Bayesian Analysis of the Two-Part Model with Endogeneity: Application to Health Care Expenditure

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Abstract
This paper studies the effect of managed care on medical expenditure using a model in which the insurance status is assumed to be endogenous. Insurance plan choice is modeled through the multinomial probit model. The medical expenditure variable, the outcome of interest, has a significant proportion of zeros that are handled using the two-part model, extended to handle endogenous insurance. The estimation approach is Bayesian, based on the Gibbs Sampler. The model is applied to a sample of 20,460 individuals obtained from Medical Expenditure Panel Survey. The results provide substantial evidence of selectivity.

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1. Introduction

This paper studies the effect of endogenous managed care insurance plans on expenditure for medical services within a Bayesian econometric framework. To study this issue, we define managed care in terms of three alternative insurance plans that are characterized by different degrees of use restrictions; health maintenance organization (HMO), preferred provider organization (PPO) and fee-for-service (FFS) plans. The HMO plans are the most restrictive, involving a gatekeeper physician and a preselected network of providers that provide the within-network coverage. The PPO plans also have a gatekeeper; but they do not have most of the other restrictions imposed by HMO plans. For example, out-of-network providers are also covered, but only partially. The FFS plan, representing the greatest flexibility of choice, does not have gatekeepers and extends coverage to all available providers.

Salient features of health expenditure data specifically, and utilization data more generally, include, in addition to nonnegativity of outcomes, a significant fraction of zero outcomes and nonnormal empirical distributions characterized by positive skewness and excess kurtosis. The econometric modeling of the effect of insurance on health care expenditures faces two challenges. First, the outcome, medical expenditure variable $Y$, typically has a substantial proportion of zero values. For example, in the data used in this paper approximately 17% of the respondents have zero ambulatory medical expenditure and 94% of respondents have zero hospital expenditures. When the data have this feature of finite point probability mass no standard parametric distribution will suffice, and, instead, some kind of mixture model is needed to provide a good fit to the data. Empirical strategies for modeling such data, in the context of a regression with homoskedastic errors estimated by least squares, have been discussed by Duan, Manning, Morris and Newhouse (1983) and Mullahy (1998), and more generally by Manning and Mullahy (2001). They have been surveyed extensively by Jones (2000), among others. Because the two-part model (TPM), pioneered by the RAND researchers in their analysis of the expenditure data from the RAND Health Insurance Experiment, is a widely used example of such a mixture model, it provides a point of departure for this paper. The TPM, also known as a hurdle model, introduces modeling flexibility by allowing the zero and positive values of expenditure to be generated by two separate processes. A complementary question whether a sample-selection model or the two-part model is a better framework for health expenditures has
generated some lively debate in the health economics literature; see Maddala (1985). Jones (2000, section 4) surveys this debate. It is well-known that likelihood-based estimation of the Tobit model, which is often considered to be an alternative benchmark model for this type of zeros-dominated data, is inconsistent under nonnormality and/or heteroskedasticity, and has been found to be an inferior modeling strategy compared with the TPM, as many studies have noted; e.g. see Melenberg and van Soest (1996).

A second modeling challenge comes from the potential endogeneity of health insurance. The standard two-part model assumes exogeneity of the insurance variable, but when working with observational data it is important to allow for endogeneity of insurance. A widely held perception in the health economics literature on selectivity into insurance plans is that healthier individuals tend to select themselves into managed care plans with a gatekeeper and smaller premiums and less healthy but more risk-averse individuals tend to select indemnity plans with higher premiums and more extensive coverage. As a result the average expenditure for the healthier group should be lower. Some studies, e.g. Goldman (1995) and Mello, Stearns, and Norton (2002), allow for endogeneity, but in these papers the endogenous treatment indicator is binary. In the case of our model, as in most rich specifications of insurance status, the insurance indicator is multinomial.

We integrate the TPM and the multinomial selection model into a single framework that we call the extended (or endogenous) two-part model (ETPM). This contrasts with most of the existing studies that, with some notable exceptions, assume exogeneity – an assumption that leads to considerable computational simplicity. However, ignoring selection effects means that we cannot separate out the pure treatment effect from that which is due to self-selection. Individuals and households are more likely to choose insurance based on personal characteristics such as overall health status, the existence and severity of chronic health conditions and physical limitations, preferences for risk, preferences over intensity of treatment, and so on. If all such variables are introduced into the outcome equation, then one could control for the effects of selection. This is difficult because some of these factors are intrinsically unobservable. Hence it is unlikely then that the observable variables included in the outcome equation will adequately control for the influence of these factors, and it seems more likely that some additional statistical controls for selection on unobservables will be required. If the assumption of exogeneity of insurance is invalid, the estimates of marginal effects and treatment effects obtained from the
TPM would be inconsistent. Therefore, to identify the pure treatment effect selection has to be modeled.

This paper offers two innovations, one substantive and the other methodological. The substantive focus of this paper is on the impact of managed care on total ambulatory and hospital health care expenditures. We use nationally representative data from the U.S. in the form of six repeated cross-sections, 1996-2001, from the Medical Expenditure Panel Survey (MEPS) and focus on two components of total medical expenditure. We model both inpatient expenditure, including all hospital treatments, and ambulatory expenditure, which includes the rest of the total expenditure for such medical treatments as office-based doctor visits, out-patient visits, emergency room visits, and expenditure on prescribed medicines. The main reason for such a division in the total expenditure is the general notion that managed care plans advocate cost containment measures, derived largely from the decreased enrollees’ use of inpatient hospital services. We compute treatment effects for two separate expenditure measures to evaluate the overall effect of insurance plans.

Our methodological contribution is a parametric estimation strategy of developing and implementing a Bayesian estimation framework based on an extended two-part model (ETPM) that respects the endogeneity and multinomial nature of insurance choice. We introduce unobserved heterogeneity through latent variables, correlated across insurance choice, hurdle and expenditure equations, that can be handled by Bayesian data augmentation with Gibbs sampling. Compared with the alternative simulation-based maximum likelihood method, our Bayesian approach is computationally efficient (Geweke, Gowrisankaran, and Town, 2003, p. 1218). Our algorithm builds on and extends the previous work by Tanner and Wong (1987), Albert and Chib (1993), McCulloch, Polson, and Rossi (2000), Munkin and Trivedi (2003), and Geweke et al. (2003).

The rest of the paper is organized as follows. Section 2 develops the two-part model with endogeneity and specifies the prior distributions of the parameters. Section 3 presents the MCMC estimation of the model. Section 4 deals with hypothesis testing of exogeneity and Section 5 calculates treatment effects. Section 6 presents an empirical application. Section 7 concludes.
2. Model Specification

The standard two-part model assumes that part one, \( \Pr(Y > 0|x) \), is governed by a binary probit model such that

\[
\Pr(Y > 0|x) = \Phi(x'\gamma),
\]

where \( \Phi(\cdot) \) is the c.d.f. of the standard normal, \( x \) is a set of exogenous explanatory variables and \( \gamma \) is a parameter vector. Part two assumes that the logarithm of the positive values of \( Y \) is linear in \( x \) such that

\[
E[\ln(Y)|Y > 0, x] = x'\beta,
\]

(2.1)

where \( \beta \) is a parameter vector. Applied economists are interested in estimating the conditional mean, \( E[Y|x] \), and the corresponding marginal effects and elasticities. Given the estimated conditional mean (2.1), one has to remove conditioning on \( Y > 0 \) and transform back from logarithm to variable \( Y \) to make inference about \( E[Y|x] \). We use the logarithmic transformation, following the RAND studies, and because it is the most popular in empirical work. Other transformations, including the Box-Cox and power transformations, are feasible and have some attractive properties; see Blough, Madden and Hornbrook (1999), and Manning and Mullahy (2001).

Our ETPM model consists of an expenditure equation with a TPM structure and a set of insurance choice equations. The multinomial probit model is used to model the probabilities of insurance choice conditional on exogenous variables. Our use of a multinomial probit is a significant extension of studies, such as Goldman (1995) and Mello et al. (2002) who use a binary choice model. The outcome variable is allowed to be correlated with the choice variables and this correlation is generated not only by dependence on common observable variables but also, as mentioned above, by dependence on common or overlapping unobservable variables. Examples of such variables are health condition and attitude towards risk, affecting both the choice of insurance and expenditure. Our measures of health status are self-perceived evaluation of health condition, number of chronic conditions and an indicator of an injury. These variables proxy actual health status which is unobservable.
2.1. TPM With Endogeneity

Assume that we observe \( N \) independent observations and each individual \( i \) \( (i = 1, ..., N) \) chooses an insurance plan among three alternatives: PPO, HMO and FFS. This choice is modeled through the multinomial probit model (MNP) with the FFS as the baseline choice such that \( d_1 = 1 \) if PPO is chosen, \( d_2 = 1 \) if HMO and \( d_3 = 1 \) if FFS (the excluded category). The choice is trinomial in our application but the model can easily be extended to any number of alternatives. The subscript \( i \) indicating observations will be suppressed unless necessary for clarity. Let \( z_1, z_2 \) and \( z_3 \) be latent utilities generated from PPO, HMO and FFS alternatives respectively with \( z_3 \) restricted to zero for identification. Two latent variables defining the MNP model are

\[
\begin{align*}
    z_1 &= w'_1 \alpha_1 + u_1 \\
    z_2 &= w'_2 \alpha_2 + u_2
\end{align*}
\] (2.2)

such that

\[
\begin{align*}
    d_1 &= 1 \text{ if and only if } z_1 > \max(z_2, 0) \\
    d_2 &= 1 \text{ if and only if } z_2 > \max(z_1, 0) \\
    d_3 &= 1 \text{ if and only if } 0 > \max(z_1, z_2).
\end{align*}
\]

The distribution of the error term \( u = (u_1, u_2)' \) is bivariate normal \( N[0_2, \Omega] \). Denote \( z' = (z_1, z_2), W' = \text{Diag}(w'_1, w'_2), \alpha' = (\alpha'_1, \alpha'_2) \), \( d = (d_1, d_2) \).

Part one, the hurdle equation, is defined by latent variable \( H^* \), and part two is logarithm of potential expenditure \( Y^* \). Both are assumed to be linear in the set of explanatory variables \( x \) and endogenous variables \( d_1, d_2 \)

\[
H^* = x' \gamma + d' \tau + \varepsilon_1
\] (2.3)

and

\[
Y^* = x' \beta + d' \rho + \varepsilon_2,
\] (2.4)

where \( \gamma \) and \( \beta \) are \( k \times 1 \) and \( \tau = (\tau_1, \tau_2)' \) and \( \rho = (\rho_1, \rho_2)' \) are \( 2 \times 1 \) parameter vectors. The standard two-part model assumes that random variables \( \varepsilon_1 \) and \( \varepsilon_2 \) are independent. We will
assume that they are independent conditionally on \((u_1, u_2)\) and follow Geweke et al. (2003) to write

\[
\begin{align*}
\varepsilon_1 &= u' \delta + v, \\
\varepsilon_2 &= u' \pi + e,
\end{align*}
\]

where \(cov[u, v] = 0\), \(cov[u, e] = 0\), \(\delta = E[u \varepsilon_1]\) and \(\pi = E[u \varepsilon_2]\) are \(2 \times 1\) covariance parameter vectors and independent random variables \(v\) and \(e\) are independently distributed as \(v \sim \mathcal{N}[0, 1]\), \(e \sim \mathcal{N}[0, \sigma^2]\). Then the specification of the hurdle and conditional parts is

\[
H^* = x' \gamma + d' \tau + (z - W' \alpha)' \delta + v
\]

and

\[
Y^* = x' \beta + d' \rho + (z - W' \alpha)' \pi + e.
\]

Positive expenditure are observed only for a portion of individuals. The rest have zero expenditure. We assume that the zeros are generated by the hurdle variable and structurally linked to the individual’s decision to use medical services at all. In other words, zero expenditure can be observed if and only if the individual never uses medical services. Thus the observability condition is

\[
h = \begin{cases} 
1 & \text{if } H^* \geq 0 \\
0 & \text{if } H^* < 0
\end{cases}
\]

and

\[
Y = \begin{cases} 
\exp(Y^*) & \text{if } h = 1 \\
0 & \text{if } h = 0,
\end{cases}
\]

and the observed data consist of \((Y, h, d_1, d_2, x)\).

The main focus of the paper is the effect of endogenous insurance variables on the medical expenditures. Two leading options for modeling insurance choice are the multinomial logit (MNL) and the multinomial probit (MNP). We have found the MNP framework to be more convenient for modeling endogeneity if certain identifying restrictions are imposed. The MNP part of the model is identified, in general, if one diagonal element of matrix \(\Omega\) is restricted. However, it has been long known that, in the absence of legitimate exclusion restrictions, identification of the correlation parameters between the MNP choice equations (Keane, 1992), as well as the hurdle and expenditure parts, is difficult, if not impossible. As mentioned earlier, the correlation
between the hurdle and expenditure parts is restricted to zero, conditionally on latent variables generating the MNP part of the model. In addition, we restrict matrix $\Omega$ to the identity matrix $I_2$. The last restriction is similar to that used by Geweke et al. (2003). Our primary goal is to identify the effect of insurance type on health care expenditure rather than studying the actual choice. The restriction of the covariance matrix of the MNP model still permits endogeneity of the insurance variables but helps avoid identification problems.

2.2. Prior Distributions

The prior information on parameters $\beta$, $\rho$, $\gamma$, $\tau$, $\alpha_1$, $\alpha_2$ is weak. We center the priors at zero mean and choose relatively large variance

$$
\beta \sim \mathcal{N}[0_k, 10I_k], \quad \gamma \sim \mathcal{N}[0_k, 10I_k],
$$

$$
\rho \sim \mathcal{N}[0_2, 10I_2], \quad \tau \sim \mathcal{N}[0_2, 10I_2],
$$

$$
\alpha_1 \sim \mathcal{N}[0_p, 10I_p], \quad \alpha_2 \sim \mathcal{N}[0_p, 10I_p].
$$

The priors for parameters $\delta$ and $\pi$ are also centered at zeros and we select them to be informative. There is no prior information on the covariance parameters $\delta$ and $\pi$. However, for tests of endogeneity to be feasible one must choose proper priors for these parameters. The choice of the priors is

$$
\delta \sim \mathcal{N}[0_2, \kappa I_2], \quad \pi \sim \mathcal{N}[0_2, \kappa I_2].
$$

We test two sets of priors for $\kappa = 1/8$ and $\kappa = 1/2$ and perform a sensitivity analysis to see how the posterior distribution and the test of endogeneity depend on the choice of priors. Finally, gamma prior for $\sigma^{-2}$ is

$$
\sigma^{-2} \sim \mathcal{G}[n/2, (c/2)^{-1}]
$$

where $n = 5$ and $c = 10$.

Details of the MCMC estimation of the ETPM model are given in the following section. We run our Markov chain for 10000 replications, following the first 1000 replications of the initial burn-in phase during which our chain converges to its stationary distribution. The chains display good mixing properties. The autocorrelation functions die off after at most 5-10 lags in all cases.
3. The MCMC estimation of the Endogenous Two-Part Model

We utilize a data augmentation approach and include latent variables \( z_i, H_i^* \) and \( Y_i^* \) in the parameter set, thus making them part of the posterior. Denote \( D_i' = (x_i', d_i), \phi_i' = (\gamma', \tau') \), \( \phi_2' = (\rho', \rho') \), \( \Delta_i = (W_i, D_i, \alpha, \phi_2, \phi_2, \delta, \pi, \sigma^2) \). Then one can derive the joint density of the observable data and latent variables for individual \( i \) as

\[
p(z_i, d_i, H_i^*, h_i, Y_i^*, Y_i|\Delta_i) = p(z_i|\Delta_i)p(d_i|z_i, \Delta_i)p(H_i^*|z_i, d_i, \Delta_i)
\]

\[
\times p(h_i|z_i, d_i, H_i^*, \Delta_i)p(Y_i^*|z_i, d_i, H_i^*, h_i, \Delta_i)p(Y_i|z_i, d_i, H_i^*, h_i, Y_i^*, \Delta_i).
\]

Substituting the conditional probabilities in the same order as in equation (3.1) one can derive

\[
\frac{1}{2\pi} \exp \left[ -0.5 \left( z_i - W'_i\alpha \right)' I_2^{-1} (z_i - W'_i\alpha) \right] \left[ \prod_{j=1}^{3} \frac{1}{2\pi} \exp \left[ -0.5 \left( H_i^* - D'_i\phi_1 - (z_i - W'_i\alpha)' \delta \right)^2 \right] \right] \left[ \prod_{l=1}^{3} I_{[0,\infty)} (z_{ii} - z_{li}) \right]
\]

\[
\times \frac{1}{\sqrt{2\pi\sigma}} \exp \left[ -0.5\sigma^{-2} \left( Y_i^* - D'_i\phi_2 - (z_i - W'_i\alpha)' \pi \right)^2 \right] \left[ h_i I_{\{Y_i=\exp(Y'_i)\}} + (1-h_i) I_{\{Y_i=0\}} \right],
\]

where \( I_{[0,\infty)} \) is the indicator function for set \([0, \infty)\). Since the individuals are independent

the joint distribution for all observations is the product of \( N \) such terms over \( i = 1, ..., N \).

The posterior density is proportional to the product of the prior density of the parameters and
the joint distribution of observables and included latent variables. Because we have selected
conjugate priors for all parameters, we can derive the full conditional densities.

The steps of the MCMC algorithm are as follows:

1. The latent vectors \( z_i \) \( (i = 1, ..., N) \) are conditionally independent with bivariate normal

   distribution \( z_i \overset{iid}{\sim} N[\mathbf{z}_i, \mathbf{H}_i^{-1}] \) where

   \[
   \mathbf{H}_i = I_2 + \delta \mathbf{I} + \pi \mathbf{I} \mathbf{I}^{-1} \left[ \delta (H_i^* - D'_i\phi_1) + \pi \sigma^{-2} (Y_i^* - D'_i\phi_2) \right].
   \]

   Each variable is truncated such that

   \[
   z_{1i} > \max (z_{2i}, 0) \text{ if } d_{1i} = 1 \text{ and } z_{1i} < \max (z_{2i}, 0) \text{ if } d_{1i} = 0
   \]

   \[
   z_{2i} > \max (z_{1i}, 0) \text{ if } d_{2i} = 1 \text{ and } z_{2i} < \max (z_{1i}, 0) \text{ if } d_{2i} = 0.
   \]
We use Geweke’s (1991) algorithm to draw values from these truncated normal distributions.

2. Variable $H_i^*$ is $\mathcal{N}[\mathbf{D}_i'\phi_1 + (z_i - \mathbf{W}_i'\alpha)'\delta, 1]$ and truncated at 0 to $[0, \infty)$ if $h_i = 1$ and to $(-\infty, 0)$ if $h_i = 0$.

3. Variable $Y_i^*$ is drawn only for those observations for which $h_i = 0$. It is drawn from normal distribution with mean $\mathbf{D}_i'\phi_2 + (z_i - \mathbf{W}_i'\alpha)'\pi$ and variance $\sigma^2$. If $h_i = 1$ then $Y_i^* = Y_i$.

4. Let the prior distribution of $\alpha$ be $\mathcal{N}[\alpha, \mathbf{H}_\alpha^{-1}]$. Then the full conditional distribution of $\alpha$ is $\alpha \sim \mathcal{N}[\bar{\alpha}, \mathbf{H}_\alpha^{-1}]$ where

$$
\mathbf{H}_\alpha = \mathbf{H}_\phi + \sum_{i=1}^N \mathbf{W}_i (\mathbf{I}_2 + \delta \delta' + \pi \pi' \sigma^{-2}) \mathbf{W}_i'
$$

$$
\bar{\alpha} = \mathbf{H}_\alpha^{-1} \left[ \mathbf{H}_\alpha \alpha + \sum_{i=1}^N \{ \mathbf{W}_i (\mathbf{I}_2 + \delta \delta' + \pi \pi' \sigma^{-2}) z_i - \mathbf{W}_i \delta (\mathbf{H}_i^* - \mathbf{D}_i'\phi_1) - \mathbf{W}_i \pi \sigma^{-2} (Y_i^* - \mathbf{D}_i'\phi_2) \} \right].
$$

5. Let $\theta_1' = (\phi_1', \delta')$, $\mathbf{C}_i = (\mathbf{D}_i', (z_i - \mathbf{W}_i'\alpha)')$ and specify prior distributions $\phi_1 \sim \mathcal{N}[\phi_1, \mathbf{H}_{\phi_1}^{-1}]$ and $\delta \sim \mathcal{N}[\delta, \mathbf{H}_{\delta}^{-1}]$. Then the conditional distribution of $\theta_1$ is $\theta_1 \sim \mathcal{N}[\bar{\theta}_1, \mathbf{H}_{\theta_1}^{-1}]$ where

$$
\mathbf{H}_{\theta_1} = \left[ \begin{array}{cc} \mathbf{H}_{\phi_1} & 0 \\ 0 & \mathbf{H}_{\delta} \end{array} \right] + \sum_{i=1}^N \mathbf{C}_i' \sigma^{-2} \mathbf{C}_i
$$

$$
\bar{\theta}_1 = \left[ \begin{array}{c} \mathbf{H}_{\phi_1} \phi_1 \\ \mathbf{H}_{\delta} \delta \end{array} \right] + \sum_{i=1}^N \mathbf{C}_i' \sigma^{-2} Y_i^*.
$$

6. Let $\theta_2' = (\phi_2', \pi')$ and specify prior distributions $\phi_2 \sim \mathcal{N}[\phi_2, \mathbf{H}_{\phi_2}^{-1}]$ and $\pi \sim \mathcal{N}[\pi, \mathbf{H}_{\pi}^{-1}]$. Then the conditional distribution of $\theta_2$ is $\theta_2 \sim \mathcal{N}[\bar{\theta}_2, \mathbf{H}_{\theta_2}^{-1}]$ where

$$
\mathbf{H}_{\theta_2} = \left[ \begin{array}{cc} \mathbf{H}_{\phi_2} & 0 \\ 0 & \mathbf{H}_{\pi} \end{array} \right] + \sum_{i=1}^N \mathbf{C}_i' \mathbf{C}_i
$$

$$
\bar{\theta}_2 = \left[ \begin{array}{c} \mathbf{H}_{\phi_2} \phi_2 \\ \mathbf{H}_{\pi} \pi \end{array} \right] + \sum_{i=1}^N \mathbf{C}_i' \mathbf{H}_i^*.
$$
7. Finally, specify the prior $\sigma^{-2} \sim G(n/2, (c/2)^{-1})$. Then the full conditional of $\sigma^{-2}$ is

$$G\left(\frac{n + N}{2}, \left[\frac{c}{2} + \sum_{i=1}^{N} \left(Y_i^* - D_i'\phi_2 - (z_i - W_i'\alpha)^2 \right)^2\right]^{-1}\right).$$

This concludes the MCMC algorithm.

4. Testing for Endogeneity

In this section we consider the two-part model without endogeneity and discuss tests of exogeneity. If the insurance variables are predetermined or exogenous then the correlation parameters $\delta$ and $\pi$ can be restricted to zeros. The MCMC algorithm for this model is a straightforward extension of that for the two-part model with endogeneity.

To test whether the assumption of endogeneity of insurance variables is valid one can test the joint null hypothesis $H_0 : \delta' = \pi' = (0, 0)$. Imposing restriction $\pi' = (0, 0)$ on the expenditure variable and restriction $\delta' = (0, 0)$ on the hurdle part collapses the benchmark model to the model that assumes exogeneity. Denote as $M_0$ the constrained model and as $M_1$ the model that leaves the correlation parameters unconstrained. The Bayes factor for the null hypotheses is defined as

$$B_{0,1} = \frac{m(y|M_0)}{m(y|M_1)},$$

where $m(y|M_j)$ is the marginal likelihood of the model specification $M_j$, $j = 1, 2$. Since models $M_0$ and $M_1$ are nested the Savage-Dickey density ratio approach (Verdinelli and Wasserman, 1995) can be taken to calculate the Bayes factor as

$$B_{0,1} = \frac{p(\delta^*, \pi^*|data)}{p(\delta^*, \pi^*)},$$

where $p(\delta, \pi|data)$ is the posterior density of $\delta, \pi$ and $p(\delta, \pi)$ is the prior with everything calculated at the points $\delta^* = (0, 0)'$ and $\pi^* = (0, 0)'$. It is straightforward to estimate the prior density at $\delta^*, \pi^*$. The unconditional joint posterior density $p(\delta, \pi|data)$ is not known. However, it can be estimated using the output from the Gibbs sampler. Given the full conditional densities of $\theta_1' = (\gamma', \tau', \delta')$ and $\theta_2' = (\beta', \rho', \pi')$ one can find the full conditional densities of $\delta$ and $\pi$, which are conditionally independent. Then the joint posterior can be approximated by averaging.
the full conditional densities with respect to the posterior sample of all conditioning parameters and augmented data
\[
\bar{p}(\delta, \pi | \text{data}) = \frac{1}{S} \sum_{s=1}^{S} p(\delta | z_s, \gamma_s, \pi_s, \alpha_s, H_{**}^s)p(\pi | z_s, \beta_s, \rho_s, \alpha_s, Y_{**}^s, \sigma_s^2),
\]
which should be evaluated at \(\delta^*\) and \(\pi^*\). Informative priors \(p(\delta)\) and \(p(\pi)\) are selected because improper priors are not appropriate for testing. Less informative priors would favor the null hypothesis. We implement this test in the application section.

5. Treatment Effects

This section discusses calculation of treatment effects; we concentrate our attention on calculating the treatment effects for treated individuals where the treated group is the PPO and HMO populations respectively. The counterfactual against which the treatment effects are calculated is the FFS outcome. The link between the observed and counterfactual outcomes is given by
\[
Y_i = d_{1i}Y_{1i} + d_{2i}Y_{2i} + d_{3i}Y_{3i}
\]
such that, for example, if an individual \(i\) has PPO coverage, then the observed outcome is \(Y_{1i}\) and the two counterfactuals are \(Y_{2i}\) and \(Y_{3i}\); and if the individual \(i\) has an HMO plan, then the observed outcome is \(Y_{2i}\), and the two counterfactuals are \(Y_{1i}\) and \(Y_{3i}\). Hence the outcomes are expressed as:
\[
Y_{ji} = I(x'_0i\gamma + (z_i - W'_0i\alpha)'\delta + \tau_j + v_i > 0) \exp[x'_0i\beta + (z_i - W'_0i\alpha)'\pi + \rho_j + e_i], \quad j = 1, 2,
Y_{3i} = I(x'_0i\gamma + (z_i - W'_0i\alpha)'\delta + v_i > 0) \exp[x'_0i\beta + (z_i - W'_0i\alpha)'\pi + e_i],
\]
where \(I(\cdot)\) is an indicator function that takes the value one if the condition in parentheses is met, and is zero otherwise. Our interest lies in estimating treatment effects for the treated individuals in groups \(d_j = 1, j = 1, 2\), against the counterfactual alternative \(Y_3\) such as
\[
E [Y_j - Y_3 | d_j = 1].
\]
Let us denote \( \eta_i = (\alpha, \beta, \gamma, \delta, \pi, \tau, \rho, \sigma^2, z_i) \). Then the conditional expected outcomes are

\[
E[Y_{ji}|\eta_i, d_{ji} = 1] = \Phi(x_i'\gamma + (z_i - W_i'\alpha)'\delta + \tau_j) \\
\times \exp(x_i'\beta + (z_i - W_i'\alpha)'\pi + \rho_j + 0.5\sigma^2),
\]

\[
E[Y_{ji}|\eta_i, d_{ji} = 1] = \Phi(x_i'\gamma + (z_i - W_i'\alpha)'\delta) \\
\times \exp(x_i'\beta + (z_i - W_i'\alpha)'\pi + 0.5\sigma^2),
\]

and

\[
E[Y_{ji} - Y_{3i}|\eta_i, d_{ji} = 1]
\]

is the value of the treatment effect for the treated individual \( i \) with the observed vectors of variables \( x_i \) and \( w_i \) against the FFS counterfactual outcome calculated at a specific numerical realization of the parameter set \( \eta_i \). We omit dependence on \( x_i \) and \( w_i \) for brevity. We also note that these expressions for treatment effects are based on the standard retransformation from log to linear models. The average treatment effects reported in this paper involve an additional step in which we integrate out \( \eta_i \) numerically with respect to the posterior distribution of the parameters in the model. One can also report the whole distribution of treatment effects for all individuals, as discussed by Chib and Hamilton (2002), and Poirier and Tobias (2003).

6. Application

In this section we apply our model to study the effect of HMO and PPO types of managed care plans on expenditure for medical services. We use data from the Medical Expenditure Panel Survey (MEPS). MEPS is a representative survey of the noninstitutionalized population in the U.S. with wide scope and excellent information on demographic characteristics, health status, employment status and earnings, and a wide variety of measures of health care utilization. We use data from the 1996-2001 waves of the survey. The design of MEPS consists of overlapping two-year panels with measurements taken over two calendar years in 5 rounds of surveys. An individual is observed for at most two consecutive years. To construct our data set we use the second year observations for each individual. Two of our exclusion restrictions are, however, taken from the first year of observations.

The sample is restricted to only those individuals who are covered by private insurance, aged between 21 and 64 years, and employed. This means that we exclude the Medicare population,
and we also restrict our discussion to issues involving plan restrictions on the insured population. Measurement of the impact of insurance on the currently uninsured involves additional complications. Self-employed and publicly insured individuals are deleted from our sample because their choice sets for insurance plans are likely to be quite different from those who are employed by firms. Typically, one expects self-employed and publicly insured individuals to have fewer insurance alternatives. The final sample size is 20,460.

Definitions and summary statistics of the variables in the data sets used in this paper are given in Table 1. The dependent variables, LNAMBEXP and LNHOSPEXP, are defined as the logarithms of positive values for the ambulatory and inpatient expenditure, respectively, and zeros for observations with no expenditures. About 83.4% and 6.1% individuals have positive ambulatory and inpatient expenditures respectively.

The covariate vector \( x \) for the hurdle and the expenditure parts is the same. It includes indicators of self-perceived health status variables (VEGOOD, GOOD and FAIRPOOR), and measures of chronic diseases and physical limitation (TOTCHR, PHYSLIM and INJURY). Health status is hard to measure, so it is likely that some variation in health status will be left unexplained with this set of proxies. We argue that this unexplained part is at least one factor that drives selection on unobservables. In addition, \( x \) includes: geographical variables NOREAST, MIDWEST, SOUTH and MSA, that are included to capture price differences in the local markets and geographical differences in the rates of managed care penetration; and socioeconomic variables BLACK, HISPANIC, FAMSIZE, FEMALE, MARRIED, EDUC, AGE and INCOME. Finally, we include the square of AGE variable, AGE2, and AGEXFEM, the interaction variable between AGE and the gender variable FEMALE as age is expected to have a nonlinear effect on expenditures and men and women are expected to have different age profiles. The covariate vector for the hurdle and expenditure equations also includes two dummy variables for type of insurance plan, HMO and PPO. Expenditure is measured in nominal dollars, so year dummies are included to capture the effects of price inflation for ambulatory and inpatient medical services, respectively.

In addition to the exogenous variables included in \( x \), the vectors \( w_1 \) and \( w_2 \) consist of variables that are assumed to affect the choice of insurance plans but not to affect the use of medical services and, consequently, medical expenditures, directly. Because the data do not contain any plan-specific information, \( w_1 \) and \( w_2 \) consist of the same variables. There are three: 1. the
age of the spouse (SPAGE); 2. whether the spouse was covered by an HMO in the previous year (LAGSPHMO), and 3. whether the spouse was covered by a PPO in the previous year (LAGSPPPO). The age of the spouse strongly affects the choice of health insurance plan chosen by the person but should not affect the person’s medical expenditures directly, conditional on observable characteristics of the person. The lagged choice of the spouse’s insurance plan is also a significant determinant of a person’s current health plan choice and is predetermined in our system of equations. In our sample, almost 15 percent of spouses change plans from the lagged to the present year showing that current and lagged plan choices of spouses are not always the same. Using linear simultaneous equations estimates of the probability of any care and expenditures, conditional on some care, we find that the instruments pass Hansen’s test for validity of overidentifying restrictions.

6.1. Ambulatory expenditure

First, the two-part model with endogeneity is applied to our data set with LNAMBEXP as the expenditure variable. Table 2 reports the posterior means and standard deviations based on the MCMC output. We describe the effects of exogenous covariates using just these means and standard deviations as these covariates are not the primary focus of our study. We then describe the effects of HMO and PPO enrollment as compared to FFS plans in greater detail below.

In general, demand side factors are not strong determinants of PPO choice. Supply factors proxied by region of the country and urbanization are significant determinants of PPO enrollment. Demand and supply factors are important for HMO choice, but here too, supply factors are especially important. The instruments, the age of the spouse and lagged plan choices of spouses, are also important and substantial determinants of the choice among insurance plans.

First, note that most of the covariates that have positive (negative) impact on the probability of seeking ambulatory care also have positive (negative) impacts on expenditures, conditional on receiving care. Individuals are both more likely to receive ambulatory care and, among those who receive care, receive greater amounts of care, as they grow older. Women are more likely to receive any care and spend more on care, but their age profile is significantly flatter than that for men. More educated individuals, those with greater incomes and those who are married are more likely to receive care and spend greater amounts on care, while minorities and those
with larger families are less likely to and spend less on care. Observed health status has highly significant and substantial effects on both the likelihood of and amounts spent on care. The year dummies have large positive effects on expenditures, conditional on receipt of care, consistent with the fact that inflation rates for medical services on average have been higher than overall inflation rates. Year dummies have no impacts on the likelihood of receiving care.

After taking into account possible selection-on-unobservables into insurance plans, the results show that individuals enrolled in HMOs are more likely to seek care than FFS enrollees. Individuals enrolled in PPOs are also more likely to seek care but this effect is not strong. However, once individuals in PPOs receive care, they spend significantly more than their FFS counterparts. The HMO effect on expenditures is not strong.

The test for the null hypothesis of no endogeneity, \( H_0 : \delta' = \pi' = (0, 0) \), is performed using Bayes factors. As mentioned earlier, the Savage-Dickey density ratio approach is used to estimate the Bayes factor because the models are nested. The estimated values of the Bayes factor is 3.296 (2.211) which gives some evidence in favor of endogeneity but it is not very strong. However, the conclusions are consistent for both prior specifications with values \( \kappa = 1/8 \) and \( \kappa = 1/2 \). Figure 1 displays the posterior distributions of the four covariance parameters for prior specification corresponding to \( \kappa = 1/2 \).

The overall effects of HMO and PPO enrollment as compared to FFS enrollment are best described using measures of treatment effects. Average treatment effects for the treated (ATET) are calculated for PPO and HMO groups against the counterfactual FFS outcomes. The results are presented in Table 3. The ATETs are also calculated for HMO and PPO subgroups defined by the health status. In addition we estimate the TPM under the assumption of random assignment (exogeneity) of insurance status. To save space we do not report these results in detail but the corresponding ATET estimates based on them are in Table 3. Also note that the posterior means and standard deviations of the PPO coefficients in expenditure and hurdle equations are, respectively 0.037 (0.036) and 0.237 (0.040); the corresponding HMO coefficients are −0.024 (0.023) and 0.148 (0.025). The results demonstrate the signs and magnitudes of the self-selection biases of the estimated average treatment effects for the treated when the assumption of endogeneity is ignored. The biases for the HMO group are not large ranging from $8 of the EXCELLENT group to $19 of the FAIRPOOR group. However, for the PPO group it ranges from $71 of the EXCELLENT group to $377 of the FAIRPOOR group.
Figure 2 reports the densities of the ATET distributions for HMO and PPO groups respectively. The mean and median of the treatment effects of HMO relative to FFS are close to zero. However, there is considerable variation in treatment effects across individuals. For 10 percent of the population, HMOs increase ambulatory expenditures by $33 or more, while for another 10 percent of the population, HMOs decrease expenditures by $44 or more. This reflects two countervailing effects, that HMOs encourage preventive or “wellness” visits, while discouraging the use of specialists and other expensive ambulatory care. PPOs, on the other hand, unambiguously increase ambulatory expenditures. The median increase is $163; for 10 percent of the population, the increase is more than $430. This estimate is also plausible. While PPOs encourage preventive and “wellness” care, they do not have the strict controls on expensive forms of care that HMOs do. While HMOs discourage expensive care by requiring pre-authorizations for such care, with no reimbursement otherwise, PPOs charge a higher price (typically a 20 percent coinsurance rate), which is not sufficient to be a substantial disincentive to PPO enrollees.

6.2. Inpatient expenditure

Table 4 reports the posterior means and standard deviations based on the MCMC output for LNHOSPEXP. Once again, we briefly describe the effects of exogenous covariates using just these means and standard deviations. We then describe the effects of HMO and PPO enrollment, as compared to FFS plans, on the probability of hospitalization and expenditures on inpatient care, in greater detail. Not surprisingly, the results for the PPO and HMO choice equations are very similar to those obtained in the ETPM model for ambulatory care.

Socioeconomic characteristics have considerably less impact on inpatient care than on ambulatory care. This is consistent with the fact that these are inpatient admissions, thus involve few admissions for elective reasons. Gender is a notable exception. Although young women are more likely to be hospitalized than young men, the age profile for men is considerably steeper and men at older ages are substantially more likely to be hospitalized. Health status is an important determinant of inpatient care. Self-perceived health status, the existence of a physical limitation, the number of chronic conditions and the existence of an injury all increase the likelihood of inpatient care substantially. But, of these, only the existence of a physical limitation affects inpatient expenditures among those who receive some inpatient care.
The test for the null hypothesis of no endogeneity, $H_0 : \delta' = \pi' = (0, 0)$, based on the estimated Bayes factors produce strong evidence against the null hypothesis, which is consistent for both prior specifications. The estimated Bayes factor is $0.00001 (0.00001)$. Figure 3 displays the posteriors of the covariance parameters for prior specification corresponding to $\kappa = 1/2$. However, the magnitude of the self-selection effect is once again better demonstrated with the calculated ATETs. Average treatment effects for the treated are calculated for PPO and HMO groups against the counterfactual FFS outcomes and their values and densities are reported in Table 3 and Figure 4 respectively. The self-selection biases range from $29 of EXCELLENT health group to $229 of the FAIRPOOR group for HMO individuals, and from $99 for the EXCELLENT group to $460 for the FAIRPOOR group for the PPO individuals. The treatment effects of HMO and PPO are significantly negative. That is, HMOs and PPOs do reduce inpatient expenditures relative to the FFS enrollees. The mean treatment effect of HMO enrollment is $63 while the corresponding effect of PPO enrollment is $95. As can be seen from the densities, for each treatment, there is substantially greater cost-savings than the mean saving for a significant proportion of the population. Put in the context that our sample consists of relatively healthy, insured and non-elderly individuals, these treatment effects make a strong case for managed care if health care cost-cutting is a primary policy goal.

6.3. Further Discussion of Results

We now briefly discuss some alternative modeling strategies along with our reasons for not pursuing them and some important data limitations. The unavailability of data on the price of insurance is a significant data limitation in our and similar other research. If such data were available, identification of the insurance choice parameters would be improved, and there would be less reason for relying on proxy variables. A second issue concerns alternative choices of exclusion restrictions for the identification of the impact of insurance. For example, employment characteristics are often used as identifying instruments. These may include the individual’s employment status (e.g., whether self-employed or employed in the government sector), the size of the firm in terms of the number of employees and whether it operates in multiple locations. Using employment characteristics as instruments for those who are covered by some type of insurance is appealing because characteristics of firms are known to be important determinants
of the supply of health plans available to individuals, as well as of the net price of the plans to the employees (Johnson and Crystal, 2000). We have explored these instruments in preliminary work but find the explanatory power of spousal characteristics to be far superior. Finally, it is important to note that HMO, PPO and FFS plan labels are very broad. There is considerable diversity within each plan label, which may be thought of as a source of measurement error. Unfortunately, without information on specific attributes of plans, it is impossible to go beyond an analysis of these broad categories of plans.

7. Concluding Remarks

We conclude by comparing our results with those from previous studies. Some previous research on this topic has indicated that HMO plans have lower hospital admission rates and lengths of stay and lower use of expensive tests and procedures (Glied, 2000; Table 3). Rapid growth of managed care population during the 1990s, with both healthy and unhealthy individuals entering the HMO and PPO population, may have changed the composition of the enrollees. Further, increased penetration of managed care plans appears to have affected local health care markets and hospital use. FFS plans may be encouraged to introduce cost control restrictions on hospital use to remain competitive.

Glied (2000, section 5) provides a textual and tabular survey of empirical findings on selection into managed care. Many of these studies differ from this study in one or two ways. First, they are often concerned with the impact of observable factors that determine selection into one of several managed care programs. The selection effect that we study concerns the differential impact of managed care plans, relative to fee-for-service plans, on total medical expenditures. Other major limitations of previous studies that are mentioned by Glied (2000, p. 732) are insufficient recognition of the heterogeneity among plans, and the potential lack of generalizability of the results because “studies rely on information from a small number of plans, providers, or employers”. Further, the utilization variables that are studied are diverse, e.g. total charges, admissions and length of stay in hospital, and number of visits, and consequently, “there is no consistent metric for measuring the effect of managed care”.

A number of previous studies have analyzed the issue of selection into managed care, but there are fewer studies that measure treatment effects controlling for the effects of selection. By
the way of comparison we note that selection studies have produced very mixed evidence, see Glied (2000, Table 2). For example, the RAND study found no evidence of selection. Goldman (1995) used a sample of military enrollees and reported evidence suggesting reverse selection. Hosek, Marquis, and Wells (1990) in their study based on data from five employers found slightly favorable selection into HMOs. Cutler and Reber (1998) also found some evidence of favorable selection into HMOs.
References


Table 1: Variable definition and summary statistics.

<table>
<thead>
<tr>
<th>Variable Type</th>
<th>Variable Description</th>
<th>mean</th>
<th>st. dev.</th>
</tr>
</thead>
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<tr>
<td>Expenditure</td>
<td>AMBEXP ambulatory expenditure</td>
<td>1207.9</td>
<td>2229.4</td>
</tr>
<tr>
<td></td>
<td>LNAMBEXP logarithm of ambulatory expenditure</td>
<td>5.369</td>
<td>2.709</td>
</tr>
<tr>
<td></td>
<td>DAMBEXP = 1 if AMBEXP &gt; 0</td>
<td>0.834</td>
<td>0.372</td>
</tr>
<tr>
<td></td>
<td>HOSPEXP inpatient expenditure</td>
<td>494.7</td>
<td>3643.5</td>
</tr>
<tr>
<td></td>
<td>LNHOSPEXP logarithm of inpatient expenditure</td>
<td>0.517</td>
<td>2.042</td>
</tr>
<tr>
<td></td>
<td>DHOSPEXP = 1 if HOSPEXP &gt; 0</td>
<td>0.061</td>
<td>0.240</td>
</tr>
<tr>
<td>Insurance plan types</td>
<td>PPO = 1 if plan has gatekeeper but is not an HMO</td>
<td>0.091</td>
<td>0.287</td>
</tr>
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<td></td>
<td>HMO = 1 if plan is an HMO</td>
<td>0.515</td>
<td>0.500</td>
</tr>
<tr>
<td></td>
<td>FFS = 1 if plan does not have a gatekeeper</td>
<td>0.395</td>
<td>0.489</td>
</tr>
<tr>
<td>Demographic characteristics</td>
<td>FAMSIZE family size</td>
<td>3.052</td>
<td>1.471</td>
</tr>
<tr>
<td></td>
<td>AGE age/10</td>
<td>4.041</td>
<td>1.101</td>
</tr>
<tr>
<td></td>
<td>EDUC years of schooling</td>
<td>13.467</td>
<td>2.548</td>
</tr>
<tr>
<td></td>
<td>INCOME $ income/1000</td>
<td>34.133</td>
<td>25.038</td>
</tr>
<tr>
<td></td>
<td>FEMALE = 1 if female</td>
<td>0.507</td>
<td>0.500</td>
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<tr>
<td></td>
<td>BLACK = 1 if black</td>
<td>0.126</td>
<td>0.332</td>
</tr>
<tr>
<td></td>
<td>HISPANIC = 1 if hispanic</td>
<td>0.162</td>
<td>0.369</td>
</tr>
<tr>
<td></td>
<td>MARRIED = 1 if married</td>
<td>0.662</td>
<td>0.473</td>
</tr>
<tr>
<td></td>
<td>NOREAST = 1 if northeast</td>
<td>0.178</td>
<td>0.383</td>
</tr>
<tr>
<td></td>
<td>MIDWEST = 1 if midwest</td>
<td>0.236</td>
<td>0.424</td>
</tr>
<tr>
<td></td>
<td>SOUTH = 1 if south</td>
<td>0.362</td>
<td>0.481</td>
</tr>
<tr>
<td></td>
<td>MSA = 1 if metropolitan statistical area</td>
<td>0.800</td>
<td>0.400</td>
</tr>
<tr>
<td></td>
<td>AG2 = AGE*AGE</td>
<td>17.542</td>
<td>9.133</td>
</tr>
<tr>
<td></td>
<td>AGEXFEM = AGE*FEMALE</td>
<td>2.056</td>
<td>2.174</td>
</tr>
<tr>
<td>Health characteristics</td>
<td>VEGOOD = 1 if very good health</td>
<td>0.373</td>
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<td></td>
<td>GOOD = 1 if good health</td>
<td>0.260</td>
<td>0.439</td>
</tr>
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<td></td>
<td>FAIRPOOR = 1 if fair or poor health</td>
<td>0.064</td>
<td>0.245</td>
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<tr>
<td></td>
<td>PHYSLIM = 1 if physical limitation</td>
<td>0.123</td>
<td>0.329</td>
</tr>
<tr>
<td></td>
<td>TOTCHR number of chronic conditions</td>
<td>0.512</td>
<td>0.791</td>
</tr>
<tr>
<td></td>
<td>INJURY = 1 if an injury</td>
<td>0.225</td>
<td>0.418</td>
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<td>Spouse characteristics</td>
<td>SPAGE age of spouse</td>
<td>2.743</td>
<td>2.193</td>
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<td>LAGSPPO = 1 if spouse’s plan the previous year was PPO</td>
<td>0.059</td>
<td>0.235</td>
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<td>LAGSPHMO = 1 if spouse’s plan the previous year was HMO</td>
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<td>Year dummies</td>
<td>YEAR98 = 1 if year 1998</td>
<td>0.166</td>
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<tr>
<td></td>
<td>YEAR99 = 1 if year 1999</td>
<td>0.162</td>
<td>0.368</td>
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<tr>
<td></td>
<td>YEAR00 = 1 if year 2000</td>
<td>0.207</td>
<td>0.405</td>
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<tr>
<td></td>
<td>YEAR01 = 1 if year 2001</td>
<td>0.163</td>
<td>0.369</td>
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Table 2. Ambulatory expenditure: ETPM parameter posterior means and standard deviations.

<table>
<thead>
<tr>
<th>Equation</th>
<th>Exp end</th>
<th>Hurdle</th>
<th>PPO</th>
<th>HMO</th>
<th>Exp end</th>
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<th>PPO</th>
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<td>CONST</td>
<td>4.490</td>
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<td>0.309</td>
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<td>0.007</td>
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Table 4. Inpatient expenditure. ETPM parameter posterior means and standard deviations.

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Figure 1
Densities of Covariance Parameters: Ambulatory Care

Figure 2
Density of Treatment Effects for Ambulatory Expenditures
Figure 3

Densities of Covariance Parameters: Hospital Care

Figure 4

Density of Treatment Effects for Inpatient Expenditures

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