

**INTRODUCTION**

- Incidence of a chronic disease varies across space and time. While at any given time point, the spatial variations can be attributable to the differences in the distribution of risk factors such as demographic and environmental risk factors, the temporal changes of the majority of local areas tend to resemble each other closely.
- However, some areas may exhibit unexpected changes over time, suggesting for example an emergence of localized risk factor(s) or a change of diagnostic techniques. Detection of areas with "unusual" temporal patterns is therefore of importance to both intervention and assessing the effectiveness of the intervention.
- We have developed a Bayesian mixture model that provides estimates of both the common temporal trend and the area-specific temporal trends. By assessing departures from the common temporal trend, we classify a local time trend as "usual" if the departure is small and as "unusual" if the departures are substantial.

**A BAYESIAN MODELLING APPROACH**

Given that the disease of interest is rare and non-contagious, we assume that the count of cases in area  $i$  at time  $t$  follows a Poisson distribution. That is,

$$y_{i,t} \sim \text{Poisson}(\theta_{i,t} \cdot e_{i,t})$$

where  $\theta_{i,t}$  and  $e_{i,t}$  are the relative risk (RR) and the expected number of cases, respectively. Using the usual log link, the RR is modelled as

$$\log(\theta_{i,t}) = \alpha + z_{i,t} \cdot (\eta_i + v_t) + (1 - z_{i,t}) \cdot \xi_{i,t}$$

Specifications of the terms are as follows.

- $z_{i,t}$  is a latent indicator variable taking a value of either 0 or 1 such that the variability of the log RR at time  $t$  in area  $i$  is explained by one of the two modelling components, in addition to the overall intercept  $\alpha$ ;
- The first component  $(\eta_i + v_t)$  represents a separable space-time model, which assumes an additive effect of space  $\eta_i$  and time  $v_t$  on the disease risks;
- The second alternative component  $\xi_{i,t}$  estimates temporal trends specifically to each area, capturing potential substantial departures from the common trend pattern;
- For the spatial term  $\eta_i$ , we imposed a convolution prior with both the conditional autoregressive (CAR) model and an unstructured random effect term [1]. For the two temporal terms,  $v_t$  and  $\xi_{i,t}$ , the time structure is imposed through a first order random walk.
- Classification is done based on the posterior mean of  $z_{i,t}$  which measures how likely the data point is from the first component with a common time trend.

The proposed model is schematically illustrated in Figure 1.



Figure 1. For fitting data of each area, the model selects either the (upper) space-time separable model with a common temporal trend or an area-specific trend model.

**CONCLUSION**

- The strength of the proposed model over others is the ability to detect changes in trends with distinctive patterns such as elevation/reduction of risks for some time points, though it performs less well with fluctuations;
- As illustrated in the COPD application, the proposed model provides a exploratory tool for informing policies.

**APPLICATION TO MODELLING COPD MORTALITY IN ENGLAND**

- We analyze the mortality data on chronic obstructive pulmonary disease (COPD) in England from 1981 to 2006. The data are available at the district level, of which there are 354 in England. For demonstration purposes, we used data for male over 45 of age only.
- We classify the 20 districts as unusual and speculate potential causes for departures.
- The 20 unusual districts are mapped in Figure 2. Some clusters are formed, scattering in the Northeast of England, the north of West Midlands, on the borders of Yorkshire and East Midlands and in east London.

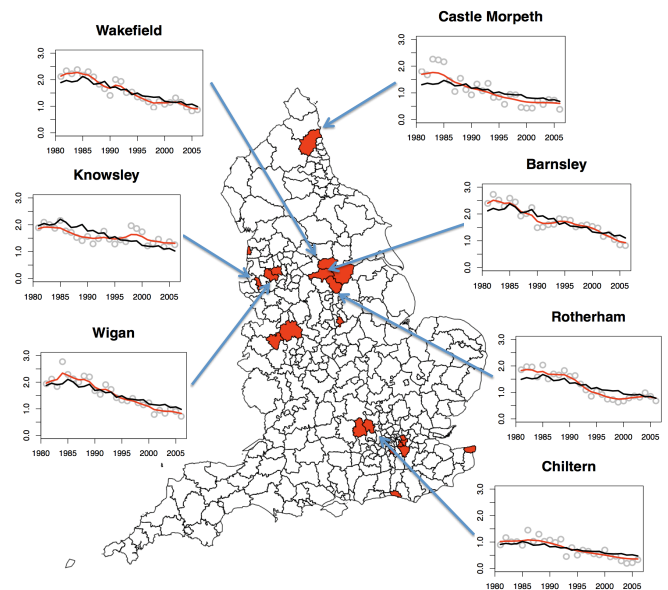


Figure 2. Locations of the top 20 unusual areas from analyzing the COPD mortality data. The inserted plots compare the locally adjusted common trends (black) and the area-specific time trends (red). The open circles represent the observed standardized mortality ratio (the observed cases divided by the expected numbers)

Careful inspection of these fitted local trends against the locally adjusted common trends reveals some interesting "stories" on impacts of policy changes, improvement of diagnostic methods and assessment of intervention.

- The local temporal patterns for **Barnsley**, **Rotherham**, **Wigan**, **Wakefield** and **Castle Morpeth** all display an elevated mortality in the 80's followed by a graduate decrease beyond 1990. These areas have a common history of coal mining, which is associated with excess risks of COPD [2]. The elevated mortality could be attributable to the mining activity in the early 80's while the closure of pits in late 80's to early 90's sees a reduction of mortality.
- Another area of interest, **Knowsley**, lies in the West Midlands. Apart from the "lower-than-usual" mortality seen in the early part of the observation period, there is a noticeable bump starting in 1998, when spirometry, an improve method of diagnosis of COPD, was first introduced for all primary-care practices in this district [3].
- Chiltern** displayed a reduction in mortality between 2003 and 2005, during which, Buckinghamshire, to which Chiltern belongs, was reported to have the lowest COPD mortality amongst 8 other counties in South England. In this report two effective interventions were emphasized: reducing smoking prevalence in general and improving the quality of primary care for COPD patients.

[1] Besag, York and Mollie. *Ann Inst Stat Math* 1991, 43, 1-59.  
[2] Coggon and Taylor. *Brit Med J* 1998, 53, 398.

[3] Walker, Mitchell, Diamantea, Warburton and Davies. *Eur Respir J* 2006, 28, 945-952.