHS Trust (2026), 'Performance standards – 999', <https://www.nwas.nhs.uk/about/performance/999-standards/>. Accessed 31 March 2026.
- NursingNotes (2022), 'Every single ambulance service in england declares 'critical incident' status', <https://nursingnotes.co.uk/news/clinical/every-single-ambulance-service-in-england-declares-critical-incident-status/>. Accessed 31 March 2026.
- O'Cathain, A., Simpson, R., Phillips, M. and Knowles, E. (2022), 'Tendency to call an ambulance or attend an emergency department for minor or non-urgent problems: A vignette-based population survey in Britain', *Emergency Medicine Journal* **39**(6), 436–442.
- Office for National Statistics (2025), 'Avoidable mortality in England and Wales: 2023', <https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/causesofdeath/bulletins/avoidablemortalityinenglandandwales/latest>. Statistical Bulletin, release date: 28 April 2025.

- Oster, E. (2019), ‘Unobservable selection and coefficient stability: Theory and evidence’, *Journal of Business & Economic Statistics* **37**(2), 187–204.
- Pauly, M. V., Nicholson, S., Xu, J., Polsky, D., Danzon, P. M., Murray, J. F. and Berger, M. L. (2002), ‘A general model of the impact of absenteeism on employers and employees’, *Health Economics* **11**(3), 221–231.
- Pierce-Hayes, I. (2009), ‘Heart attacks and circadian rhythms’, *British Journal of Cardiac Nursing* **4**(9), 416–423.
- Pittet, V., Burnand, B., Yersin, B. and Carron, P.-N. (2014), ‘Trends of pre-hospital emergency medical services activity over 10 years: a population-based registry analysis’, *BMC health services research* **14**(1), 380.
- Shen, K., McGarry, B. E., Grabowski, D. C., Gruber, J. and Gandhi, A. D. (2022), ‘Staffing patterns in us nursing homes during covid-19 outbreaks’, in ‘JAMA Health Forum’, Vol. 3, American Medical Association, pp. e222151–e222151.
- South East Coast Ambulance Service NHS Foundation Trust (2026), ‘Response time targets’, <https://www.secamb.nhs.uk/how-we-do-it/our-performance/response-time-targets/>. Accessed 31 March 2026.
- Stewart, W. F., Ricci, J. A., Chee, E. and Morganstein, D. (2003), ‘Lost productive work time costs from health conditions in the United States: results from the American Productivity Audit’, *Journal of Occupational and Environmental Medicine* **45**(12), 1234–1246.
- Stoye, G. and Warner, M. (2023), ‘The effects of doctor strikes on patient outcomes: evidence from the English NHS’, *Journal of Economic Behavior & Organization* **212**, 689–707.
- Turner, A. J., Anselmi, L., Lau, Y.-S. and Sutton, M. (2020), ‘The effects of unexpected changes in demand on the performance of emergency departments’, *Health Economics* **29**(12), 1744–1763.
- Turner, A. J., Francetic, I., Watkinson, R., Gillibrand, S. and Sutton, M. (2022), ‘Socioeconomic inequality in access to timely and appropriate care in emergency departments’, *Journal of Health Economics* **85**, 102668.
- UK Office for National Statistics (2024), ‘Expectation of life: High life expectancy variant, England’, <https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/datasets/expectationoflifehighlifeexpectancyvariantengland>. Dataset.
- UNISON (2023), ‘Nhs spending over £1m a week on private ambulances for 999 call-

- outs, says unison', <https://www.unison.org.uk/news/press-release/2023/04/nhs-spending-over-1m-a-week-on-private-ambulances-for-999-callouts-says-unison/>. Press release; Accessed 31 March 2026.
- Wilde, E. T. (2013), 'Do emergency medical system response times matter for health outcomes?', *Health Economics* **22**(7), 790–806.
- Winter, V., Schreyögg, J. and Thiel, A. (2020), 'Hospital staff shortages: Environmental and organizational determinants and implications for patient satisfaction', *Health Policy* **124**(4), 380–388.
- Zaranko, B., Sanford, N. J., Kelly, E., Rafferty, A. M., Bird, J., Mercuri, L., Sigsworth, J., Wells, M. and Propper, C. (2023), 'Nurse staffing and inpatient mortality in the English National Health Service: a retrospective longitudinal study', *BMJ Quality & Safety* **32**(5), 254–263.

Appendix A. Additional Tables & Figures

Figure A1. Data linkages for the sample construction

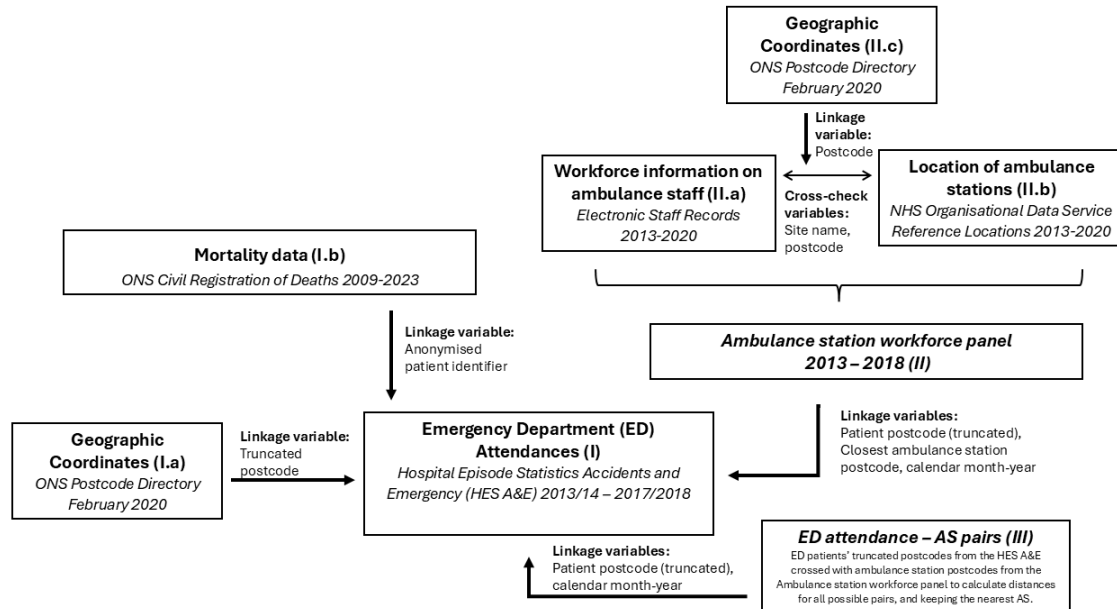


Figure A2. NHS Ambulance Stations and Emergency Departments across mainland England, 2013-2018

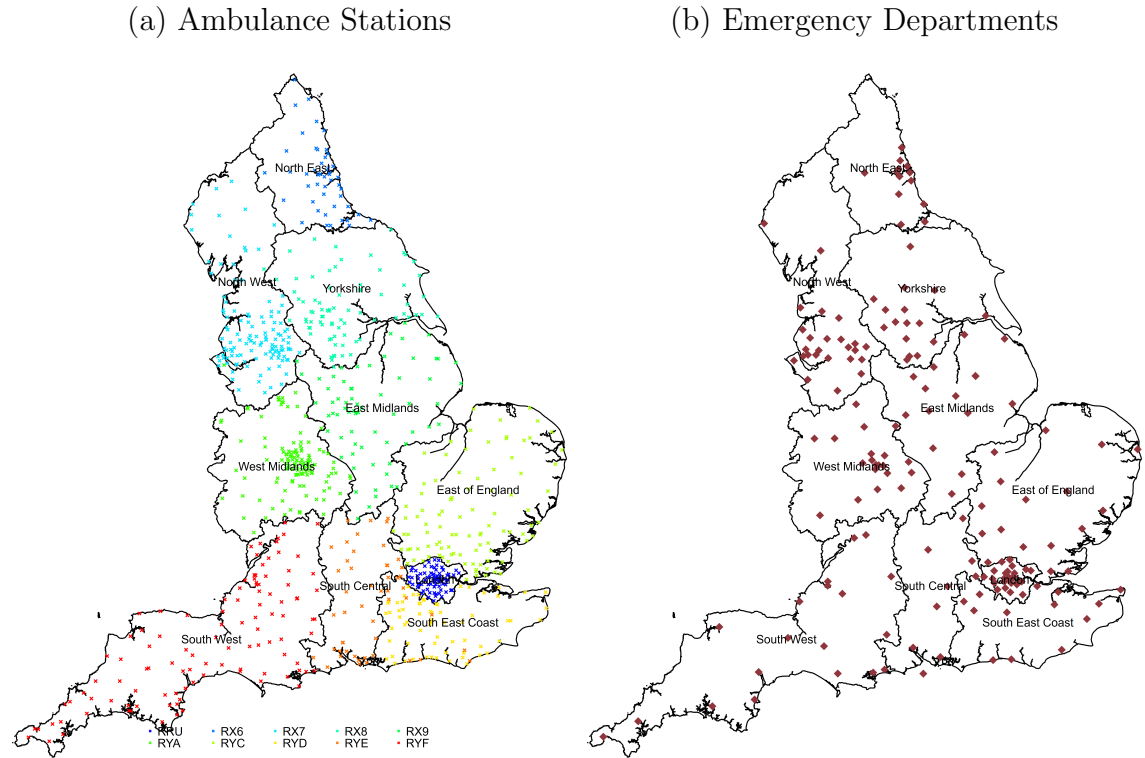
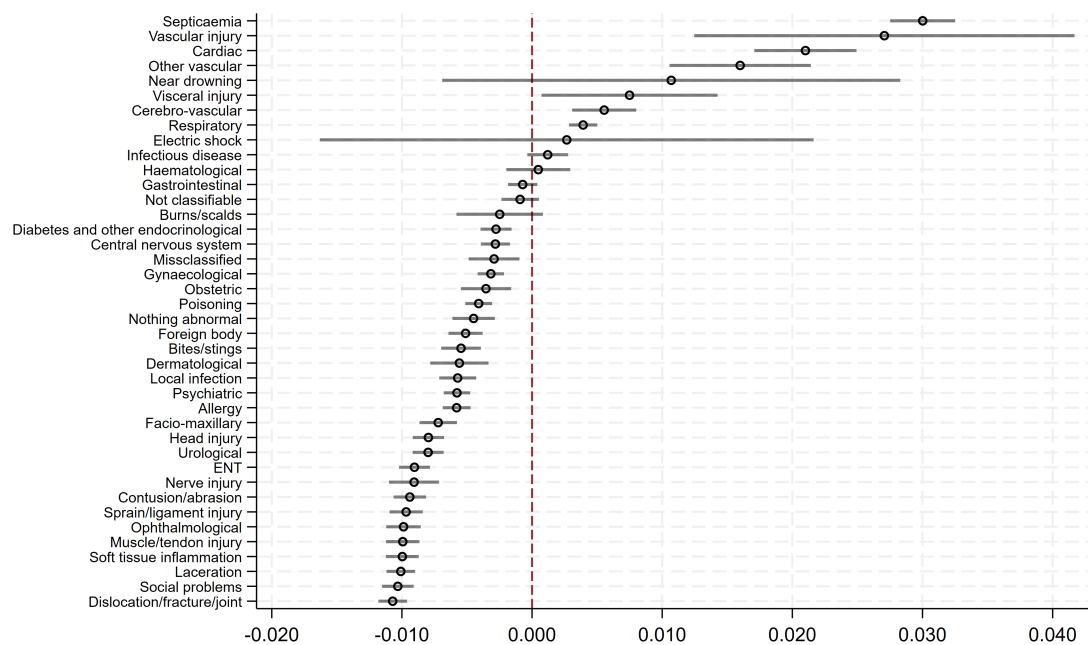


Figure A3. Coefficient estimates of ED diagnoses on ED mortality within 1 day



Notes. Estimation sample. Estimates are based on Equation 5 and include ED diagnosis dummies (reference: no or missing diagnosis). Circles denote coefficients; vertical bars show 95% confidence intervals based on standard errors clustered at the ED level.

Table A1. 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
<i>Share of staff</i>		
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. Ambulance Station Workforce Panel. The unit of observation is an ambulance station-month.

Table A2. 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

Notes. Column (1) considers the sample that uses the nearest station regardless of distance. Column (2) restricts the sample to patients whose nearest station is within 15 km, while Column (3) further restricts the sample to observations with non-missing UASA.

Table A3. Definitions of variables

Variable name	Definition
<i>Patient mortality</i>	
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 .
<i>Ambulance station characteristics</i>	
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.
<i>ED characteristics</i>	
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 International Classification of Diseases, Tenth Revision (ICD-10) codes.
<i>Patient characteristics</i>	
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 A4. ED patient mortality and ED diagnoses

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

Notes. Estimation sample. Diagnoses are ordered by one-day mortality following ED attendance and are based on a harmonised classification combining ED diagnostic codes and ICD-10 codes. [†] Central nervous system conditions exclude stroke. [‡] Social problems include chronic alcoholism and homelessness.

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

	ASA < median ASA		ASA ≥ median ASA		Normalised Δ(Mean)
	Mean	Std	Mean	Std	
<i>Patient characteristics</i>					
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
<i>Share of patients in income deprivation</i>					
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
<i>Diagnoses</i>					
Septicaemia	0.013	0.112	0.012	0.109	0.00905
Vascular injury	0.001	0.023	0.001	0.025	0.00000
Cardiac conditions	0.067	0.251	0.069	0.254	-0.00792
Other vascular conditions	0.005	0.070	0.005	0.071	0.00000
Cerebro-vascular conditions	0.016	0.125	0.017	0.130	-0.00784
Visceral injury	0.000	0.016	0.000	0.016	0.00000
Near drowning	0.000	0.005	0.000	0.005	0.00000
Respiratory conditions	0.082	0.274	0.082	0.275	0.00000
Haematological conditions	0.004	0.061	0.004	0.060	0.00000
Infectious disease	0.014	0.117	0.015	0.122	-0.00837
Electric shock	0.000	0.011	0.000	0.014	0.00000
Gastrointestinal conditions	0.071	0.256	0.070	0.255	0.00391
Diabetes/endocrine	0.009	0.095	0.010	0.098	-0.01036
Central nervous system conditions	0.035	0.185	0.036	0.186	-0.00539
Local infection	0.008	0.087	0.007	0.083	0.01176
Burns and scalds	0.002	0.041	0.002	0.046	0.00000
Urological conditions	0.032	0.177	0.033	0.178	-0.00563
Dermatological conditions	0.003	0.051	0.003	0.050	0.00000
Head injury	0.022	0.146	0.022	0.145	0.00000
Foreign body	0.001	0.033	0.001	0.035	0.00000
Social problems	0.006	0.080	0.007	0.081	-0.01242
Contusion/abrasion	0.009	0.093	0.010	0.098	-0.01047
Nerve injury	0.001	0.029	0.001	0.030	0.00000
Facio-maxillary conditions	0.001	0.025	0.001	0.025	0.00000
Soft tissue inflammation	0.011	0.105	0.011	0.103	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
ENT conditions	0.008	0.090	0.008	0.090	0.00000
Ophthalmological conditions	0.001	0.027	0.001	0.027	0.00000
Laceration	0.012	0.109	0.013	0.112	-0.00905
Psychiatric conditions	0.018	0.132	0.017	0.128	0.00769
Obstetric conditions	0.001	0.038	0.002	0.042	-0.02500
Gynaecological conditions	0.006	0.076	0.005	0.072	0.01351
Muscle/tendon injury	0.006	0.079	0.006	0.078	0.00000
Allergy	0.003	0.057	0.003	0.056	0.00000
Sprain/ligament injury	0.007	0.082	0.008	0.087	-0.01183
Nothing abnormal detected	0.022	0.146	0.023	0.150	-0.00676
Diagnosis not classifiable	0.171	0.376	0.183	0.387	-0.03145
No/missing diagnosis	0.245	0.430	0.232	0.422	0.03052
Misclassified	0.034	0.182	0.029	0.167	0.02865

Notes. Estimation sample. Diagnoses are defined and ordered as in Table A4. The median ASA is computed from the Ambulance Station Workforce Panel. Normalised $\Delta(\text{Mean})$ is $(X_{low} - X_{high}) / \sqrt{\frac{\sigma_{low}^2 + \sigma_{high}^2}{2}}$, where X_{low} and X_{high} denote sample means below and above the median ASA, and σ^2 the corresponding variances.

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

	Coefficient	Standard error
<i>Age groups (share of staff)</i>		
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)
<i>Nationality (share of staff, ref: British)</i>		
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)
<i>Month FE (ref: April)</i>		
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)
<i>Year FE (ref 2013/14)</i>		
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. Ambulance Station Workforce Panel. 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)
<i>Time of day (ref: Afternoon)</i>		
Morning	0.00352***	(0.00014)
Evening	-0.00124***	(0.00010)
Night	0.00054***	(0.00011)
<i>Day of week (ref: Friday)</i>		
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)
<i>Month FE (ref: April)</i>		
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)
<i>Year FE (ref: 2013/14)</i>		
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. Estimation Sample. 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. Robustness check: Effect on ED patient mortality due to UASA in the two nearest 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)
<i>Percentage change in ED mortality, Θ</i>		
$\Theta(UASA1)$	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

Contrast	Uncontrolled regression (U)	R^2	Controlled regression (C)	R^2	R^2_{max}	Oster (2019) projection	
	Estimate (Standard Error)		Estimate (Standard Error)			Estimate	95% CI
1. no controls, no ED fixed effects (U) <i>vs.</i> 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) <i>vs.</i> 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) <i>vs.</i> 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) <i>vs.</i> 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.



competence in competition + health

series



CINCH working paper series

- 1 Halla, Martin and Martina Zweimüller. **Parental Responses to Early Human Capital Shocks:** Evidence from the Chernobyl Accident. CINCH 2014.
- 2 Aparicio, Ainhoa and Libertad González. **Newborn Health and the Business Cycle:** Is it Good to be born in Bad Times? CINCH 2014.
- 3 Robinson, Joshua J. **Sound Body, Sound Mind?:** Asymmetric and Symmetric Fetal Growth Restriction and Human Capital Development. CINCH 2014.
- 4 Bhalotra, Sonia, Martin Karlsson and Therese Nilsson. **Life Expectancy and Mother-Baby Interventions:** Evidence from A Historical Trial. CINCH 2014.
- 5 Goebel, Jan, Christian Krekel, Tim Tiefenbach and Nicolas R. Ziebarth. **Natural Disaster, Environmental Concerns, Well-Being and Policy Action:** The Case of Fukushima. CINCH 2014.
- 6 Avdic, Daniel, **A matter of life and death? Hospital Distance and Quality of Care:** Evidence from Emergency Hospital Closures and Myocardial Infarctions. CINCH 2015.
- 7 Costa-Font, Joan, Martin Karlsson and Henning Øien. **Informal Care and the Great Recession.** CINCH 2015.
- 8 Titus J. Galama and Hans van Kippersluis. **A Theory of Education and Health.** CINCH 2015.
- 9 Dahmann, Sarah. **How Does Education Improve Cognitive Skills?:** Instructional Time versus Timing of Instruction. CINCH 2015.
- 10 Dahmann, Sarah and Silke Anger. **The Impact of Education on Personality:** Evidence from a German High School Reform. CINCH 2015.
- 11 Carbone, Jared C. and Snorre Kverndokk. **Individual Investments in Education and Health.** CINCH 2015.
- 12 Zilic, Ivan. **Effect of forced displacement on health.** CINCH 2015.
- 13 De la Mata, Dolores and Carlos Felipe Gaviria. **Losing Health Insurance When Young:** Impacts on Usage of Medical Services and Health. CINCH 2015.

- 14 Tequame, Miron and Nyasha Tirivayi. **Higher education and fertility:** Evidence from a natural experiment in Ethiopia. CINCH 2015.
- 15 Aoki, Yu and Lualhati Santiago. **Fertility, Health and Education of UK Immigrants:** The Role of English Language Skills. CINCH 2015.
- 16 Rawlings, Samantha B., **Parental education and child health:** Evidence from an education reform in China. CINCH 2015.
- 17 Kamhöfer, Daniel A., Hendrik Schmitz and Matthias Westphal. **Heterogeneity in Marginal Non-monetary Returns to Higher Education.** CINCH 2015.
- 18 Ardila Brenøe, Anne and Ramona Molitor. **Birth Order and Health of Newborns:** What Can We Learn from Danish Registry Data? CINCH 2015.
- 19 Rossi, Pauline. **Strategic Choices in Polygamous Households:** Theory and Evidence from Senegal. CINCH 2016.
- 20 Clarke, Damian and Hanna Mühlrad. **The Impact of Abortion Legalization on Fertility and Maternal Mortality:** New Evidence from Mexico. CINCH 2016.
- 21 Jones, Lauren E. and Nicolas R. Ziebarth. **US Child Safety Seat Laws:** Are they Effective, and Who Complies? CINCH 2016.
- 22 Koppensteiner, Martin Foureaux and Jesse Matheson. **Access to Education and Teenage Pregnancy.** CINCH 2016.
- 23 Hofmann, Sarah M. and Andrea M. Mühlenweg. **Gatekeeping in German Primary Health Care – Impacts on Coordination of Care, Quality Indicators and Ambulatory Costs.** CINCH 2016.
- 24 Sandner, Malte. **Effects of Early Childhood Intervention on Fertility and Maternal Employment:** Evidence from a Randomized Controlled Trial. CINCH 2016.
- 25 Baird, Matthew, Lindsay Daugherty, and Krishna Kumar. **Improving Estimation of Labor Market Disequilibrium through Inclusion of Shortage Indicators.** CINCH 2017.
- 26 Bertoni, Marco, Giorgio Brunello and Gianluca Mazzarella. **Does postponing minimum retirement age improve healthy behaviors before retirement?** Evidence from middle-aged Italian workers. CINCH 2017.
- 27 Berniell, Inés and Jan Bietenbeck. **The Effect of Working Hours on Health.** CINCH 2017.
- 28 Cronin, Christopher, Matthew Forsstrom, and Nicholas Papageorge. **Mental Health, Human Capital and Labor Market Outcomes.** CINCH 2017.

- 29 Kamhöfer, Daniel and Matthias Westphal. **Fertility Effects of College Education:** Evidence from the German Educational Expansion. CINCH 2017.
- 30 Jones, John Bailey and Yue Li. **The Effects of Collecting Income Taxes on Social Security Benefits.** CINCH 2017.
- 31 Hofmann, Sarah and Andrea Mühlenweg. **Learning Intensity Effects in Students' Mental and Physical Health –** Evidence from a Large Scale Natural Experiment in Germany. CINCH 2017.
- 32 Vollmer, Sebastian and Juditha Wójcik. **The Long-term Consequences of the Global 1918 Influenza Pandemic:** A Systematic Analysis of 117 IPUMS International Census Data Sets. CINCH 2017.
- 33 Thamarapani, Dhanushka, Rockmore, Marc, and Willa Friedman. **The Educational and Fertility Effects of Sibling Deaths.** CINCH 2018.
- 34 Lemmon, Elizabeth. **Utilisation of personal care services in Scotland:** the influence of unpaid carers. CINCH 2018.
- 35 Avdic, Daniel, Büyükdurmus, Tugba, Moscelli, Giuseppe, Pilny, Adam, and Ieva Sriubaite. **Subjective and objective quality reporting and choice of hospital:** Evidence from maternal care services in Germany. CINCH 2018.
- 36 Hentschker, Corinna and Ansgar Wübker. **Quasi-experimental evidence on the effectiveness of heart attack treatment in Germany.** CINCH 2018.
- 37 Pasha, Mochamad, Rockmore, Marc, and Chih Ming Tan. **Early Life Exposure to Above Average Rainfall and Adult Mental Health.** CINCH 2018.
- 38 Elsner, Benjamin and Florian Wozny. **The Human Capital Cost of Radiation:** Long-run Evidence from Exposure outside the Womb. CINCH 2019.
- 39 de la Mata, Dolores and Carlos Felipe Gaviria Garcés. **Exposure to Pollution and Infant Health:** Evidence from Colombia. CINCH 2019
- 40 Besstremyannaya, Galina and Sergei Golovan. **Physicians' altruism in incentives contracts:** Medicare's quality race. CINCH 2019.
- 41 Hayen, Arthur P., Klein, Tobias J., and Martin Salm. **Does the framing of patient cost-sharing incentives matter?** The effects of deductibles vs. no-claim refunds. CINCH 2019.
- 42 Molina, Teresa. **Pollution, Ability, and Gender-Specific Responses to Shocks.** CINCH 2019.

- 43 Fischer, Martin, Gerdtham, Ulf-G, Heckley, Gawain, Karlsson, Martin, Kjellsson, Gustav, and Therese Nilsson. **Education and Health: Long-run Effects of Peers, Tracking and Years.** CINCH 2019.
- 44 Bannenberg, Norman, Førland, Oddvar, Iversen, Tor, Karlsson, Martin, and Henning Øien. **Preventive Home Visits.** CINCH 2019.
- 45 Pestel, Nico and Florian Wozny. **Low Emission Zones for Better Health:** Evidence from German Hospitals. CINCH 2019.
- 46 Bartoli, Paola, Grembi, Veronica, and The Linh Bao Nguyen. **Ethnic Density and Health at Birth.** CINCH 2019.
- 47 Atal, Juan Pablo, Fang, Hanming, Karlsson, Martin, and Nicolas R. Ziebarth. **Long-Term Health Insurance:** Theory Meets Evidence. CINCH 2020.
- 48 Briody, Jonathan. **Parental Unemployment During the Great Recession and Childhood Adiposity.** CINCH 2020.
- 49 Miller, Grant, Paula, Áureo de, and Christine Valente. **Subjective Expectations and Demand for Contraception.** CINCH 2020.
- 50 Kronenberg, Christoph. **New(spaper) Evidence of a Reduction in Suicide Mentions during the 19th-century Gold Rush.** CINCH 2020.
- 51 Avdic, Daniel, Ivets, Maryna, Lagerqvist, Bo, and Ieva Sriubaite. **Providers, Peers and Patients:** How do Physicians' Practice Environments Affect Patient Outcomes? CINCH 2021.
- 52 Alexander Ahammer, Dominik Grübl and Rudolf Winter-Ebmer. **The Health Externalities of Downsizing.** CINCH 2021.
- 53 Emilia Barili, Paola Bertoli, Veronica Grembi, and Veronica Rattini. **COVID Angels Fighting Daily Demons?** Mental Health of Healthcare Workers and Religion. CINCH 2021.
- 54 Signe A. Abrahamsen, Rita Ginja, and Julie Riise. **School Health Programs:** Education, Health, and Welfare Dependency of Young Adults. CINCH 2021.
- 55 Martin Fischer, Martin Karlsson, and Nikolaos Prodromidis. **The Long-Term Effects of Hospital Deliveries.** CINCH 2021.
- 56 Cristina Borra, Libertad González, and David Patiño. **Maternal Age and Infant Health.** CINCH 2021.
- 57 Nicola Barban, Elisabetta De Cao, and Marco Francesconi. **Gene-Environment Effects on Female Fertility.** CINCH 2021.
- 58 Daniel Avdic and Katharina E. Blankart. **A Hard Look at "Soft" Cost-control Measures in Healthcare Organizations:** Evidence from Preferred Drug Policies in Germany. CINCH 2021.

- 59 Sarah Hofmann. **Disease Perception and Preventive Behavior:** The Vaccination Response to Local Measles Outbreaks. CINCH 2022.
- 60 Apostolos Davillas, Victor Hugo de Oliveira, and Andrew M Jones. **A Model of Errors in BMI Based on Self-reported and Measured Anthropometrics with Evidence from Brazilian Data.** CINCH 2022.
- 61 Peter Eibich and Xianhua Zai. **Are the Grandparents Alright?** The Health Consequences of Grandparental Childcare Provision. CINCH 2022.
- 62 Anne Kathrin Heynold, Michael Haylock, and Stefanie Ehmann. **Getting up to Speed:** Informing Prior and Prospective Blood Donors about Supply Uncertainty and Hygiene Measures during the COVID-19 Lockdown. CINCH 2022.
- 63 Elena Ashtari Tafti. **Technology, Skills, and Performance:** The Case of Robots in Surgery. CINCH 2023.
- 64 Kazuya Masuda and Hitoshi Shigeoka. **Education and Later-life Mortality:** Evidence from a School Reform in Japan. CINCH 2023.
- 65 Kai R. Miele. **The Mental Health and Labor Market Effects of Anticipating Job Loss.** CINCH 2024.
- 66 Kaveh Majlesi, Elin Molin, and Paula Roth. **Severe Health Shocks and Financial Well-Being.** CINCH 2024.
- 67 Dora Costa, Lars Olov Bygren, Benedikt Graf, Martin Karlsson, and Joseph Price. **The Economy, the Ghost in Your Gene, and the Escape from Premature Mortality.** CINCH 2025.
- 68 Pablo Muñoz and Cristóbal Otero. **Managers and Public Hospital Performance.** CINCH 2025.
- 69 Christoph Kronenberg, Ulf-Göran Gerdtham, and Martin Karlsson. **Remote Schooling during the Pandemic: A Double Burden for Working Parents in Sweden?** CINCH 2025.
- 70 Nisha Vernekar and Karan Singhal. **Breaking the Night Barrier: Night-Shift Reforms and Women's Work in India.** CINCH 2025.
- 71 Christoph Kronenberg and Kai R. Miele. **Supply Constraints and Negative Selection: Evidence from Mental Healthcare Markets.** CINCH 2026
- 72 Yannick Hoga and Martin Karlsson. **Extremal Expected Shortfall Regressions: Inference and an Application to Health Care Spending.** CINCH 2026
- 73 Nisha Vernekar and Karan Singhal. **Breaking the Night Barrier: Night-Shift Reforms and Women's Work in India.** CINCH 2026

- 74** Melisa Sayli, Cheti Nicoletti, and Giuseppe Moscelli. **Unexpected Worker Absences as Labor Supply Shocks: Evidence from Ambulance Services.** CINCH 2026

DuEPublico

Duisburg-Essen Publications online

UNIVERSITÄT
DUISBURG
ESSEN

Offen im Denken

ub | universitäts
bibliothek

Dieser Text wird via DuEPublico, dem Dokumenten- und Publikationsserver der Universität Duisburg-Essen, zur Verfügung gestellt. Die hier veröffentlichte Version der E-Publikation kann von einer eventuell ebenfalls veröffentlichten Verlagsversion abweichen.

DOI: 10.17185/duepublico/86511

URN: urn:nbn:de:hbz:465-20260623-142809-2

Alle Rechte vorbehalten.