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The Impact of Temperature Disparity on Emergency Readmissions and Patient Flows

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Abstract

According to the World Health Organisation (WHO), global estimates there are approximately 210 million people suffering from chronic obstructive pulmonary disease (COPD) [1]. It is assumed that climate change could have an adverse effect on COPD patient readmission. Given that the impact of climate change on health has seen a tremendous amount of public and media attention with limited quantitative understanding, this paper develops a frailty model to examine the effect of temperature variation on COPD readmission. Using the national Hospital Episodes Statistics dataset linked with the temperature data provided by the Met Office. The exploratory analysis and the multivariate frailty model revealed some interesting relationship with temperature. The outcome of the results might be helpful to understand and show the evidence of the impacts of the long-term temperature disparity on the hazard rate of COPD readmissions and measure the spatial significances.

1. Introduction

The last decade was the warmest on record, followed by the 1990s and 1980s. The five warmest years were, in ascending order, 2002, 2003, 2005, 1998 and 2009 [2]. According to WHO (WHO Europe, 2008), scientists have agreed that the changes in meteorological variables is adversely affecting health, making the youngest and the elderly more vulnerable than ever. Temperature is considered as one of the most important predictors for health related issues and outcomes [3, 4] in the context of climate change. A significant relationship was found between exposure to heat and excess deaths in 2004 heat waves in Brisbane, Australia (on average 23% increase in deaths due to non-external cause and 20% increase in cardiovascular deaths compared to 2001-03) [4]. In France, an estimated 15,000 excess deaths was reported due to heat wave from 1st to 20th August 2003 [5].

COPD (Chronic Obstructive Pulmonary Disease) is one of the leading causes of morbidity and mortality throughout the world due to its continuous increasing trend [6]. According to WHO, it will become the seventh leading cause of disability-adjusted life-years and the fourth leading cause of mortality worldwide by 2030 [7]. Temperature increase will contribute to the burden of disease and premature deaths in Europe, particularly in population subgroups, such as the elderly and patients with COPD [8]. In UK, climate change might increase COPD, asthma, and tick-infected disease (e.g. Lyme disease infected ticks during spring and autumn) and some food-borne disease during the warmer summers [9].

Frailty models are an extension of the classical Cox proportional hazard model and useful for describing the nature of risk function for individuals or observations that are grouped or clustered into groups and non-independent in various health and environmental settings [10, 11]. Such groups can be geographical areas, families, any common environmental and(/or) economic domains forming any specific clusters resulting from the fact that the subject of the same cluster share similar unobserved environmental or genetic factors affecting their survival. Often, we have situations to deal with the statistical analysis of correlated survival data and random effect modelling applied to deal with such repeated measurements on persons as well as to account for the dependency within the subjects. Moreover, such models can be comprised of recurrent events in a wide variety of settings, including public health, psychology, sociology, economics and so forth.

Some practical examples can be recurrent hospitalisations of patients with chronic diseases, bouts with migraine headaches, episodes of hypoglycaemia in diabetics and so on [12].

The main objective of this work is to characterize COPD readmission due to temperature variations. The time is measured as "number of days" and the corresponding event as COPD readmission. We investigated whether there is any relationship of such rehospitalisation time for COPD due to the variations in daily temperature (maximum, minimum, mean) adjusted for gender and age. To highlight the regional heterogeneity among the time of COPD readmissions, we included a random effect term (frailty) in the Cox Proportional Hazard model and fit the frailty model. Here, the Cox-proportional part is quantifying the significance of the explanatory variables (age, gender, various lags of daily temperatures) and frailty term is measuring the regional (Spatial) heterogeneity in this process.

The outcome of the results can be useful to the general public and government institutions (i.e. departments of health) to better understand the issues surrounding the long-term impact of temperature disparity on COPD readmissions. This can also boost the understanding of future patients flow related to temperature and help to revise the seasonal hospital demands for some specific diseases. The analysis can be replicated to other disease categories that are known to be related to temperature variations.

2. Data

In this study, we used two datasets, namely the national Hospital Episodes Statistics (HES)[1] dataset and the observational temperature (maximum, minimum and mean) data collected from the Met Office. For both cases, we used 25 local authorities of which seven are from London, six from Cumbria, five from Somerset, and seven from West Sussex. We chose these regions in a purposive manner to check the regional variations in readmissions.

HES is a data warehouse containing all the admission statistics of personal, medical and administrative details of all patients admitted to, and treated in, NHS hospitals in England. It also contains details of all NHS outpatient attendances. There are approximately 12 million records for each financial year (in UK, a financial year is from 1 April to 31 March to the following year). The dataset includes all the consultant episodes of a patient during their stay in hospital by using specific variables under different categories (e.g. admissions, augmented/critical care

period, clinical, geographical). Since our aim is to study patients with COPD (ICD-10 codes J40-J44) as their first diagnosis, we select all the COPD patients for the financial year of 1997 to 2003 for 25 local authorities across England covering London, Cumbria, Somerset, and West Sussex.

The Met Office is the UK's national weather service, and deals with weather predictions, forecast, climate change and weather science research. Hourly measurements of air temperature are taken at Met Office weather observation stations throughout the UK. They are converted by interpolation to gridded datasets by the National Climate Information Centre[2] [13]. The interpolation method adjusts for topography and urban and coastal effects. For this study, daily observational data for temperature (maximum, minimum and mean) were extracted from the gridded datasets for the study period (April 1997 to March 2004) and for the same regional units (local authorities) mentioned above. The observations (measurements) were then gridded using interpolation techniques and adjusted for surface characteristics–averages for regional units were obtained from the gridded datasets. For each of these temperatures (maximum, minimum and mean), we calculate the various lags of temperatures (lag 1 to lag 5) and 5 days moving averages and exponential moving averages starting from the day of admission to see the effect of various lag values.

Data were imported to MySQL version 5.0[3] and necessary steps were taken to build a longitudinal dataset (1997-2004), where meteorological data were linked for each inpatient admissions based on matching region (local authorities) and time (e.g. admission date and various temperature of that day).

2.1. Data cleansing and Readmission

The initial number of COPD admission in the selected 25 local authority areas for the period of study was 39,980. During a hospital stay, a patient might encounter several successive episodes, collectively known as a spell. If a spell has not ended, (i.e. a patient is still in care) and/or discharge date is missing then these cases are removed from analysis (approximately for 7,458 cases).

We selected patients with more than one admission for the period 1997-2004, which accounted for 20,496 admissions. After further cleaning, we had 14058 cases for the model fitting using frailty model.

For a particular COPD patient, the first readmission time was considered by the time between the first discharge date and the second admission date for

[1] www.hesonline.nhs.uk

[2] www.metoffice.gov.uk/weather/uk/climate.html
[3] www.mysql.com

COPD during the study period. Each subsequent readmission time was defined as the difference between date of previous discharge date (Figure 1) within the study period 1997 to 2004.
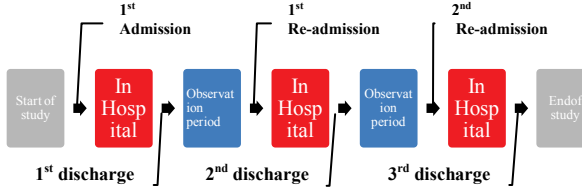
Figure 1. Time interval of successive admissions for a patient

3. Methodology

We considered the Gamma shared frailty model in which the hazard function depends on an unobservable random variable (frailty) which acts multiplicatively on the hazard. We treat the case of right-censored and left truncated data. For the jth $(j = 1, \ldots, n_i)$ individual of the of the ith group $(i = 1, \ldots, G)$, let T_{ij} denote the survival time under study and let C_{ij} be the corresponding right-censoring times. The observations are $Y_{ij} = \min(T_{ij}, C_{ij})$ and the censoring indicator $\partial_{ij} = l_{\{T_{ij} \leq C_{ij}\}}$. Then the frailty model becomes:

$$\lambda_{ij}(t|Z_i) = Z_i \lambda_0(t) exp(\beta' X_{ij}) \qquad (1)$$

Where $\lambda_0(t)$ is the baseline hazard function; $X_{ij} = (X_{1ij}, \ldots, X_{pij})'$ denotes the covariate vector for the jth individual and group i, β is the corresponding vector of the regression parameters, and there $Z_i s$ are the unobserved random variables (frailties). Here group is based on the selected counties and frailties are related to the unobserved county level variability in readmissions. It is assumed for mathematical convenience that $Z_i s$ are independently and identically distributed from a gamma distribution with mean 1 and unknown variance θ at origin time; the density probability function is thus

$$g(Z) = \frac{Z^{(1/\theta-1)} exp\{-Z/\theta\}}{\sqrt{(1/\theta)\theta^{1/\theta}}} \qquad (2)$$

For the gamma model, the hazard ratio is independent of time and the measures of dependence are unchanged by truncation [14]. In a frailty model, events from the same subjects are potentially correlated and different time scales are available for subsequent events and their corresponding interpretations [15]. We used the gap time scales for our analysis. In gap time scale, after an event, the subject starts again at time 0 and the time to the next event corresponds to the number of days that takes to experience the next event. On the other hand, a calendar time keeps track of time since randomization.

4. Data analysis

Some exploratory analysis has been conducted to see any visible pattern of temperature changes and the COPD admission counts. For that, we only consider the period of 1999 to 2003 because London borough data were available from mid 1998 onwards and since HES covers the financial year we have only the values up to March 31, 2004.

From Figure 2, we notice a seasonal trend on the number of COPD admissions, i.e. winter followed by spring has higher COPD counts compared to other seasons, indicating that COPD admissions increases due to a decrease on temperature. Same pattern is evident from Figure 3 as we can see that for all the areas (London, Cumbria, Somerset and West Sussex) COPD admissions increases due to the decrease of temperature (maximum, minimum and mean) at the day of admission.

4.1. Model fitting

We used univariate and multivariate Cox proportional hazard model and shared gamma-frailty model to model the readmission time for each of the COPD patient adjusted for temperature (maximum, minimum, mean), age and gender for the period January 1999 to December 2003 for 25 local authorities in England. We calculated the hazard ratios (HR) and 95% confidence intervals for each covariate. Using the Wald statistic (0.00121/0.001=1.21), we
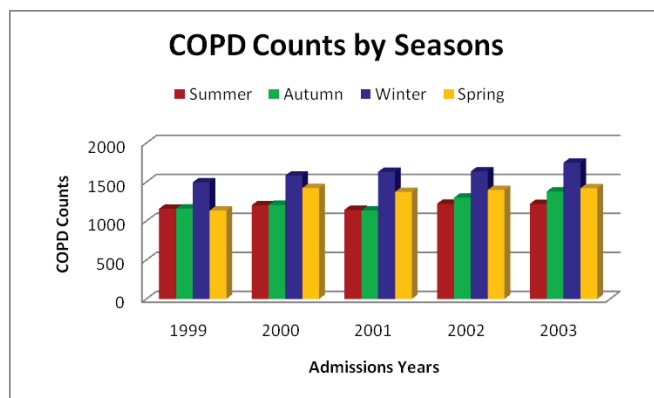
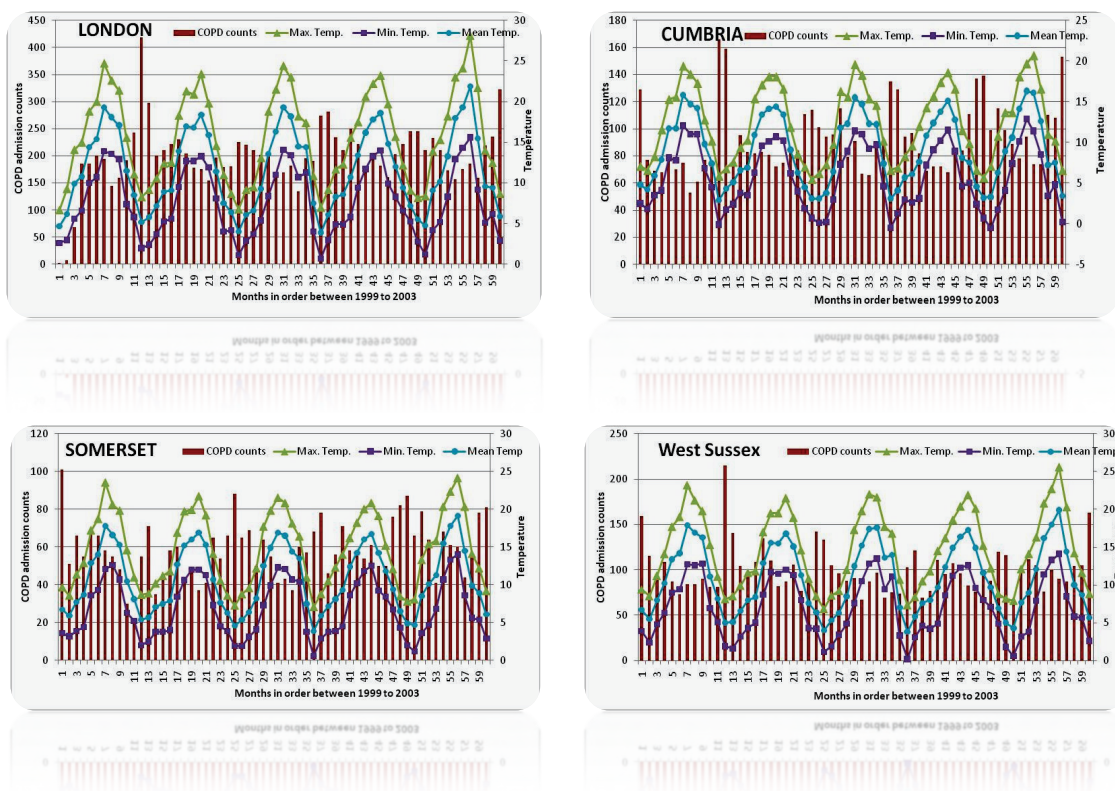**Figure 2. Seasonal COPD admissions for the period 1999 to 2003**

Figure 3. COPD counts with temperature (maximum, minimum and mean) changes from January 1999 to December 2003

found that the frailty indicating heterogeneity among the selected counties and/or boroughs is not significant. Interesting to see that all the variables were significant in the non-adjusted model but only age, gender, and exponential moving average of maximum and mean temperature are significant adjusting for all the variables considered. The frailty parameter, describing the heterogeneity of selected boroughs and counties is statistically non-significant, suggesting that there is no variability in terms of risk of readmission among selected counties.
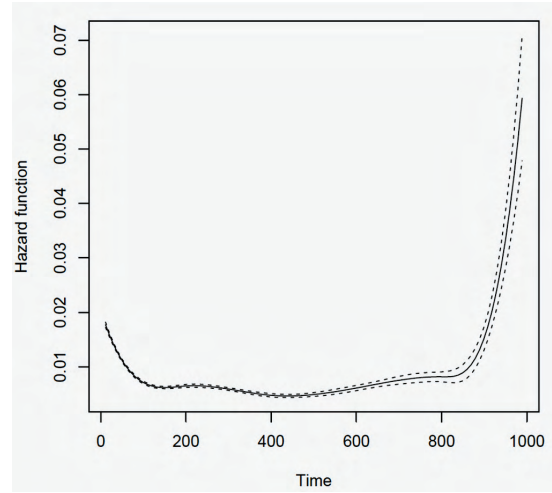
The hazard function for the readmission of COPD patients is illustrated with a 'bathtub shape' (Figure 4). Patients that are readmitted on the same day of discharge have the highest risk of readmission, where the risk gradually decreases up to 100 days. We notice a stable risk of readmission for those patients who are readmitted between 100 to 820 days after discharge and dramatically increase afterwards.

**Table 1. Hazard Ratio of readmissions for selected variables**

Covariate (s)	Cox model		Shared Gamma Frailty models	
	Univariate model	Multivariate model	Univariate model	Multivariate model
	HR(CI), p	HR(CI), p	HR(CI), p	HR(CI), p
Start Age	0.99 (0.99-1.00) <0000*	0.99 (0.99-1.00), <0000*	1(0.99-1.00), <0000*	1(0.99-1.00), <0000*
Sex	0.91(0.88-0.94), <0000*	0.91(0.88-0.94), <0000*	0.91(0.88-0.94), <0000*	0.91(0.88-0.94), <0000*
Maximum Temp	1.01 (1.00-1.01), <.0000*	1.27(0.92-1.76), .15	1.01 (1.00-1.01) , <.0000*	1.27(0.93-1.73), .13
M. A. of Max Temp	1.01 (1.01 - 1.01),<.0000*	1.12(0.87-1.43), .37	1.01 (1.00 - 1.01) <.0000*	1.11(0.85-1.45), .45
Exp.Mov. Max Temp.	1.01 (1.00-1.01), <.0000*	0.69(0.48-1.00), .04*	1.01 (1.00-1.01), <.0000*	0.69(0.50-0.96), .03*
Minimum Temp	1.01 (1.00-1.01), <.0000*	1.26(0.91-1.74), .17	1.01 (1.00-1.01), <.0000*	1.26(0.92-1.72), .15
M. A. of Min Temp	1.01 (1.00-1.01), <.0000*	1.08(0.84-1.38),.57	1.01 (1.00-1.01), <.0000*	1.06(0.82-1.39), .64
Exp.Mov. Min Temp.	1.01 (1.00-1.01), <.0000*	0.74(0.51-1.06), .1	1.01 (1.00-1.01), <.0000*	0.74(0.53-1.03), .07
Mean Temp	1.01 (1.00-1.01), <.0000*	0.63(0.33-1.20), .16	1.01 (1.00-1.01), <.0000*	0.63(0.34-1.16), .14
M. A. of Mean Temp	1.01 (1.00-1.01), <.0000*	0.81(0.50-1.33), .41	1.01 (1.00-1.01), <.0000*	0.83(0.49-1.41), .5
Exp.Mov. Mean Temp.	1.01 (1.00-1.01), <.0000*	2.02(0.98-4.17), .05*	1.01 (1.00-1.01), <.0000*	2.02(1.05-3.88),.04*
Frailty $\theta, (S.E. \theta)$				0.00121(0.^{4}0 01)

*significant

From Figure 5, we can see that men are slightly more susceptible for COPD readmission compared to women.

Figure 4. Baseline hazard function for readmission of COPD with 95% C.I.
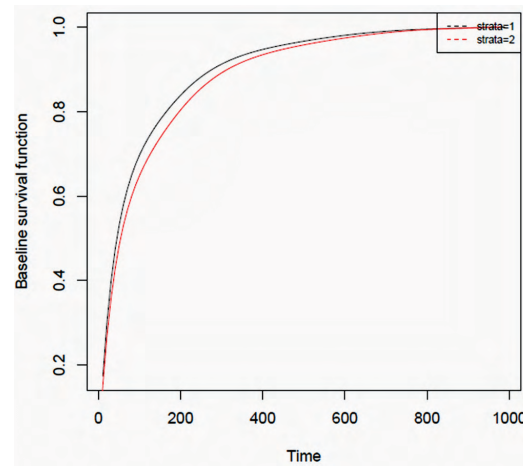
Figure 5. Probability of readmission according to sex (strata 2 = Female and strata 1 = male)

6. Conclusion

This paper explored the relationship between COPD admission with the changing pattern of temperatures (maximum, minimum and mean) to indicate the seasonality of COPD admissions based on 25 local authorities across London, Cumbria, Somerset and West Sussex. COPD readmission times in days were calculated and a frailty model was developed to measure the significant relationships of variables (age and gender) along with temperature variable

(maximum, minimum and mean temperature). We further calculated 5 days moving and exponential moving averages. The exploratory analysis revealed some seasonal patterns of COPD admission across time and region, however from the adjusted multivariate frailty model only the exponential moving average for maximum and mean temperature were found to be significant, which could be due to the choice of lags. Research shows that heat waves and high temperature has quicker consequences and any effects from heat operate with little delay [16, 17, 18]. The vice versa is also true for cold weather. As a result of our data cleansing process, a fair number of cases were removed from analysis (e.g. missing discharge dates) which may have had an impact on our results. Future works may include the development of advanced multilevel survival models to capture between/within regional changes on the risk of readmission using meteorological (e.g. humidity, rainfall) and socio-economic variables (e.g. smoking status, socio-economic status) for other disease categories, such as Pneumonia, ASTHMA, Influenza. Our results can be useful for commissioners and senior managers to better understand seasonal and regional variations on patient readmissions, hence better planning of hospitals regarding the demand and supply of services. Furthermore, healthcare decision makers could improve patient flow management and revise policies to cope with the changing climate.

7. Acknowledgement

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