A Bayesian Two-Part Latent Class Model for Longitudinal Medical Expenditure Data

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FEHB Parity Mandate of 2001

- The Federal Employees Health Benefits (FEHB) Program provides health insurance to more than 8.5 million federal employees, spouses and dependents
- In 2001, the U.S. Office of Personnel Management implemented a "parity directive"
- Required FEHB health plans to provide mental health benefits on par with general medical benefits
    - Comparable deductibles and copays
    - 1996: Mental Health Parity Act
    - 2008: Mental Health and Addiction Equity Act

Previous Research on Parity

- A previous study examined total mental health spending two years before and two years after policy initiation (Goldman et al., 2006)
- On average, no significant impact of parity
  - No large increases in annual expenditures as predicted by opponents of parity
  - Nor increased use of mental health services as anticipated by proponents

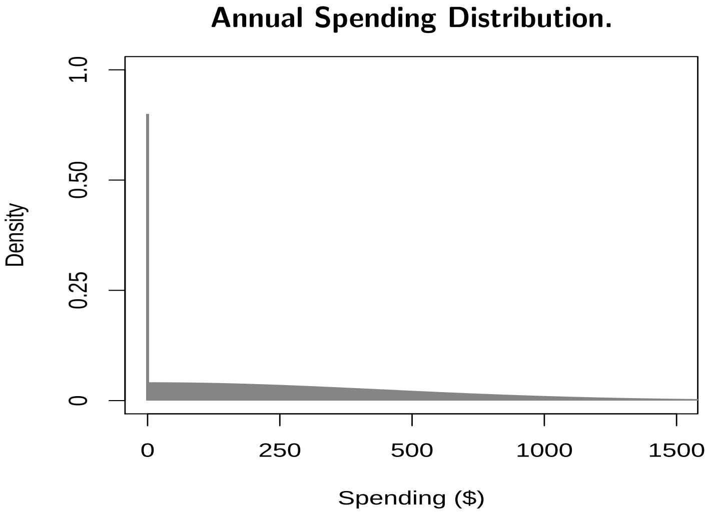
Research Question

- However, the study focused on the average effect across the entire population of participants
- Certain patient subgroups may respond to parity more than others
- Research Question: Do specific subgroups benefit from parity?

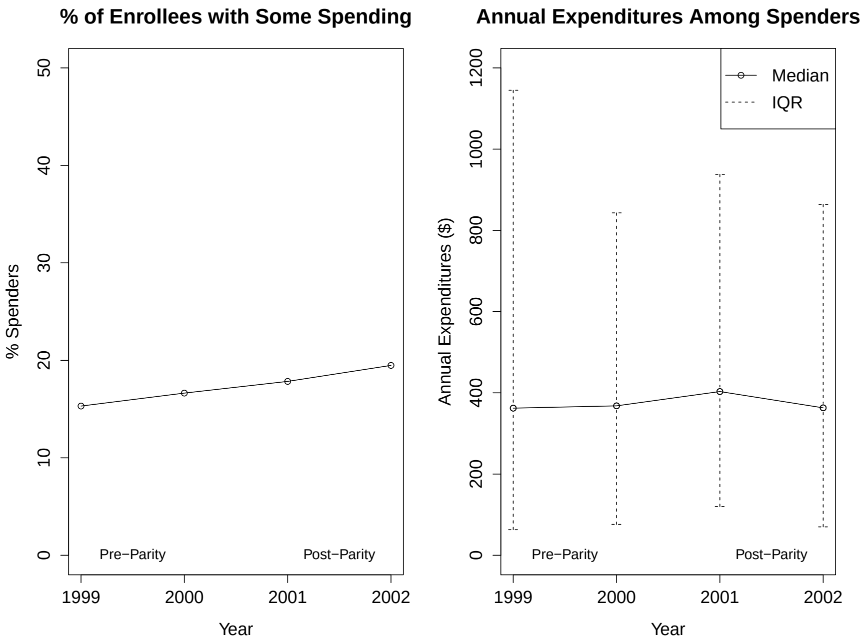
FEHB Data

- We examined annual expenditures for 1581 FEHB enrollees from 1999–2002
- Each subject had four observations ($N = 6324$)
- Over 80% zeros
- A small fraction had large annual expenditures (max $> \$13,000$)

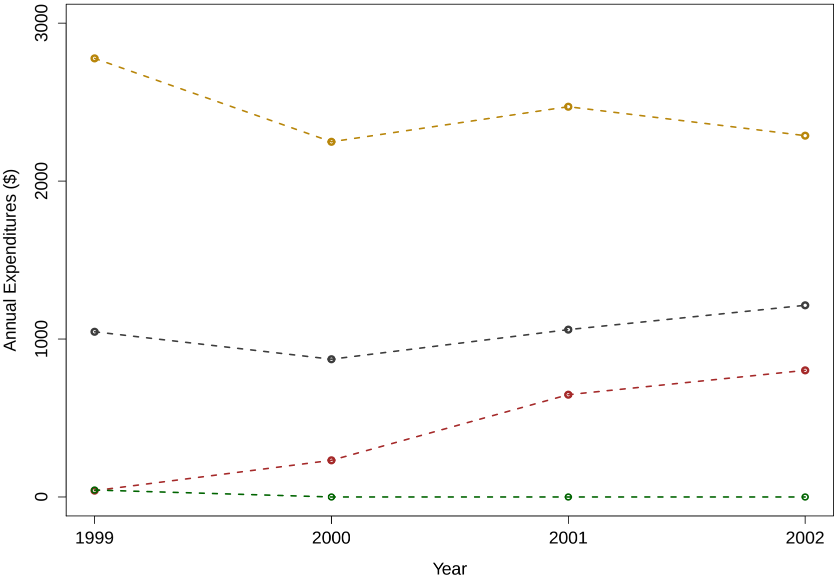
Semicontinuous Data



Annual Spending Patterns for FEHB Enrollees



Annual Expenditures for Four Subjects



Two-Part Model for Semicontinuous Data

- Semicontinuous data can be viewed as arising from two distinct processes: one governing the occurrence of zeros, and the second determining the value given a nonzero response
- Two-part mixture models (Manning, 1981) are an ideal choice for modeling semicontinuous data, since they accommodate both processes:

$$f(y;\phi,\mu,\sigma^2) \;=\; (1-\phi)1_{(y=0)} + \left[\phi \times \mathrm{LN}(y;\mu,\sigma^2)\right] 1_{(y>0)}$$

where:

$\phi = \Pr(Y > 0) \quad 0 < \phi < 1$

$\mathrm{LN}(y;\mu,\sigma^2) =$ lognormal density

μ and σ^2 denote the mean and variance of $\log(Y|Y > 0)$.

Repeated Measures Two-Part Model

Two-part models can easily be extended to the longitudinal regression setting (Olsen and Shafer, 2001; Tooze, 2002):

$$
\begin{aligned}
f(y_{ij}|b_{1i}, b_{2i}) &= (1-\phi_{ij})1_{(y_{ij}=0)} + \phi_{ij}\mathrm{LN}(y_{ij};\mu_{ij},\sigma^2)1_{(y_{ij}>0)} \\
\Phi^{-1}(\phi_{ij}) &= \mathbf{x}_{ij}'\boldsymbol{\beta}_1 + b_{1i} \\
\mu_{ij} &= \mathbf{x}_{ij}'\boldsymbol{\beta}_2 + b_{2i}
\end{aligned}
$$

where:

$y_{ij} = j$-th response for the i-th subject

$\phi_{ij} = \Pr(Y_{ij} > 0|b_{1i})$

$\mathbf{x}_{ij} = p \times 1$ covariate vector

$\begin{pmatrix} b_{1i} \\ b_{2i} \end{pmatrix} \sim \mathrm{N}_2(\mathbf{0}, \boldsymbol{\Sigma}) =$ correlated random intercepts

Latent Class Approach

- Recall, our aim is to identify groups of enrollees with distinct pre- and post-parity spending patterns
- In particular, do we observe some groups who are more or less responsive to the parity mandate?
- To answer this, we fit a latent class (finite mixture) two-part model

Latent Class Two-Part Model

$$
\begin{aligned}
f(y_{ij}|\mathbf{b}_i) &= \sum_{k=1}^{K} \pi_{ik} \left[(1-\phi_{ijk}) 1_{(y_{ij}=0)} + \phi_{ijk} \mathrm{LN}(y_{ij}; \mu_{ijk}, \sigma_k^2) 1_{(y_{ij}>0)} \right] \\
\Phi^{-1}(\phi_{ijk}) &= \mathbf{t}_{ij}' \boldsymbol{\beta}_{1k} + b_{1i} \\
\mu_{ijk} &= \mathbf{t}_{ij}' \boldsymbol{\beta}_{2k} + b_{2i} \\
(\mathbf{b}_i | i \in k) &\sim \mathrm{N}_2(\mathbf{0}, \boldsymbol{\Sigma}_k),
\end{aligned}
$$

where:

$$\pi_{ik} = \Pr(\text{subject } i \in \text{class } k)$$

$$\phi_{ijk} = \Pr(Y_{ij} > 0 | i \in k)$$

$\mathbf{t}_{ij} = 4 \times 1$ vector of time variables (i.e., dichotomous indicators for year)

Modeling the Mixing Weights

Next, we model π_{ik} as a function of baseline covariates via a multinomial logit model:

$$\pi_{ik}(\mathbf{w}_i) = \frac{e^{\mathbf{w}_i'\boldsymbol{\gamma}_k}}{\sum_{h=1}^{K} e^{\mathbf{w}_i'\boldsymbol{\gamma}_h}}, \text{ with } \boldsymbol{\gamma}_1 = \mathbf{0},$$

where:

$\mathbf{w}_i$ = vector of covariates (sex and employee status)

$\boldsymbol{\gamma}_k$ = vector of regression parameters for class k ($k \geq 2$)

Parameter Estimation

- Maximum Likelihood Estimation: EM algorithm (Mplus)

- Bayesian Inference: Place prior distributions on model parameters and use Markov chain Monte Carlo (MCMC) to draw from joint posterior

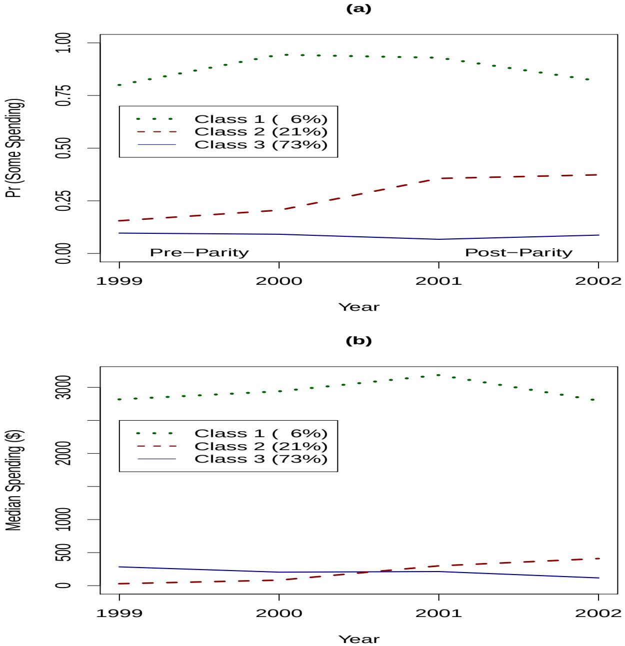
    - Weakly informative proper priors for all model parameters

    - All updates have closed-form full conditionals except γ and $\mathbf{b}_i$

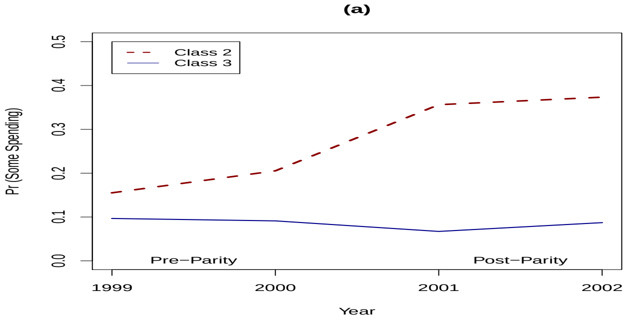
    - Used a modified DIC to select the optimal number of classes (Spiegelhalter et al., 2002; Celeux et al., 2006)

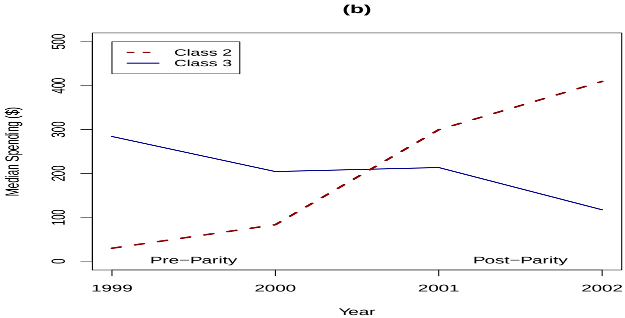
    - Stephens's (2000) relabeling algorithm for label switching

Class Trajectories



Trajectories for Classes 1 and 2

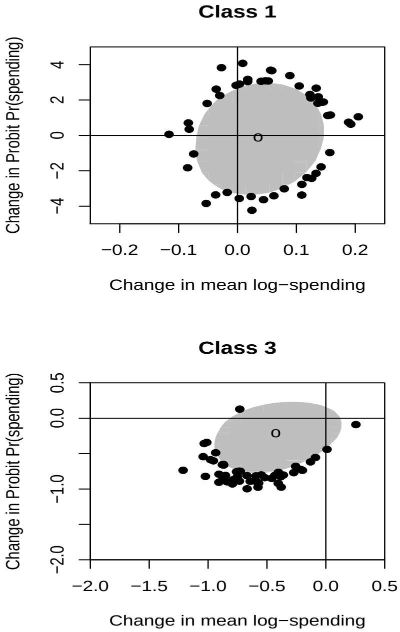




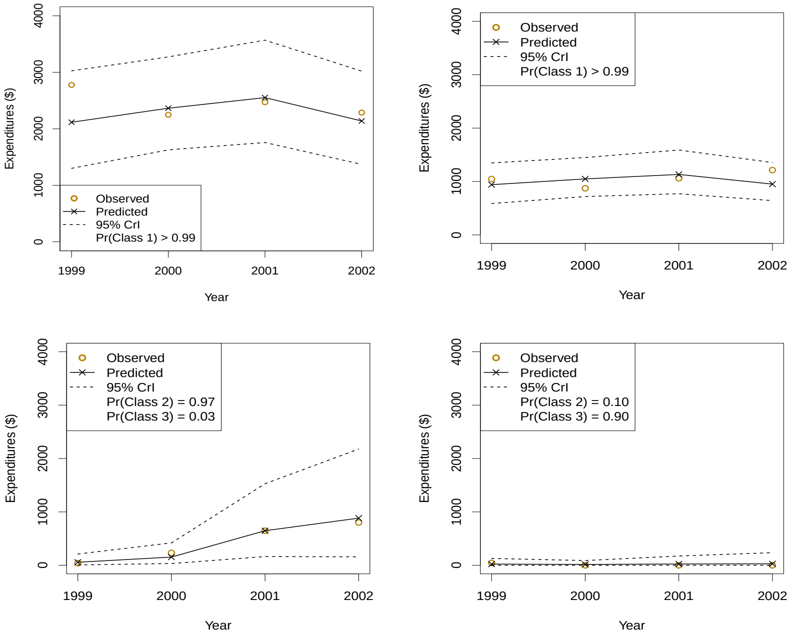
Contrasts for Assessing Parity Effect

- To assess parity effect, we can form contrasts that compare average spending before and after parity
- Form one contrast on the probit scale for the binary part, and a second on the log scale for the lognormal part
- Then plot the bivariate 95% highest posterior density (HPD) regions for the two contrasts
- Regions that exclude the origin suggest a change in spending following parity
- Can do this separately for each class
- Analogous to a 2-df test of parity effect

95% HPD Regions for Assessing Parity Effect



Predicted Spending Curves

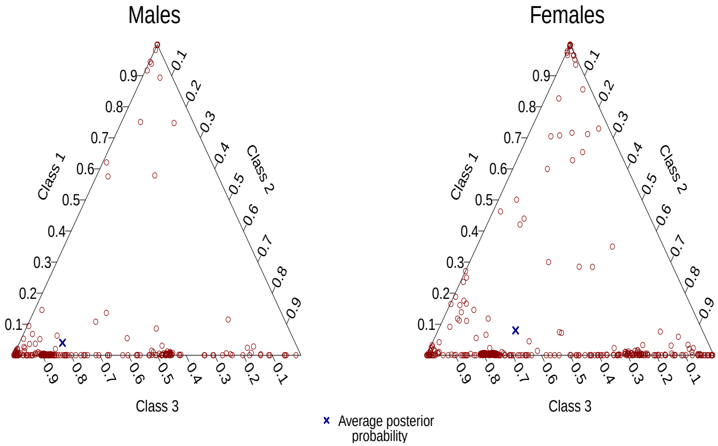


Class-Membership Probabilities

Posterior class-membership probabilities by covariate profile.

		Class-Membership Probabilities		
Gender	**Employee Status**	Class 1	Class 2	Class 3
Male	Non-Employee	0.04	0.17	0.79
Male	Employee	0.04	0.14	0.82
Female	Non-Employee	0.08	0.29	0.63
Female	Employee	0.09	0.25	0.66

Triangle Plot of Posterior Probabilities



Recap

The latent class two-part model allowed us to accomplish four goals:

1) Estimate mean spending trajectories for latent subgroups
2) Formally assess the impact of parity through the use of joint contrasts statements (class 2 most responsive)
3) Obtain accurate predictions of individual trajectories
4) Estimate class membership probabilities for various covariate profiles (women more likely to belong to classes 2 and 3)

Recent Extensions

- Growth mixture model for gestational blood pressure and correlated binary endpoints (Neelon et al., *Stats in Med*, 2011)
- Spatial Poisson hurdle model of emergency department visits, with bivariate CAR random effects for each component (Neelon et al., *JRSS-A*, forthcoming)
- Spatial multivariate mixture model for standardized exam scores

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