# Trends, variations, and prediction of staff sickness absence rates among NHS ambulance services in England: a time series study


## ABSTRACT

### Objectives

Our aim was to measure ambulance sickness absence rates over time, comparing ambulance services and investigate the predictability of rates for future forecasting.

### Setting

All English Ambulance Services, UK.

### Design

We used a time series design analysing published monthly NHS staff sickness rates by gender, age, job role and region, comparing the ten regional ambulance services in England between 2009 and 2018. Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models were developed using Stata v14.2 and trends displayed graphically.

### Participants

Individual participant data was not available. The total number of Full Time Equivalent (FTE) days lost due to sickness absence (including non-working days) and total number of days available for work for each staff group and level were available. In line with The Data Protection Act, if the organization had less than 330 FTE days available during the study period it was censored for analysis.

### Results

A total of 1117 months of sickness absence rate data for all English ambulance services were included in the analysis. We found considerable variation in annual sickness absence rates between ambulance services and over the 10-year duration of the study in England. Across all the ambulance services the median days available were 1,336,888 with inter quartile range (IQR) of 54,8796 and 73,346 median days lost due to sickness absence, with IQR of 30,551 days. Amongst clinical staff sickness absence varied seasonally with peaks in winter and falls over summer. The winter increases in sickness absence were largely predictable using seasonally adjusted (SARIMA) time series models.

### Conclusion

Sickness rates for clinical staff were found to vary considerably over time and by ambulance trust. Statistical models had sufficient predictive capability to help forecast sickness absence, enabling services to plan human resources more effectively at times of increased demand.

**Strengths and limitations of this study**

- Sickness absence data is limited and there is variation in recording of data amongst ambulance services, the seasonal modelling is limited to professionally clinically qualified ambulance staff due to missing and incomplete data in other staff groups.
- Reasons for sickness absence across ambulance trusts are poorly reported or recorded, and a lack of gender and age information were further imitations.
- This was an analysis across and entire public ambulance clinical workforce in England over multiple years.
- Predictive models can help to forecast sickness absence in a wider variety of health settings, leading to resource planning and potential financial savings.

## INTRODUCTION

Ambulance services in England have the highest level of sickness absence rates compared to other healthcare organisations in the UK National Health Service(1). Against the national average absence rate of 4.3 per cent over an eight-year period (data available since 2009), ambulance staff showed an average absence rate of 6.2 per cent with year-on-year increases. An independent review (2) estimated that a 1 per cent reduction in staff absence could save the ambulance Trusts £15 million per year.

Systematic analysis of sickness absence in ambulance services is lacking despite staff health and well-being having been identified as a key priority among all NHS employees (3). An early study examining sickness absence in West Midlands Metropolitan Ambulance Service compared with the Post Office and Fire Service in the 1980s (4) found that musculoskeletal injury was the main cause of sickness absence and this was exacerbated by the nature of ambulance work. Sickness absence has been highlighted as a concern for health in ambulance services (5, 6) but detailed reasons for this and potential solutions are needed.

Previous research suggests that high rates of mental health problems including burn-out, substance misuse and suicide in emergency ambulance workers, which may highlight occupation-specific stressors and health related sequelae (7-9). In a survey by the charity Mind of over 1,300 UK ambulance service responders, problems at work including excessive workload, pressure from management, long hours, changing shift patterns, and exposure to traumatic incidents, were often cited as the main cause of mental health problems (10). While reasons for absence are not included in reported figures, a previous study identified that mental health problems were in the top three reasons for sickness absence in the NHS (2) and has been identified as a key area for action (11).

Our aim was to measure ambulance sickness absence rates over time, comparing ambulance services and investigating the predictability of rates.

## METHODS

### Study design and data

We used a time series design analysing published NHS staff sickness rates by gender, age, job role and region comparing the ten ambulance services in England. Data were specifically requested and provided by NHS Digital for this study. The dataset included sickness absence rates for NHS ambulance staff calculated from the Electronic Staff Record (ESR). Rates were obtained by dividing the “Full Time Equivalent (FTE) Number of Days Sick” by the “FTE Number of Days Available” from the absence dimension on the ESR Data Warehouse which gave the following information: FTE days available, FTE days lost, sickness absence rate by staff group, qualification level and ambulance trust for October to September for the 10-year period from 2009 to 2018. In line with The Data Protection Act, if the organization had less than 330 FTE days available during the study period it was censored for analysis. Ambulance Trusts were randomly assigned an alphabetical letter (A to J) to protect confidentiality of individual trusts where higher or lower rates are apparent. While there is some merit in naming individual services, our approach was to present the data anonymously to the participating trusts for a shared learning.

Positivistic theory underpinning the analysis is that future trends can be predicated from the past (12) provided that the variation is not large and that suitable parameters such as wellbeing and sickness are a good proxy to capture the sickness absence trend.

**Ethical approval**

Ethical approval for the study was obtained through University of Lincoln REC (Ref: 2019-Aug-0723), no Health Research Authority Approval was sought. Participant consent was deemed not to be required for the use of these data.

**Statistical analysis**

Initial analysis was performed using Stata v14.2, and subsequent analysis for forecasting was done in Wolfram Mathematica 11.3. The Autoregressive Moving Average (ARMA) is based on taking the previous linear incidence termed autogressive (AR) together with the linear moving average (MA) which considers the current and previous residual time series. We used the Box-Jenkins method of Autoregressive Integrated Moving Average (ARIMA), where a univariate time series model is based on the generalised model of ARMA with a differencing process which converts non-stationary (seasonally variable) data to stationary data. The differencing is a measure of how many non-seasonal differences are needed to achieve stationarity, if there is no differencing then we simply revert back to ARMA.

As there was strong evidence of seasonality within our data, Seasonal Autoregressive Integrated Moving Average (SARIMA) models were also used. SARIMA models are based on the ARIMA model but include seasonal differencing, where periodicity within the dataset is accounted for. We focused the model on sickness absence in clinical staff groups which included professionally qualified clinical staff (Hospital and Community Health Service (HCHS) doctors; Ambulance Paramedic; Ambulance Technician; Emergency Care Practitioner; Manager; Medical Technical Officers (MTO) / Technician; Nurse; Other Senior Technicians (ST) & Technician Manager (TM); Scientist; Tutor)

We used the auto correlation functions (ACF) to determine whether seasonality was present (non-stationarity) within the model or not, that is we measured the amount of linear dependence between observations separated by a lag and the partial autocorrelation function (PAF) determined the number of autoregressive terms. If the ACF and the PAF showed points outside the acceptance value then this was taken to indicate seasonality within the time series, requiring the use of SARIMA model.

Akaike information criterion (AIC), Bayesian information criterion (BIC) or Schwarz Bayesian information criterion (SBC) likelihood values were calculated but AIC was used for model selection.

**Patient and Public Involvement**

There was no patient or public involvement in the study.

**RESULTS**

A total of 1117 months of sickness absence rate data for all English ambulance services were included in the analysis. Across all the ambulance services the median days available were 1,336,888 with inter quartile range (IQR) of 54,8796 and 73,346 median days lost due to sickness absence, with IQR of 30,551 days. The sample size of months for individual ambulance services was the same (N=109), except ambulance service trust I where data was only available until November 2016 (N=76). For model validation, 6 months data was used to compare model forecasts. We found considerable variation in annual sickness absence rates among all clinical staff across each ambulance service in England and over the 10 years between 2009 and 2018 (1) (Figure 1). Within an organisation, ambulance sickness absence rates do not vary greatly over time, with the exception of ambulance service G, where a drop of 3.2% absence between the annual averages in 2010 and 2018 was observed. Figure 1 illustrates that this reduction in absence, the rate is sustained in subsequent years. There is also a slight drop in in average rates across all the ambulance services; this drop is still persistent when the outlier ambulance service is removed.

**Figure 1 Annual sickness absence rates for all clinical staff in each (A-J) NHS ambulance service in England**

Further analysis of variation in absence data for professionally qualified clinical staff (HCHS doctors; Ambulance Paramedic; Ambulance Technician; Emergency Care Practitioner; Manager; MTO / Technician; Nurse; Other ST&T Manager; Scientist; Tutor) was carried out.

Models ARIMA or SARIMA were developed and selected based on information criteria which estimated prediction errors of the models for the given ambulance service data including Akaike information criterion (AIC), Bayesian information criterion (BIC) or Schwarz Bayesian information criterion (SBC) likelihood values. Lower values indicated higher quality of fit and therefore the model with lowest values was selected. SARIMA models were selected because of seasonality in the data; most services showed differences between ARIMA and SARIMA model statistics, but this was less so for ambulance service I (Table 2).

We present graphs showing sickness absence rates for clinical staff in individual ambulance services at monthly intervals between 2009 and 2018. We forecast rates for 2019 based on the SARIMA models shown as dotted lines. We then obtained data for 2019 where actual rates for the year are shown as different coloured solid lines and compared the actual and predicted graphs. Predicted values corresponded well for services D, E, G and H (Figures 2 and 3).

Trusts E and H had similar means and standard deviations, models predicted the seasonality and trends well. Although both ambulance trusts A and G had the largest standard deviations (Table 1), trust G had better model fit. Trusts D and G showed clear decline in sickness absence trend. Forecasted sickness absence rates were higher than actual rates for services I (Figure 4) and C (Figure 5), 95% confidence intervals around forecasts suggest that predictions are still within range of acceptance.

**Table 1. Mean sickness absence rate and Standard Deviation for each Ambulance service**

| Ambulance Service | N | Mean [ 95% Confidence Interval ] | Standard Deviation |
|---|---|---|---|
| A | 109 | 7.35 [7.07 - 7.62] | 1.43 |
| B | 109 | 5.61 [5.46 - 5.77] | 0.82 |
| C | 109 | 7.19 [6.97 - 7.42] | 1.19 |
| D | 109 | 5.57 [5.42 - 5.73] | 0.81 |
| E | 109 | 6.2 [6.00 - 6.40] | 1.06 |
| F | 109 | 5.86 [5.71 – 6.00] | 0.77 |
| **G** | **109** | **4.82 [4.55 - 5.09]** | **1.41** |
| H | 109 | 6.24 [6.06 - 6.41] | 0.91 |
| I | 76 | 7.28 [7.05 - 7.52] | 1.01 |
| J | 109 | 6.25 [6.06 - 6.44] | 1.00 |

**Table 2 Model fit tests for each ambulance service (Trusts C and I are in Table 3, Trusts A, B and J are in the Appendix 1, Table 4)**

| Ambulance Service | Model fitness Tests | **Akaike's information criterion (AIC)** | corrected Akaike's information criterion (AICc) | Bayesian information criterion (BIC) | Schwarz Bayesian information criterion (SBC) | Model selected |
|---|---|---|---|---|---|---|
| D | ARIMA | **-130.063** | -127.481 | -119.862 | -119.298 | |
| | SARIMA | **-169.131** | -166.022 | -152.606 | -152.983 | SARIMA $\{1,0,1\},\{0,1,2\}_{12}$ |
| | | | | | | |
| G | ARIMA | **-113.001** | -110.634 | -100.595 | -104.792 | |
| | SARIMA | **-155.229** | -152.444 | -134.769 | -141.548 | SARIMA $\{0,1,0\},\{1,1,2\}_{12}$ |
| | | | | | | |
| E | ARIMA | **-127.562** | -125.006 | -117.629 | -116.617 | |
| | SARIMA | **-123.077** | -120.021 | -110.713 | -106.66 | SARIMA $\{1,0,1\},\{1,1,1\}_{12}$ |
| | | | | | | |
| H | ARIMA | **-150.431** | -147.608 | -135.31 | -136.975 | |
| | SARIMA | **-120.737** | -117.913 | -107.612 | -107.28 | SARIMA $\{1,0,0\},\{2,1,0\}_{12}$ |

**Figure 2 Sickness absence rates over time (2009-2018) for ambulance services D (blue line) and G (Black line) with forecasted (dotted lines, 12 months period). Solid green line shows new data rates for the period 01-10-2018 to 01-03-2019.**

**Figure 3 Sickness absence rates over time (2009-2018) with forecast (dotted line) and actual rates for 2019 (solid line) for ambulance services E (blue line) and H (Black line). Solid green (service H) and Solid orange (service E) lines show new data for the period 01-10-2018 to 01-03-2019**

**Table 3. Model fits with 95% confidence intervals showing variation in prediction over 12 months.**

| Ambulance Service | Model fitness Tests | **Akaike's information criterion (AIC)** | corrected Akaike's information criterion (AICc) | Bayesian information criterion (BIC) | Schwarz Bayesian information criterion (SBC) | Model selected |
|---|---|---|---|---|---|---|
| C | ARIMA | **-90.1803** | -87.5977 | -77.4113 | -79.4149 | |
| | SARIMA | **-116.747** | -113.923 | -100.169 | -103.29 | SARIMA $\{1,0,0\},\{1,1,1\}_{12}$ |
| | | | | | | |
| I | ARIMA | **-47.7445** | -45.1811 | -40.9185 | -40.7523 | |
| | SARIMA | **-47.7705** | -44.1235 | -37.5104 | -33.7861 | SARIMA $\{1,0,0\},\{2,1,1\}_{12}$ |

**Figure 4 Sickness absence rates over time (2009-2018) with forecast (Orange dotted line) and actual rates for 2019 (Blue and Green solid lines) for ambulance service I. The shaded area represents the 95% forecast confidence intervals for 12 months prediction.**

**Figure 5 Sickness absence rates over time (2009-2018) with forecast (Orange line) and actual rates for 2019 (solid blue and green line) for ambulance service C. The shaded area represents the 95% forecast confidence intervals for 12 months prediction.**

## DISCUSSION

### Main findings

This is the first study to analyse published NHS staff sickness absence data for ambulance services. We found that sickness absence rates varied over time and by ambulance service, showing seasonal variation and predictability using seasonally adjusted (SARIMA) time series models which helped to predict future sickness absence rates. This model has been used widely in many disciplinary fields including forecasting epidemiological surveillance data (13) and hospital visits (14). These models generally provide a good fit for processes that exhibit stationary means and do not show covariance over time.

For one ambulance Trust, the absence rate varied monthly between 2.97%-6.49% during second quarter of 2018. This may have been because of inaccuracies in data, organisational changes affecting sickness rates or other unknown reasons which need to be investigated further.

A clear pattern emerged of seasonal variation in sickness absence rates which peaked during January and February and then showed a drop before climbing again in the autumn months of October and November. This was an important finding which should be explored in other NHS organisational groups, including hospital and primary care. In the case of two ambulance trusts (F and G in Figure 1), a sustained drop in absence was noted from 2015 but seasonal variation in sickness absence persists. Reasons for the absences were not available so the impact of interventions cannot be determined. The models were able to predict future sickness absence rates for individual ambulance services and may therefore be used as a tool for workforce management.

**Strengths and limitations**

This is a first study to analysis across and entire public ambulance clinical workforce in England over multiple years. We have shown that within an organisation, ambulance sickness absence rates do not vary greatly over time and that predictive models can help to forecast sickness absence in health care setting.

There were several limitations to this study. The first is that it was based on data for some clinical ambulance staff, but excluded those in the support staff category, because of missing and incomplete data. The second limitation is the lack of availability of data for gender and age of staff or the reasons for absence, although reported absence reasons are generally not well recorded (2). Although these models can capture some of the underlying dynamics of trusts, there are many complex organisational, economic, environmental, social and political changes which can make prediction difficult. These include urgent and emergency care service reconfigurations, changes to operational delivery models through contracting arrangements for non-emergency patient transfer and 111 services, changes to commissioning and consequent budget changes in the face of increasing demand for emergency care (Carter, 2018).

Some of models did not predict as wells as others, this needs further investigation as these parsimony simple models may not be capturing all of the heterogeneities relating to the services, we are aware that there were some structural changes taking place as well as recruitment drives could create slightly more troughs or peaks out of sync with the model predictions. The COVID-19 pandemic will be likely to alter the patterns of absence during 2020-21, but it is not clear if the seasonality in this staff cohort will be re-established once vaccines efficacy and policies that reduce requirements for quarantine take effect.

**Findings in relation to previous research**

Seasonal variation has been noted in a previous study of sickness absence in NHS workers, with rates in doctors peaking during December to January and lowest during August but with smaller differences between highest and lowest rates (1.0 to 1.3%) compared with ambulance staff (up to 3.5% monthly).

Minor respiratory illnesses, frequent during winter, are the commonest cause of sickness absence across all UK workers, accounting for a quarter of days lost (15). One previous study, of US civil servants, found that seasonal trends were very predictable and suggested that specific causes could be targeted to reduce sickness absence (16). In another study, effectiveness of early sickness absenteeism intervention for seasonal/pandemic flu seasonal variation has shown interesting results(17).

Long term sickness is more likely to be related to musculoskeletal and mental health problems and these are the costliest sources of sickness absence (18). In paramedics and Emergency Medical Technicians (EMTs), back pain is the most common musculoskeletal condition, with back injuries and contusions, falls, slips, and trips often caused in healthcare by to overexertion or when lifting patients (19). Numerous studies indicate ambulance and staff have high rates of post-traumatic stress, anxiety and burnout (20, 21) associated with lack of support, time pressures and physical demands of the role (8).

**Implications for policy, practice, and research**

Accurately predicting sickness absence may help healthcare organisations plan for the expected winter peaks. Other seasonal infections such as norovirus ('winter vomiting virus') can affect both staff and patients at huge cost (22). Winter illnesses such as influenza and other viral infections may lead to presenteeism, reducing quality of work, increasing time to recover and worsening the risk of cross infection (23), with influenza vaccination known to reduce winter sickness absence (24).

Although the reasons for variation in sickness absence across ambulance trusts is poorly understood, the finding that the trust with the lowest rate had half that of the highest suggests that sustained reduction in reported absence can be achieved. However, whether this resulted from implementing wellbeing initiatives or other factors such as leadership styles, culture and levels of resourcing in those trusts with lower absence rates requires further empirical scrutiny (25).

Simmons and colleagues (5)conducted a systematic review investigating randomised controlled trials of interventions to reduce sickness absence among healthcare workers and found one exercise (Tai Chi), one multicomponent (policy, exercise, psychosocial and workplace review) and an influenza vaccination intervention were effective but four other trials (including one influenza vaccination, two multicomponent and a process consultation designed to enhance relationships between managers and staff) showed no effect. Workplace counselling including to healthcare workers has been shown to reduce sickness absence (26). A systematic review of whole system approaches, suggests that a combination of identifying and response to local need, engaging staff and leaders, and management and board-level training improve wellbeing (27).

Future research should investigate reasons for the two-fold variation in sickness absence rates among ambulance services and whether differences might be explained by differences in organisational culture, management support, wellbeing provision or other factors.

In conclusion, we demonstrated that seasonality plays a key role in determining the extent of sickness absence in the ambulance service. The models have sufficient predictive capability to help ambulance trusts plan for periods of increased absence which coincide with increased winter demands on the service. Predictive models may help to forecast sickness absence in a wider variety of health settings, leading to resource planning and potential financial savings.

**Contributors:** ZBA wrote the first draft and analysed the data. He conceptualised the study and methodology, conducted formal analyses, drafted the original version of the manuscript with PW and was involved in all manuscript revisions leading to submission. PW and FB obtained the data. ANS, FB, PW, ZBA and KS supervised the study. ZBA, ANS, PW, FB, KH and VHP were involved in manuscript revisions leading to submission.

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