



## **Bayesian Multivariate Modelling of Patient Level Healthcare Resource Use Data in RCTs**

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## Outline

- ◆ Backdrop
- ◆ Modelling Approach
- ◆ ATLAS: a Test-Bed
  - Model Formulation
  - Model Validation and Selection
  - Drawing Predictions
- ◆ Concluding Remarks

## Backdrop

- ◆ CEA informs allocation decisions in UK health policy
  - RCTs typically offer (a wealth of) IPD on health-care resource use
  - analyses often proceed from converting data into monetary figures
- ◆ By direct modelling of health-care resources
  1. a more efficient and transparent analytic perspective is enabled
  2. features of the underlying distributions are explicitly addressed
  3. relationships between the different cost drivers are accounted for
- ◆ The Bayesian approach provides sound and powerful model building, criticism and selection tools

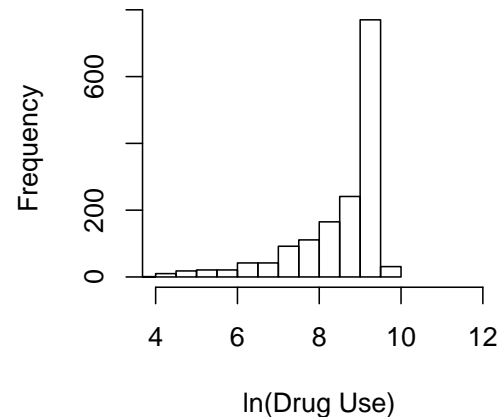
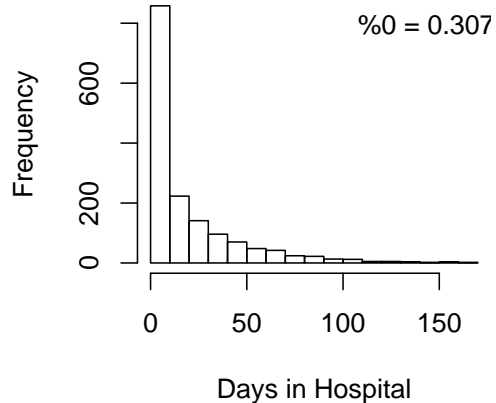
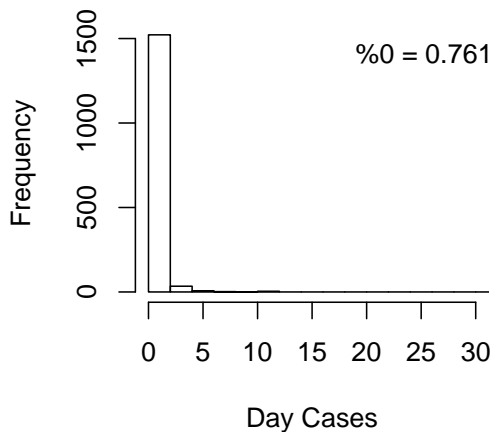
## Modelling Approach

- ◆ Patients  $r = 1, \dots, n_t$  in arm  $t \in \{C, T\}$  of a RCT consume resource items  $i = 1, \dots, I$ 
  - individual resource uses  $R_{rit}$  are recorded
  - their distributions are characterised by unknown parameters  $\vartheta_t$
- ◆ Experience and tractability drive model choices for  $R_{1t}, \dots, R_{It} \mid \vartheta_t$ 
  - joint modelling of heterogeneous variables is not viable
  - conditioning facilitates the model structuring process
  - reliance on (arguable) Normal approximations is not required

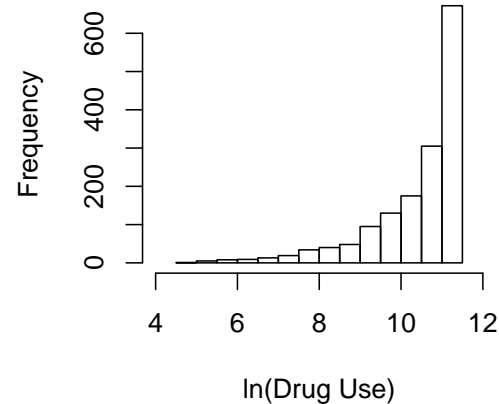
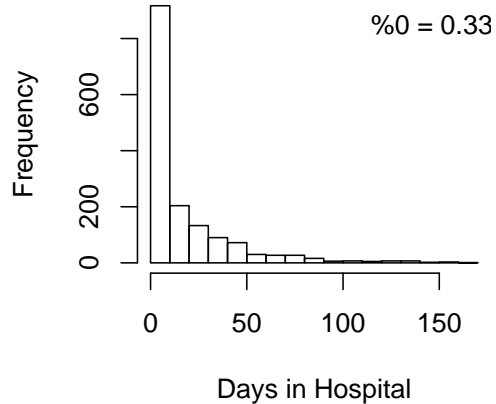
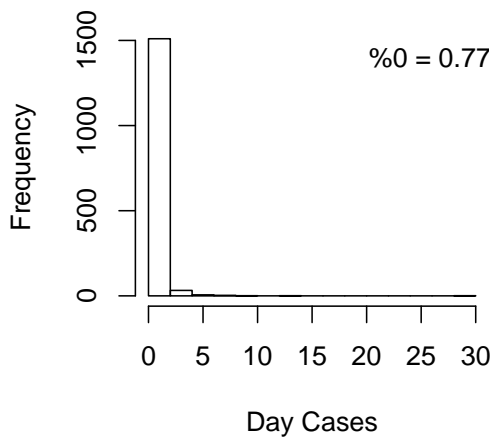
**ATLAS: a Test-Bed**

- ◆ The ATLAS trial compared low- versus high-dose ACE-inhibitor lisinopril in the study of chronic heart failure
- ◆ Focus is upon “Day Cases”, “Days in Hospital” and “Drug Use”, with  $n_C = 1571$  and  $n_T = 1554$ 
  - discrete variables  $R_1, R_2$  are over-dispersed and strongly concentrated at zero  $\implies$  N, Poi, HPoi, NBin, HNBin, ZINBin
  - continuous variable  $R_3$  is strongly asymmetric – and negatively (!) log-skewed  $\implies$  N, LN, G, LSN, LST

**Control arm**



**Treatment arm**



## Model Formulation

$$\left\{ \begin{array}{l} R_{1t} \sim \text{Dist}_1(\vartheta_{1t}, \vartheta_{2t}) \\ R_{2t} | R_{1t} \sim \text{Dist}_{2|1}(\vartheta_{3t} + \vartheta_{4t}[R_{1t} - \mathbb{E}(R_{1t})], \vartheta_{5t}) \\ R_{3t} | R_{1t}, R_{2t} \sim \text{Dist}_{3|1,2}(\vartheta_{6t} + \vartheta_{7t}[R_{1t} - \mathbb{E}(R_{1t})] \\ \quad + \vartheta_{8t}[R_{2t} - \mathbb{E}(R_{2t} | R_{1t})], \vartheta_{9t}) \end{array} \right.$$

- locations are linear in their conditioning variables (as in Normal case)
- reviewed distributions were fitted with ‘vague’ priors
- parametrisation meets constraints on variables (e.g. non-negativity)
- non-Normal distributions are fitted by means of MCMC simulation

## Model Validation and Selection

- ◆ Conventional Bayesian diagnostics are based around residuals
  - RMSPEs measure the fit of marginal predictive distributions
  - SMDs account for how well the observed relationships are modelled
- ◆ Various statistical tools for model selection are available off-the-shelf
  - AIC, BIC and DIC offset model adequacy and complexity
  - consistent scores to be expected in non-hierarchical contexts
  - models should not just be ranked at their score's face value

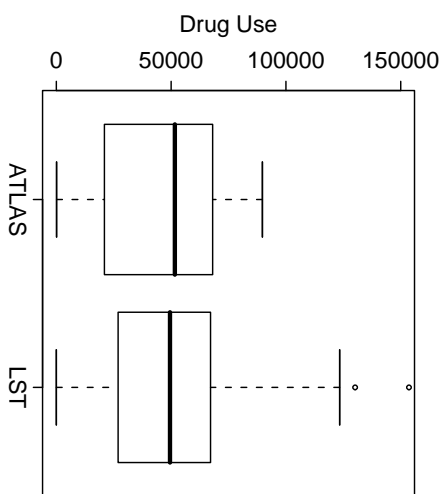
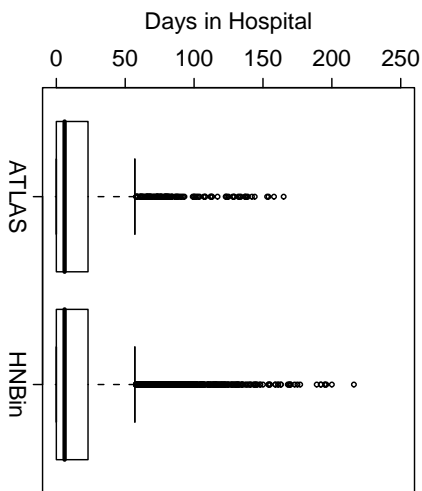
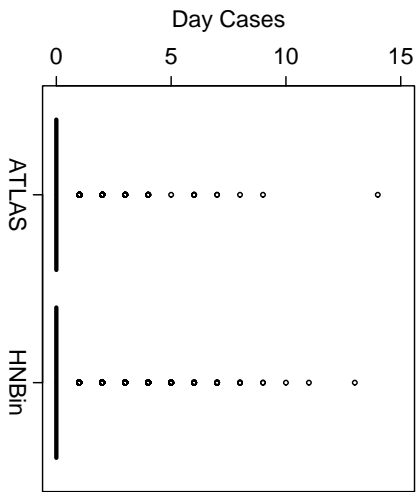
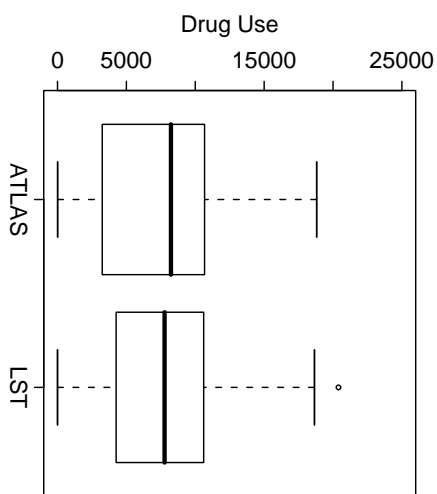
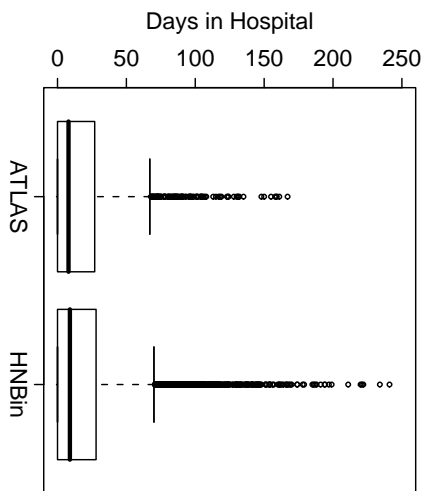
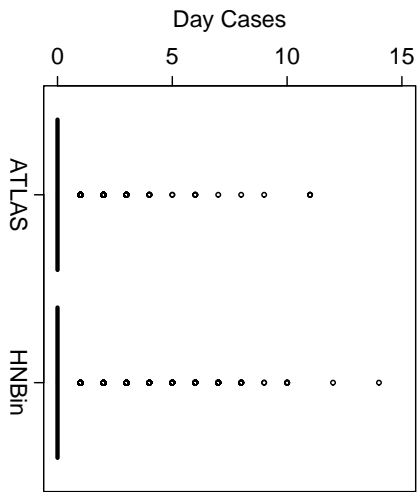


Table 1: Diagnostic checks from models with lowest AIC, BIC &amp; DIC

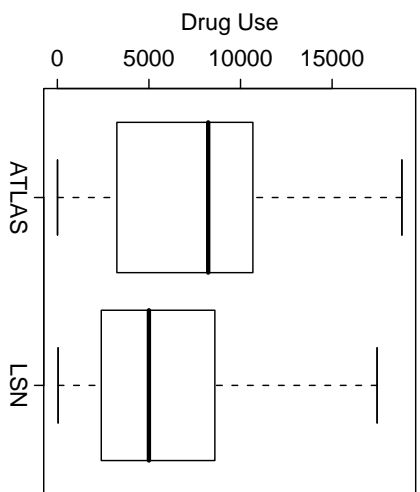
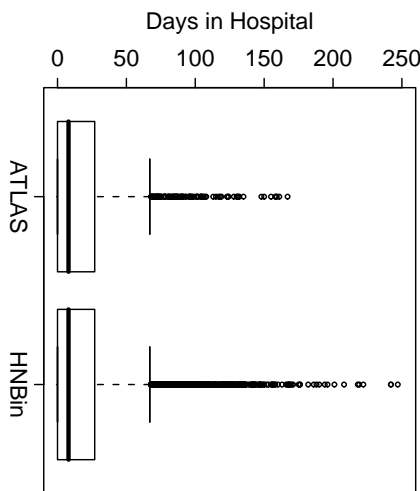
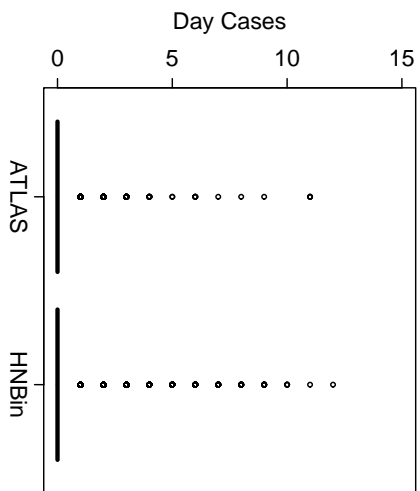
<b>Control</b>	HNBin-HNBin-LST	ZINBin-ZINBin-LST	HNBin-HNBin-LSN	ZINBin-ZINBin-LSN
RMSPE <sub>1</sub>	1.964	1.951	1.957	1.96
RMSPE <sub>2</sub>	1.001	1.001	0.999	0.999
RMSPE <sub>3</sub>	0.001	0.001	1.149	1.151
SMD	4.857	4.806	6.141	6.157

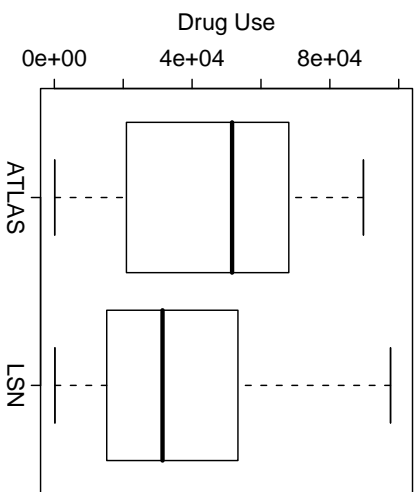
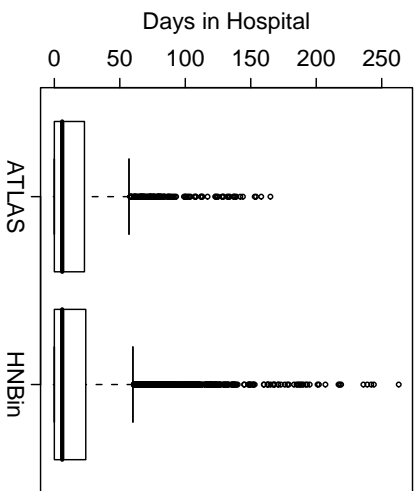
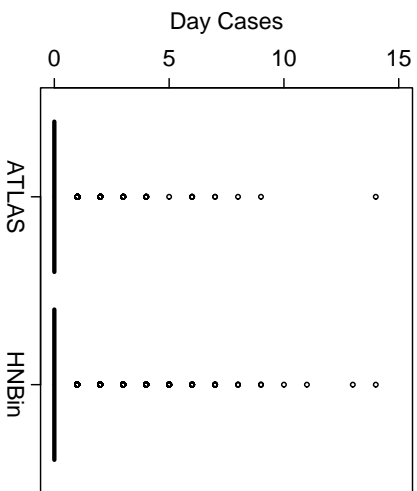
<b>Treatment</b>	HNBin-HNBin-LST	ZINBin-ZINBin-LST	HNBin-HNBin-LSN	ZINBin-ZINBin-LSN
RMSPE <sub>1</sub>	1.304	1.309	1.316	1.308
RMSPE <sub>2</sub>	1.001	1.006	1.007	1.008
RMSPE <sub>3</sub>	0.003	0.001	1.175	1.176
SMD	2.71	2.73	4.106	4.087



ATLAS vs. HNBin-HNBin-LST



Control arm



Treatment arm

ATLAS vs. HNBin-HNBin-LSN

## Drawing Predictions

Table 2: Predictive means (std. dev.) from preferred model

Arm	Resource Use	ATLAS	HNBin-HNBin-LSN
<b>Control</b>	$R_1$	0.434 (2.063)	0.436 (1.053)
	$R_2$	19.022 (26.797)	19.022 (26.8)
	$R_3$	7244.613 (4183.973)	5691.996 (3886.575)
<b>Treatment</b>	$R_1$	0.381 (1.185)	0.382 (0.902)
	$R_2$	16.936 (25.569)	16.845 (25.44)
	$R_3$	45893.03 (26216.35)	35838.7 (23913.19)

## Concluding Remarks

- ◆ Estimated distributions appear to fit the data reasonably well
  - proposed models outperform more popular instances (e.g. Normal)
  - added complexity of multivariate structure is offset by its efficiency
- ◆ Promising start can be fruitfully followed by additional refining work
  - original distributions are still to some extent misrepresented
  - only fairly standard (and parametric) distributions were reviewed
- ◆ What comes next?
  - hierarchical models would naturally account for multi-centre scenarios
  - introduction of covariates would lead into a regression framework