A Bayesian Analysis of the OPES Model with a Non-parametric Component: Application to Dental Insurance and Dental Care

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Abstract

This paper analyzes the effect of dental insurance on utilization of general dentist services by adult US population aged from 25 to 64 years using the ordered probit model with endogenous selection (OPES). Our econometric framework accomm-dates endogeneity of insurance and the ordered nature of the measure of dental utilization. The study finds strong evidence of endogeneity of dental insurance to utilization and identifies interesting patterns of nonlinear dependencies between the dental insurance status and individual's age and income. The calculated average treatment effect supports the claim of adverse selection into the treated (insured) state and indicates a strong positive incentives effect of dental insurance.

1. Introduction

This paper analyzes the effect of dental insurance on utilization of general dentist services by adult US population, with the main focus on the role of dental insurance and income. The central research questions we confront are: What is the causal impact of dental insurance on dental use, differentiated by age and gender and what is the relationship between the probability to have dental insurance and income? In addition, we investigate the relationship between general medical insurance and income. The Markov Chain Monte Carlo (MCMC) methods are used to estimate the posterior distribution of the parameters and treatment effects.

Compared with general medical insurance the problem of endogeneity has not been properly addressed in the dental insurance literature. This is surprising given the fact that there are some specific features of dental insurance that make it econometrically easier to identify its pure treatment effects. The levels of risks against which dental insurance provides coverage are much lower than those of general medical insurance. The amount of dental coverage is usually limited and the dental coinsurance rates are much higher. As a result the US population is almost evenly split between those with and without dental insurance coverage. In the case of general medical insurance only about 15 percent of the US population is uninsured, a variation with a relatively low signal-to-noise ratio, which makes it potentially difficult to identify the treatment effects.

One direct and commonly used impact measure is the average difference in the number of dental visits by those with dental insurance and those without. This is a valid measure for data from clinical trials with random assignment to treatment, but for observational data it is not. This is because the measured difference has two components consisting of the "pure" effect of insurance incentives and the added sample selection effect. Indeed, the selection problem can be ignored when the studied data come from a well-designed social experiment in which the insurance status is randomly assigned such as in the work published by the Rand Health Insurance Experiment Group (Manning et. al, 1984, 1985). However, most empirical studies including ours are based on observational data. The sample selection effect arises because individuals are not randomly assigned to treatment, but are self-selected, in the sense that one can choose not to have insurance. Individuals make dental insurance choices based on personal characteristics and plan features. Some of these can be observed and measured but the others are not measurable. Therefore, whether or not employer offers a choice of dental insurance plans is irrelevant to the existence of the sample selection. Failure to statistically control for the effect of the unobservables when they also affect the outcome equation leads to the problem of endogeneity, generates a bias in estimates of treatment effect that is akin to the omitted variable bias, which may be positive, negative, or zero. The selection effect may be positive, negative, or zero. A positive selection effect means adverse selection and a negative one means advantageous selection. Hence ignoring it can result in biased estimates of the effect of insurance on service use. Causal models, of the type proposed in this project, attempt to separate these two components; this entails greater conceptual and computational complexity in estimation of models. By contrast, statistically simpler models of association are easier to handle but cannot identify the key parameters of interest in an economic analysis.

Economic theory predicts that risk-averse individuals prefer to purchase insurance against catastrophic or simply costly evens because they value eliminating risk more than money at sufficiently high wealth levels. This is modeled by assuming that a risk-averse individual's utility is a monotonically increasing function of wealth with diminishing marginal returns. This is certainly true for general medical insurance when liabilities could easily exceed any reasonable levels. However, in the context of dental insurance the potential losses have reasonable bounds with the least desirable but nevertheless cheapest prospect of simply loosing a tooth, which is not life threatening. It is interesting to see if there is a nonlinear relationship between dental insurance and wealth and whether this relationship is monotonic. We also estimate the relationship between general medical insurance and wealth to see whether out findings are consistent with economic theory. Our estimation approach allows income to enter the insurance equation nonparametrically. However, as a baseline model we try a parametric specification of the insurance equation with income dummies representing 20 income groups. These groups are formed by first sorting the sample with respect to income and then evenly dividing it into 20 groups and representing each group with a dummy variable.

The incentives effect of dental insurance should be positive since the economic theory predicts that when the out-of-pocket share of the cost is reduced the level of utilization increases. However, it is not clear what the sign and magnitude of the selection effect are. It is expected that less healthy with respect to dental health individuals self-select to purchase dental insurance. Therefore the unobservable dental health status is one of the driving forces behind the selection process which also affects utilization. On the other hand, more risk-averse people are likely to purchase dental insurance. More risk-averse people should also have more sound dental health life-time habits which drives the level of utilization down. It is a matter of empirical investigation to identify the actual direction and level of self-selection.

This paper finds strong evidence of diminishing marginal returns of our measure of wealth on dental insurance status and even a non-monotonic pattern. Additionally, we identify a non-monotonic relationship between age and dental insurance status and utilization and find evidence of different gender dental utilization patterns. The estimated treatment effects support the claim of adverse selection of possibly less healthy with respect to dental health individuals into the insured (treated) state. The rest of the paper is organized as follows. Section 2 reviews the literature related to the effect of dental insurance on utilization. Section 3 describes the model, selects priors and outlines the MCMC estimation procedure. Section 4 describes the data, deals with an application and discusses the results. Section 5 concludes.

2. Background and literature review

Following experimental literature, we interpret the purchase of dental insurance as a "treatment", and non-purchase as "control". Then a useful, though crude, measure of the impact of insurance on a suitable measure of use of dental care such as number of general dental visits, is the average difference in the number of visits between those with and those without dental insurance. Generically we refer to such measures of impact as "average treatment effects". In estimating treatment effects, controlling for the presence of systematic observed and unobserved differences between those with and those without insurance poses a challenge. A multivariate regression model, which controls for observed differences, is still potentially flawed because it fails to account for mutual dependence between insurance status and use of dental services. There are several established methodologies for capturing the effects of sample selection. One is to include in the utilization equation all factors that can capture the effects of sample selection. Data limitations usually cannot guarantee such a degree of control because some determinants of selection bias are unobserved and hence cannot be controlled for. These omitted factors include personal preferences, tastes, habits, knowledge of and attitudes towards health risks.

2.1. Models of insurance

In sharp contrast to the published research on dental care use, there are relatively few studies that model the choice of private dental insurance, e.g. Manski et al. (2004). This is so despite the fact that the proportion of uninsured adult non-Medicare population is close to half, and hence much higher than that for general health insurance. On the other hand, the consequences of this high uninsured rate are generally not perceived to be as severe as those due to lack of health insurance. Employer-sponsored private dental coverage offered by some employers is the principal source of insurance. Models similar to those for health insurance choice therefore provide a natural starting point for a modeling exercise.

2.2. Models of utilization

A recent comprehensive survey of the economics of dental services from an international perspective is Sintonen and Linnosmaa (2000). Like much of related literature, their article emphasizes modeling individual's demand for dental care as measured by either the number (count) of dental visits or the total dental expenditure on dental care. Both measures have been widely used; some studies that use the count measure include: Manning and Phelps (1979) who used RHIE data; Rosenqvist et al. (1995), Arinen et al (1996), Melkersson and Olssen (1999), Olssen (1999), who use Swedish cross section data. Empirical analyses based on dental care expenditure data include: Manning et al. (1985) using RHIE data; Conrad et al. (1987), Mueller and Monheit (1988), and Manski, Macek, and Mueller (2002) using US data; Grytten et al. (1996) using Norwegian data; and Sintonen and Maljanen (1995) using Finnish data. Manski et al. (2004) model the probability of a dental visit conditional on insurance status. By standard economic theory, reduction in out-of-pocket costs of care due to insurance will increase utilization. Therefore, a positive association between utilization and insurance status is expected. Several US studies cited above confirm such a relationship (Manski et al., 2002). Potentially, however, these results are subject to sample selection bias of unknown magnitude. In observational studies the recorded insurance status will generally reflect the optimizing behavior of a consumer. If, as seems reasonable, there exist factors (typically unmeasured in the data) such as health habits, genetic proclivities, and oral health status, that are known to individuals, and that are likely to affect future dental care utilization, optimizing individuals will take them into account when insurance is purchased. Indeed, adverse selection considerations suggest that those purchasing dental insurance may well be less healthy on average than those who do not. As a consequence, we expect that dental insurance status and utilization will be interdependent. Sintonen and Linnosmaa (2000: p. 1273) have observed that, with some notable exceptions, "...little attention has been paid to the effect of model specification and estimation techniques in dental utilization studies, or to examining whether the distributional assumptions of the model are met".

2.3. Dental insurance and utilization in the USA

Some well established basic facts about dental insurance and utilization include the following.

1. During the last four decades, the coverage of dental insurance has increased steadily. Currently many health plans are expanding dental benefits and providing additional incentives for preventive dental services, amid evidence that it improves overall health (Wall Street Journal, September 19, 2006). In 1996 the private coverage was 51.2% overall; only 6.8% of those with Medicaid had dental insurance. According to the Report of the Surgeon General, private dental care benefits are available to most full-time employees in medium-sized and large businesses, either as part of a comprehensive medical and dental plan or as a separate plan. Firms often offer employees a choice of medical plans plus a dental plan,

or a dental plan that can supplement any medical plan. Employer sponsorship of dental plans is changing with the expansion of managed care and rising medical costs, see Bailit (1999). Most participants in employer-sponsored dental plans receive insurance reimbursements on a fee-for-service basis, typically by type of service performed. Coinsurance rates are typically higher than those for medical care. The coverage typically includes dental examinations, sealants, radiographs, and prophylaxes. Restorative procedures such as restorations are more commonly covered than crowns. Orthodontic care coverage is less common, and when provided may be limited to dependent children and up to set maximums. Implants and cosmetic procedures are usually not covered.

2. Certain populations, e.g. African Americans and Hispanics, register significantly lower rates of dental insurance coverage. They also seek dental care less often. The relative importance of economic and non-economic factors as determinants of utilization is a topic of continuing research (Gilbert et. al, 2002).

3. Dental insurance is a strong predictor of access to care. Those with dental insurance had on average 2.65 visits and those without insurance had 2.42 visits, the difference being statistically significant. The average total dental expenditure for those with insurance was $417 vs. $299 for those without. Similar differentials between the insured and the uninsured persist in more detailed comparisons by various demographic characteristics; see Cohen et al. (2002, 2003). The percentage of population with at least one annual visit to the dentist was 56.6% among the privately insured, and 28.6% among the uninsured. In the year 2000, private health insurance accounted for 42% of the total dental care expenses, and out-of-pocket payments accounted for 49.3%.

4. The positive impact of insurance on utilization persists even in a regression analysis that controls for other socioeconomic determinants of utilization; see Manski (2001a, 2001b). Recent studies do not control for sample selection, but the Rand Health Insurance Experiment (RHIE) used randomized assignment to insurance plan. However, the RHIE studies are more than 20 years old. In the interim, con-

siderable changes have occurred in the proportion of Americans undergoing regular dental visits (www.nidr.nih.gov/sgr/sgrohweb/chap4.htm), losing teeth (Douglas et al., 2002), and enjoying dental insurance coverage (Bailit, 1999). Not only the composition of dental services has changed over time, but it is likely to continue to suffer transformations (Anderson, 2005) – in part as a response to evolving healthcare insurance and markets, as well as living standards and affordability (Macek et al., 2004), but also as a result of paradigm shifts in the understanding of common oral diseases, such as periodontitis (Papapanou, 1999).

3. Econometric framework

This section will outline our ordered probit model with endogenous selection (OPES) through which we will study the effect of dental insurance on the demand for general dentist services.

3.1. The model

Assume that we observe N independent observations for individuals who choose whether to purchase dental insurance. Let d_i be the binary random variable ($i = 1, ..., N$) representing this choice such that $d_i = 1$ if dental insurance is purchased and $d_i = 0$ otherwise. Define this binary choice using the random utility approach which specifies a latent variable representing the gain in utility received from having dental insurance relative to the alternative. To allow for income to enter it nonparametrically we follow recent work on Bayesian semiparametric techniques by Koop and Poirier (2004) and Koop and Tobias (2006) and building on the Bayesian treatment of the ordered probit model with endogenous selection by Munkin and Trivedi (2007). Let the insurance equation be specified as

$$Z_i = f(s_i) + \mathbf{W}_i\boldsymbol{\alpha} + \varepsilon_i, \tag{3.1}$$

where $\mathbf{W}_i$ is a vector of regressors, $\boldsymbol{\alpha}$ is a conformable vector of parameters, and the distribution of the error term ε_i is $\mathcal{N}(0, 1)$. Function $f(.)$ is unknown and s_i is income of individual i and parameter $\boldsymbol{\alpha}$ does not include an intercept. The recorded income variable takes almost the same number of different values as the number of observations, which potentially leads to the problem of too many parameters. It seems reasonable that the probability of purchasing dental insurance will not change much for small increments in income. We try two roundings of the income variable: up to a thousand and a hundred dollars. This gives us $k_\gamma = 254$ and $k_\gamma = 1626$ different values out of $N = 19,911$ respectively. We sort the data by values of s so that s_1 is the lowest level of income (in our data set it is zero) and s_N is the largest. The main assumption that we make on function $f(.)$ is that it is smooth such that its slope does not change too fast.

Then the treatment variable is defined as

$$d_i = I_{[0,+\infty)}\left(Z_i\right),$$

where $I_{[0,+\infty)}$ is the indicator function for the set $[0,+\infty)$.

To model the ordered dependent variable we assume that there is another latent variable Y_i^* that depends on the outcomes of d_i such that

$$Y_i^* = \mathbf{X}_i\boldsymbol{\beta} + d_i\rho + u_i$$

where $\mathbf{X}_i$ is a vector of exogenous regressors, $\boldsymbol{\beta}$ and ρ are conformable parameter vectors. Define Y_i, an ordered variable measuring the degree of dental service utilization as

$$Y_i = \sum_{m=1}^{M} m I_{[\tau_{m-1},\tau_m)}\left(Y_i^*\right)$$

where τ_0, τ_1, ...,τ_M are threshold parameters and $m = 1, ..., M$. For identification, we restrict $\tau_0 = -\infty$, $\tau_1 = 0$ and $\tau_M = \infty$.

The dental insurance variable is potentially endogenous to utilization and this endogeneity is modeled through correlation between u_i and ε_i. Assume that they are jointly normally distributed with the covariance $cov(u_i, \varepsilon_i) = \delta$. Assume that $Var\left(u_i\right) = 1 + \delta^2$ (or stated conditionally $Var\left(u_i|\varepsilon_i\right) = 1$), a restriction made for identification since Y_i^* is latent. Then the model can be rewritten as

$$Y_i^* = \mathbf{X}_i\boldsymbol{\beta} + d_i\rho + \varepsilon_i\delta + \zeta_i$$

where

$$\begin{pmatrix} \zeta_i \\ \varepsilon_i \end{pmatrix} \overset{i.i.d.}{\sim} \mathcal{N}\left(0, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right).$$

This representation can be interpreted as follows. Endogeneity of dental insurance is generated by latent factors not controlled for in both the dental insurance and utilization equations. Once the unexplained utility generated from dental insurance, variable ε_i, is included in the outcome equation the remaining random error ζ_i is uncorrelated with the dental insurance variable such that $\mathrm{E}(\zeta_i|d_i) = 0$.

3.2. The priors

Stacking (3.1) over i we obtain

$$\mathbf{Z} = \mathbf{P}\boldsymbol{\gamma} + \mathbf{W}\boldsymbol{\alpha} + \boldsymbol{\varepsilon},$$

where

$$\boldsymbol{\gamma} = \begin{bmatrix} f(s_1) \\ f(s_2) \\ \dots \\ f(s_N) \end{bmatrix},$$

and $\mathbf{P}$ is an $N \times k_\gamma$ matrix constructed to select the appropriate element of γ for each observation i.

Define an $k_\gamma \times k_\gamma$ matrix $\mathbf{R}$ such that $\boldsymbol{\psi} = \mathbf{R}\boldsymbol{\gamma}$ is a vector of slope changes of function $f(.)$,

$$\psi_j = \frac{\gamma_j - \gamma_{j-1}}{s_j - s_{j-1}} - \frac{\gamma_{j-1} - \gamma_{j-2}}{s_{j-1} - s_{j-2}}, \quad j = 3, ..., k_\gamma,$$

and the first two elements are simply $\psi_1 = f(s_1)$ and $\psi_2 = f(s_2)$. Then

$$\mathbf{Z} = \mathbf{P}\mathbf{R}^{-1}\boldsymbol{\psi} + \mathbf{W}\boldsymbol{\alpha} + \boldsymbol{\varepsilon},$$

and we place a flat prior on (ψ_1, ψ_2) as $\mathcal{N}(\mathbf{0}_2, \mathbf{I}_2)$ and an informative prior for the rest of the parameter vector

$$\psi_j \sim \mathcal{N}(0, \eta), \quad j = 3, ..., k_\gamma.$$

where

$$\eta \sim G(a, b),$$

with $a = 3$ and $b = 10^6$.

We select proper prior distributions for parameters. $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ and ρ

$$\boldsymbol{\alpha} \sim \mathcal{N}\left(\mathbf{0}, 10\mathbf{I}_k\right), \ \boldsymbol{\beta} \sim \mathcal{N}\left(\mathbf{0}, 10\mathbf{I}_p\right), \ \rho \sim \mathcal{N}\left(0, 10\right).$$

For the covariances between the error ε_i and the error u_i, we select prior distributions

$$\delta \sim \mathcal{N}\left(0, 1/2\right)$$

The priors for the threshold parameters $\boldsymbol{\tau} = (\tau_2, ..., \tau_{M-1})$ must respect the order restrictions placed on them. It is easier to choose priors by reparameterizing these parameters first which we do in the next subsection.

3.3. The MCMC algorithm

Let $\Delta_i = (\mathbf{X}_i, \mathbf{W}_i, \boldsymbol{\psi}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \rho, \delta, \boldsymbol{\tau})$, and denote $\mathbf{P}_i$ the i^{th} row of matrix $\mathbf{P}$. For each observation i the likelihood is

$$\begin{aligned}
\Pr[Y_i, Y_i^*, d_i, Z_i | \Delta_i] &= (2\pi)^{-1/2} \exp\left[-0.5\left(Z_i - \mathbf{P}_i\mathbf{R}^{-1}\boldsymbol{\psi} - \mathbf{W}_i\boldsymbol{\alpha}\right)^2\right] \\
&\times \left[d_i I_{[0,+\infty)}\left(Z_i\right) + \left(1 - d_i\right) I_{(-\infty,0)}\left(Z_i\right)\right] \\
&\times \left[\sum_{m=1}^{M} I_{\{Y_i = m\}} I_{[\tau_{m-1}, \tau_m)}\left(Y_i^*\right)\right] \\
&\times \exp\left[-0.5\left(Y_i^* - \left(\mathbf{X}_i\boldsymbol{\beta} + d_i\rho + \left(Z_i - \mathbf{P}_i\mathbf{R}^{-1}\boldsymbol{\psi} - \mathbf{W}_i\boldsymbol{\alpha}\right)\delta\right)\right)^2\right]
\end{aligned}$$

The joint distribution for all observations is the product of such $\mathcal{N}$ independent observations 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.

We block the parameter set as Z_i, $\left[Y_i^*, \boldsymbol{\tau}\right]$, $[\boldsymbol{\psi}, \boldsymbol{\alpha}]$ and $[\boldsymbol{\beta}, \rho, \delta]$ and adopt a hybrid Metropolis-Hastings/Gibbs algorithm. The steps of the MCMC algorithm are the following:

1. The latent vectors Z_i $(i = 1, ...N)$ are conditionally independent with bivariate normal distribution $Z_i \overset{iid}{\sim} \mathcal{N}\left[\overline{Z}_i, \overline{H_i}^{-1}\right]$ where

$$\overline{H_i} = 1 + \delta^2, \ \overline{Z}_i = \mathbf{P}_i\mathbf{R}^{-1}\boldsymbol{\psi} - \mathbf{W}_i\boldsymbol{\alpha} + \overline{H_i}^{-1}\left[\delta\left(Y_i^* - \mathbf{X}_i\boldsymbol{\beta} - d_i\rho\right)\right]$$

and subject to

$$\begin{aligned} Z_{ji} &\geqslant 0 \text{ if } d_{ji} = 1 \text{ and} \\ Z_{ji} &< 0 \text{ if } d_{ji} = 0. \end{aligned}$$

2. The full joint conditional density of block $[Y_i^*, \boldsymbol{\tau}]$ is

$$\begin{aligned} \Pr[Y_i^*, \boldsymbol{\tau} | Z_i, \boldsymbol{\beta}, \rho, \delta, \boldsymbol{\psi}, \boldsymbol{\alpha}] &= \\ & \prod_{i=1}^{N} \left[\sum_{m=1}^{M} I_{\{Y_i = m\}} I_{[\tau_{m-1}, \tau_m)} (Y_i^*) \right] \\ & \times \exp \left[-0.5 \left(Y_i^* - \left(\mathbf{X}_i \boldsymbol{\beta} + d_i \rho + \left(Z_i - \mathbf{P}_i \mathbf{R}^{-1} \boldsymbol{\psi} - \mathbf{W}_i \boldsymbol{\alpha} \right) \delta \right) \right)^2 \right], \end{aligned}$$

which we write as

$$\Pr[Y_i^*, \boldsymbol{\tau} | Z_i, \boldsymbol{\beta}, \rho, \delta, \boldsymbol{\psi}, \boldsymbol{\alpha}] = \Pr[[Y_i^* | \boldsymbol{\tau}, Z_i, \boldsymbol{\beta}, \rho, \delta, \boldsymbol{\psi}, \boldsymbol{\alpha}]] \Pr[\boldsymbol{\tau} | Z_i, \boldsymbol{\beta}, \rho, \delta, \boldsymbol{\psi}, \boldsymbol{\alpha}].$$

Latent variable Y_i^* is $\mathcal{N}\left[\mathbf{X}_i \boldsymbol{\beta} + d_i \rho + \left(Z_i - \mathbf{P}_i \mathbf{R}^{-1} \boldsymbol{\psi} - \mathbf{W}_i \boldsymbol{\alpha} \right) \delta, 1 \right]$ and truncated on the left and right. Conditional on $Y_i = m$ it is truncated on left by τ_{m-1} and on the right by τ_m. The full conditional density of vector $\boldsymbol{\tau} = (\tau_2, ..., \tau_{M-1})$ is

$$\prod_{i=1}^{N} \left[\sum_{m=1}^{M} I_{\{Y_i = m\}} \Pr(\tau_{m-1} < Y_i^* < \tau_m | \Delta_i, d_i, Z_i) \right]$$

where

$$\begin{aligned} \Pr(\tau_{m-1} < Y_i^* < \tau_m | \Delta_i, d_i, Z_i) &= \\ & \Phi\left(\tau_m - (\mathbf{X}_i \boldsymbol{\beta} + d_i \rho + \left(Z_i - \mathbf{P}_i \mathbf{R}^{-1} \boldsymbol{\psi} - \mathbf{W}_i \boldsymbol{\alpha} \right) \delta) \right) \\ & - \Phi\left(\tau_{m-1} - (\mathbf{X}_i \boldsymbol{\beta} + d_i \rho + \left(Z_i - \mathbf{P}_i \mathbf{R}^{-1} \boldsymbol{\psi} - \mathbf{W}_i \boldsymbol{\alpha} \right) \delta) \right) \end{aligned} \tag{3.2}$$

Since the elements of vector $\boldsymbol{\tau}$ are ordered the prior assigned to the threshold parameters must be restricted. Instead, we follow Chib and Hamilton (2000) and reparameterize them as

$$\gamma_2 = \log(\tau_2), \ \gamma_j = \log(\tau_j - \tau_{j-1}), \ 3 \leqslant j < M - 1$$

and assign a normal prior $\mathcal{N}(\boldsymbol{\gamma}_0, \boldsymbol{\Gamma}_0)$ without any restrictions since elements of vector $\boldsymbol{\gamma} = (\gamma_2, ..., \gamma_{M-1})$ do not have to be ordered. The full conditional for vector $\boldsymbol{\gamma}$ is the product of the prior and the full conditional (**??**) after substituting

$$\tau_j = \sum_{k=2}^{j} \exp(\gamma_k).$$

This density is intractable and we utilize the Metropolis-Hastings algorithm to sample from it, using t-distribution centered at the modal value of the full conditional density for the proposal density. Let

$$\widehat{\boldsymbol{\gamma}} = \arg\max \log p(\boldsymbol{\gamma}|\Delta_i, d_i, Z_i)$$

and $V_{\widehat{\gamma}} = -(H_{\widehat{\gamma}})^{-1}$ be the negative inverse of the Hessian of $\log p(\boldsymbol{\gamma}|\Delta_i, d_i, Z_i)$ evaluated at the mode $\widehat{\boldsymbol{\gamma}}$. Choose the proposal distribution $q(\boldsymbol{\gamma}) = f_T(\boldsymbol{\gamma}|\widehat{\boldsymbol{\gamma}}, \varphi V_{\widehat{\gamma}}, \upsilon)$, a t-distribution with υ degrees of freedom and tuning parameter φ, an adjustable constant selected to obtain reasonable acceptance rates. When a proposal value $\boldsymbol{\gamma}^*$ is drawn the chain moves to the proposal value with probability

$$\Pr(\boldsymbol{\gamma}, \boldsymbol{\gamma}^*) = \min\left\{\frac{p(\boldsymbol{\gamma}^*|\Delta_i, d_i, Z_i)\, q(\boldsymbol{\gamma})}{p(\boldsymbol{\gamma}|\Delta_i, d_i, Z_i)\, q(\boldsymbol{\gamma}^*)}, 1\right\}.$$

If the proposal value is rejected then the next state of the chain is at the current value $\boldsymbol{\gamma}$.

3. Let the prior distributions of $\boldsymbol{\psi}$ be $\mathcal{N}\left[\underline{\boldsymbol{\psi}}, \underline{\mathbf{H}}_{\psi}^{-1}\right]$ and $\boldsymbol{\alpha}$ be $\mathcal{N}\left[\underline{\boldsymbol{\alpha}}, \underline{\mathbf{H}}_{\alpha}^{-1}\right]$. Denote $\mathbf{G}_i = \left(\mathbf{P}_i\mathbf{R}^{-1}, \mathbf{W}_i\right)$, $\boldsymbol{\theta}' = \left(\boldsymbol{\psi}', \boldsymbol{\alpha}\right)$ with the prior distribution $\mathcal{N}\left[\underline{\boldsymbol{\theta}}, \underline{\mathbf{H}}_{\theta}^{-1}\right]$. Then the full conditional distribution of $\boldsymbol{\theta}$ is $\mathcal{N}\left[\overline{\boldsymbol{\theta}}, \overline{\mathbf{H}}_{\theta}^{-1}\right]$ where

$$\begin{aligned}
\overline{\mathbf{H}}_{\theta} &= \underline{\mathbf{H}}_{\theta} + \sum_{i=1}^{N} \mathbf{G}_i' \left(1 + \delta^2\right) \mathbf{G}_i \\
\overline{\boldsymbol{\theta}} &= \overline{\mathbf{H}}_{\theta}^{-1} [\underline{\mathbf{H}}_{\theta}\underline{\boldsymbol{\theta}} + \sum_{i=1}^{N} \{\mathbf{G}_i' \left(1 + \delta^2\right) Z_i \\
&\quad - \mathbf{G}_i'\delta\left(Y_i^* - \mathbf{X}_i\boldsymbol{\beta} - d_i\rho\right)\}].
\end{aligned}$$

4. Let $\mathbf{C}_i = (\mathbf{X}_i, d_i, (Z_i - \mathbf{P}_i\mathbf{R}^{-1}\boldsymbol{\psi} - \mathbf{W}_i\boldsymbol{\alpha}))$, $\boldsymbol{\chi}' = (\boldsymbol{\beta}', \rho, \delta)$ and denote the prior distribution $\boldsymbol{\chi} \sim \mathcal{N}\left[\underline{\boldsymbol{\chi}}, \underline{\mathbf{H}}_{\chi}^{-1}\right]$. The full conditional distribution of $\boldsymbol{\chi}$ is $\mathcal{N}\left[\overline{\boldsymbol{\chi}}, \overline{\mathbf{H}}_{\chi}^{-1}\right]$ where

$$\begin{aligned}\overline{\mathbf{H}}_{\chi} &= \underline{\mathbf{H}}_{\chi} + \sum_{i=1}^{N} \mathbf{C}_i'\mathbf{C}_i \\ \overline{\theta} &= \overline{\mathbf{H}}_{\chi}^{-1}\left[\underline{\mathbf{H}}_{\chi}\underline{\boldsymbol{\chi}} + \sum_{i=1}^{N} \mathbf{C}_i' Y_i^*\right]\end{aligned}$$

5. Finally,

$$\eta \sim IG\left(\frac{k_\gamma - 2}{2} + a, \left(b^{-1} + \frac{1}{2}\sum_{i=3}^{k_\gamma}\psi_j^2\right)^{-1}\right).$$

This concludes the MCMC algorithm.

4. Application

Following Grossman's (1972) seminal work, dental care, personal characteristics, and oral health practices are viewed by health economists as an input into a production process whose output is oral health. The inputs in the health production are determined partly by economic constraints. For example, the decision to seek dental care will partly depend upon having dental insurance. Having dental insurance is an economic decision which in turn can be modeled using demographic factors, personal health characteristics, cost of insurance and family income.

In reality oral health, dental insurance and dental utilization are intertemporally linked. For example: private investments made through preventive care or sound health habits during childhood will yield returns later in life; a past history of poor oral health may cause purchase of insurance and subsequent greater use of dental care. One needs good quality longitudinal data to model such dynamic interdependencies, especially that between dental care use and oral health. But as in much existing empirical work we only have available individual level cross sectional data, resulting in a limited empirical analysis. Another limitation of the data base that we use is that it does not have any measures of oral health or a measure of individual wealth. Instead of wealth we use the annual total income, which includes both wage and non-wage sources.

4.1. Identification strategy

An important element of our identification strategy is the utilized instrumental variable or an exclusion restriction, a variable that affects the dental insurance choice but not the utilization. We propose to use the size of the firm where the individuals are employed. For that matter we study only employed population of the US. However, there is a great degree of heterogeneity in availability of dental benefits among the employed. Since self-employed individuals are likely to have different dental insurance choices we delete them from the simple. Further, we restrict our sample to only privately employed individuals. Governmental jobs are known to be more generous in providing insurance benefits. Additionally, individuals might choose governmental jobs for the benefit reasons which makes the firm size potentially endogenous since governmental firms tend to be larger in size. Even though this arguments is usually used in regards to general medical insurance it might still be valid for dental insurance. Firm size should not affect utilization but it should affect availability of dental benefits with larger firms more likely to offer such benefits. The restricted sample reduces a possibility for our instrument to fail as being strictly exogenous, however, it does not eliminate such a possibility entirely. We decide to rely on this instrument because of its robustness as a predictor of dental insurance, and because there is no measurable impact on general dentist visits. The instrument has also been used in health literature before (Bhattacharya, Goldman, and Sood (2003); Johnson and Crystal (2000); and Olson (2002); Deb, Munkin and Trivedi (2006)).

4.2. Data

The application section investigates the effect of dental insurance on a measure of the demand for dental services by the U.S. population between the ages of 25 and 64 years using data from the Medical Expenditure Panel Survey (MEPS). Specifically, we look at the number of general dentist visits. The sample does not include children and young adults since their utilization patterns are likely to be completely different from those of the adult non-elderly population. MEPS is a nationally representative survey of health care use including dental, expenditure, sources of payment and insurance coverage for the US civilian non-institutionalized population, and it is publicly available at the Agency for Health care Research and Quality (AHRQ). We use data from the 1996, 1997, 1998, 1999 and 2000 surveys and restrict our sample to only those who are employed by private firms but not self-employed. The sampling scheme of the MEPS data is a two-year overlapping panel, i.e., in each calendar year after the first survey year, one sample of persons is in its second year of responses while another sample of persons is in its first year of responses. To avoid panel and clustering issues, we only use observations on "new" survey respondents in each year. The final sample size is 19,911.

Tables 1 gives a summary statistics of all variables used in our analysis. Table 2 describes the distribution of the general dentist visit variable up to cell 6. Since it is not feasible to estimate threshold parameters for very slim cells we combine all observations of at least 6 visits into the last cell, making sure that there is at least one percent of the whole sample (200 observations) in all cells. It can be seen that the dependent variable has a substantial (greater than 62 percent) share of zero utilization. The maximum number of visits in the original variable is 28. The distribution has a short tail. This utilization pattern justifies our use of the ordered probit framework since it is hard to expect that even mean preserving transformations of the Poisson model allowing for overdispersion would fit such a pattern well. The model has five threshold parameters to estimate.

Table 2 also presents the distribution of the dependent variable by dental insurance. The no insurance group has a larger portion of zeroes, but it also has a shorter tail. If the assignment of dental insurance were random then one would expect that the group means are not significantly different from each other. The Pearson test statistic for categorical independence produces $\chi^2(6) = 959$ ($p < 0.0001$). This gives a strong signal that the assignment of dental insurance is non-random and, therefore, a full investigation of the problem permitting endogeneity of insurance status is needed.

Table 3 gives the distribution of self-reported health status with respect to dental insurance. The adverse selection arguments support the claim that less healthy individuals are more likely to self-select themselves into being insured. However, the frequencies presented in Table 3 tell the opposite story. The dental insured group appears to look more healthy with respect to the general health status (not dental health) than the uninsured one. This seems to favor the possibility that the main driving force behind the selection process is risk preferences and not the underlined health status with more risk-averse people choosing to purchase dental insurance. Being risk-averse has made them healthier than their less risk-averse counterparts. On the other hand, it is not clear how general health status is correlated with dental health. We perform the formal Pearson test for categorical independence which produces $\chi^2(3) = 196$ ($p < 0.0001$) rejecting the null hypothesis of categorical independence.

The covariate vector X consists of self-perceived health status variables VEGOOD, GOOD, FAIRPOOR, measures of chronic diseases and physical limitation, TOTCHR and PHYSLIM, respectively, geographical variables NOREAST, MIDWEST, SOUTH and MSA, demographic variables BLACK, HISPANIC, FAMSIZE, FEMALE, MARRIED, EDUC, AGE and additional variables AGEX2, AGEXFEM which are defined as the square of AGE and product of AGE and FEMALE respectively, year dummies YEAR97, YEAR98, YEAR99, YEAR00, economic variable INCOME and insurance variable DENTAL. The insurance equation includes all variables included in X, except for the dental insurance dummy, income and the age related variables, plus an additional variable, FIRMSIZE, our exclusion restriction. The exclusion restriction serves to identify the correlation between the insurance equation and the dependent variable.

As a baseline model we estimate a spline regression in which vector $\mathbf{W}$ contains INCOME dummies constructed to capture the effects of these variables for different income categories in the following way. We divide all individuals in the sample into 20 income groups according to percentiles based on 5 percent increments and include nineteen income dummies in the insurance equation omitting the dummy related to the first income group ($\leqslant 5\%$). This makes it roughly 995 observations per category. The semiparametric model corresponding to $k_\gamma = 254$ is estimated next in which we allow INCOME to enter the insurance equation nonparametrically.

Additionally, we divide our sample into 8 age categories for the ages from 25 to 64 years with each group including 5 years and include 7 age dummies in the insurance equation. This should allow one to see how the probability of purchasing dental insurance changes with the age dummies.

4.3. Results

We estimate the two specifications of the ordered probit model with endogenous selection for the number of general dentist visits corresponding to our different treatments of INCOME variable in the insurance equation. It happens that the posterior distributions of all parameters not related to INCOME and including the treatment effects and predicted frequencies, are practically identical for both specifications and, therefore, we report posterior means and standard deviations of parameters $\boldsymbol{\beta}$, $\boldsymbol{\alpha}$, ρ, δ and $\boldsymbol{\tau}$ in Table 4 only for the specification corresponding to the spline regression. The results are based on Markov chains run for 10,000 replications after discarding first 1000 draws of the burn-in-phase. We collect every 10^{th} iteration discarding the rest. The Markov chains have good mixing properties with autocorrelation functions of the chain dying-off after 1-2 lags for all parameters. The predicted cell probabilities are given in Table 2. The model does a very accurate job in predicting these probabilities. This level of precision is difficult to achieve with Poisson-based models.

It is interesting to notice that health status indicators GOOD and FAIRPOOR have strong negative impacts on dental insurance with worsening health conditions decreasing the probability of having dental insurance. Alternatively, this can be interpreted as individuals with better health status are more likely to have dental coverage. At the same time the number of chronic conditions increases the probability of purchasing dental insurance and the indicator of physical limitations has no impact. However, the health indicators, except for TOTCHR, have no impact on utilization which supports the claim that general health status is not strongly correlated with dental health.

Education, being female and married increase both the probability of being insured and the level of utilization. It is interesting that blacks are more likely to have dental coverage and at the same time are less likely to see a general dentist. Living in a metropolitan statistical area increases the likelihood of dental coverage perhaps because of more choices available to the non-rural population. Family size and HISPANIC are the only variables the impacts of which are strong and negative both on the utilization and insurance variables.

4.3.1. Role of age

The impact of the AGE dummies shows a nonlinear relationship between age and dental insurance coverage as expected. For relatively younger individuals the probability of being insured increases with age (AGE35, AGE40 and AGE50) but then for older patients the effect of age on dental insurance becomes negative (AGE60 and AGE65) and much stronger in magnitude. Dental insurance seems to be a less desirable good for older near elderly adults. As a comparison exercise we estimate the model including AGE variable itself assuming a linear form. As a result we find a negative impact of age on dental insurance. Even though the true relationship is non-monotonic the overall effect of age is dominated by the negative impact of that for the near elderly. This shows the importance of allowing for nonlinear dependence.

The interaction term AGEXFEM has a strong negative impact which indicates that, indeed, there are different gender patterns of aging and its impact on dental utilization. Females with age are less likely to use dental services than their male counterparts, possibly indicating having on average better life-time preventive habits. The effects of AGE and AGEX2 on utilization show that there is an increasing but at a diminishing rate effect of age on the number of general dentist visits.

4.3.2. Role of income

The level of utilization increases with income as expected. The effect of INCOME on the probability of having dental insurance is presented in Figures 1 and 2 for the spline regression and nonparametric model respectively. The nonparametric specification does not have an intercept in definition of parameter $\boldsymbol{\alpha}$. In order to make the results comparable we subtract the posterior mean of the intercept in the spline regression (-1.521) from the estimated posterior means of vector $\boldsymbol{\gamma}$. The solid lines in the Figures correspond to the estimated parameters and the dotted lines correspond to the two-standard deviation bounds. The results present different patterns in how income affects the probability of purchasing dental insurance at different income levels. At low income levels as estimated by both specifications there is no significant impact of income on the probability of having dental insurance which is consistent with the fact that risk-averse individuals are willing to purchase dental insurance only at high enough levels of income when diminishing marginal returns of wealth start to apply. If the income level is very low and the basic life necessities have not been satisfied then even being risk-averse would not lead to valuing eliminating risk more than money. As income goes up the probability of dental coverage starts to rise but the increases occur at diminishing rates.

Figure 1 shows that given the two standard deviation error band one cannot conclude that the probability of dental insurance drops below the previous level at any income category. That means that the spline regression supports the claim that dental insurance is always a desirable good. It is interesting to notice that the standard deviations for all nineteen income dummies are at about the same level of 0.06.

The nonparametric model provides a different pattern in which the probability of having dental insurance starts to drop at income level of $120,000 until the $200,000 level is reached. One should be cautious interpreting this result since the standard deviations increase substantially with income. In addition, only about 3.5% of individuals in the sample has income exceeding $120,000 and only 0.4% has income greater than $200,000.

As a robustness check we estimate the model for a different specification of the income variable corresponding to rounding up to a hundred dollars which produces $k_\gamma = 1626$. Figure 3 presents the estimated relationship between dental insurance and income. The figure suggests that the probability of dental insurance coverage drops at income level of $120,000. Our interpretation for this result is that at higher income level above $120,000 dental insurance becomes a less desirable good because the monetary value of risks eliminated by the coverage decreases relative to the income.

This should not be the case for general medical insurance since there is no effective upper bound in the level of potential losses due to general (not just dental) health status. We investigate the relationship between the medical insurance coverage, variable PRIVATE in Table 1, and income using the semiparametric probit model defined for the insurance equation only. Figures 4 and 5 provide estimates corresponding to $k_\gamma = 254$ and $k_\gamma = 1626$ respectively. The main definite conclusion that we could reach for both specifications is that strong evidence is found in favor of diminishing marginal returns and a monotonic relationship which are consistent with economic theory.

4.3.3. Role of insurance

The exclusion restriction FIRMSIZE is strongly correlated with the dental insurance choice variable. Lager firms are more likely to offer greater insurance benefits including dental insurance which is consistent with the positive impact of this variable on the insurance status. The correlation parameter, -0.272, is separated from zero by more than six standard deviations (0.042) which is strong evidence in favor of endogeneity of dental insurance. We perform a formal test of the null hypothesis $H_0 : \delta = 0$ against $H_A : \delta \neq 0$. Based on the calculated Bayes factor the hypothesis of no endogeneity is overwhelmingly rejected.

The effect of dental insurance on utilization is very strong and positive, 0.783 (0.069). However, based on the signs and magnitudes of this parameter and those of the covariance it is impossible to assess the direction of the incentives and selection effects in the ordered probit model. In order to do that we calculate the ATE.

4.3.4. The average treatment effect

Definition of dependent variable Y_i establishes the link between the observed and counterfactual outcomes as

$$Y_i = d_i Y_i^1 + (1 - d_i) Y_i^0.$$

The average treatment effect is defined as the expected outcome gain from receipt of treatment, $\mathrm{E}\left[Y^1 - Y^0 | \mathbf{X}\right]$, for a randomly chosen individual . The ATE is calculated as

$$\mathrm{E}\left[Y^1 - Y^0 | \mathbf{X}\right] = \frac{1}{N} \sum_{i=1}^{N} \mathrm{E}\left(Y_i^1 - Y_i^0 | \mathbf{X}_i\right). \tag{4.1}$$

where the average is taken with respect to the sample. Denote $\boldsymbol{\eta}_i = (Z_i, \boldsymbol{\beta}, \rho, \delta, \boldsymbol{\psi}, \boldsymbol{\alpha}, \boldsymbol{\tau})$ and define the expected utilization gain evaluated at $\boldsymbol{\eta}_i$ for a randomly selected individual i between the treated state (with dental insurance) and the baseline choice (no dental insurance) as

$$\mathrm{E}\left(Y_i^1 - Y_i^0 | \mathbf{X}_i, \boldsymbol{\eta}_i\right) = \sum_{m=1}^{M} m \left[\Pr\left(Y_i = m | d_i = 1, \boldsymbol{\eta}_i\right) - \Pr\left(Y_i = m | d_i = 0, \boldsymbol{\eta}_i\right)\right]. \tag{4.2}$$

In order to calculate $\mathrm{E}\big(Y_i^1 - Y_i^0|\mathbf{X}_i\big)$ we integrate η_i out numerically from (4.2) with respect to the posterior distribution of the parameters and substitute it into (4.1).

The estimated ATE value is 0.373 (0.003) which indicates the average number of general dentist visit by which the level of utilization is increased with availability of dental insurance for a randomly chosen individual. The observed difference in utilization between the insured individuals in the sample (1.958) and the uninsured (1.495) is 0.463 visits. This difference is composed of the pure incentives effect and the selection effect. The selection effect happens to be positive (0.090) in our application which accounts for 19 percent of the observed difference in the utilization rates. Positive selection effect is consistent with adverse selection. All those unobservable factors based on which individuals make their dental insurance choices contribute positively to utilization. One potential explanation for this is that, indeed, those individuals who self-select to purchase dental insurance have on average worse dental health, which contributes to their higher levels of utilization.

5. Conclusion

This paper analyzes the effect of dental insurance on utilization of general dentist services for adult US population using the MEPS data. The ordered probit approach extended to account for potential endogeneity of dental insurance status is used. Bayesian estimation of the model allows to avoid the intractability of the distributional forms by using the MCMC methods to approximate the posterior distribution of the parameters in the model and treatment effects. We find strong evidence that dental insurance is endogenous to utilization. Ignoring this fact can result in substantial selection biases. The calculated average treatment effect shows a positive incentives effect of dental insurance. It also provides evidence of adverse selection into dental insurance. The selection effect accounts for 19 percent of the observed difference in utilization between insured and uninsured individuals. A semiparametric approach is used to model the effect of income on the probabilities of having dental and general medical insurance coverage. We find a non-monotonic relationship between income and dental insurance. The results also support the claim of diminishing marginal returns of income on the probability of general insurance coverage.

References

Anderson MH., (2005). Future trends in dental benefits. *Journal of Dental Education*, 69(5), 586-94

Arinen, SS, Sintonen, H, Rosenqvist, G. (1996). Dental utilization by young adults before and after subsidization reform in Finland. DP # 149. Center for Health Economics, York University.

Bailit, H. (1999). Dental Insurance, Managed Care, and Traditional Practice. *Journal of the American Dental Association,* 130(12), 1721-7.

Bhattacharya, J., Goldman, D., and Sood, N. (2003). The Link Between Public and Private Insurance and HIV-related Mortality. *Journal of Health Economics*, 22, 1105-1122.

Cohen, LA, Manski, RJ, Magder, LS, Mullins, D (2002). Adult Medicaid Patients' Dental Visits in Hospital Emergency Departments. *Journal of the American Dental Association*, 133(6), 715-724.

Cohen, LA, Manski, RJ, Magder, LS., Mullins, D (2003). A Medicaid Population's Use of Physicians' Offices for Dental Problems. *American Journal of Public Health*, 93(8), 1297-1301.

Conrad, DA, Grembowski, D, Milgrom, P (1985). Adverse Selection within Dental Insurance Markets. Advances in Health Economics and Health Services Research. Volume 6. Biased Selection in Health Care Markets, 171-90

Deb, P., Munkin M.K. and P.K. Trivedi, (2006). Private Insurance, Selection, and the Health Care Use: A Bayesian Analysis of a Roy-type Model. *Journal of Business and Economic Statistics*, 24, 403-415.

Douglass CW, Shih A, Ostry L., (2002). Will there be a need for complete dentures in the United States in 2020? *J Prosthet Dent,* 87(1), 5-8.

Gilbert GH, Shah GR, Shelton BJ, Heft MW, Bradford, EH, Chavers LS. (2002). Racial Differences in Predictors of Dental Care Use. *Health Services Research*, 37(6), 1487-1507.

Grossman, M (1972). On the Concept of Health Capital and the Demand for Health. *Journal of Political Economy*, vol. 80(2), 223-55.

Grytten, J, Rongen, G, Asmyhr, O. (1996). Subsidized Dental Care for Young Men: Its Impact on Utilization and Dental Health. *Health Economics*, 5(2), 119-28

Johnson, R.W. and Crystal, S. (2000). Uninsured Status and Out-of-pocket Costs at Midlife. *Health Services Research*, 35, 911-932.

Koop, G. and D.J. Poirier (2004). Bayesian Variants of some Classical Semiparametric Regression Techniques. *Journal of Econometrics*, 123, 259-282.

Koop, G. and J.L. Tobias (2006). Semiparametric Bayesian Inference in Smooth Coefficient Models. *Journal of Econometrics*, 134, 283-315.

Macek MD, Cohen LA, Reid BC, Manski RJ., (2004). Dental visits among older US adults, 1999. *Journal of the American Dental Association*, 135(8), 1154-62.

Manning, W.G., A. Leibowitz, G.A. Goldberg, W.H. Rogers and J. Newhouse (1984). A Controlled Trial of the Effect of a Prepaid Group Practice on the Use of Services. *New England Journal of Medicine*, 310 (23), 1505-1510.

Manning, WG, Phelps, CE (1979). The Demand for Dental Care. *Bell Journal of Economics*, 10(2), 503-25.

Manski, RJ, (2001a). Access to Dental Care: An Opportunity Waiting. *Journal of the American College of Dentists*, 68(2), 12-15.

Manski, RJ, (2001b). Dental Insurance: Design, Need and Public Policy. *Journal of the American College of Dentists*, 68(1), 29–32.

Manski, RJ, Macek, MD, and Moeller, JF (2002). Private Dental Coverage: Who Has it and How Does it Influence Dental Visits and Expenditures? *Journal of the American Dental Association*, 133(11), 1551-1559.

Manski, RJ, Goodman, HS, Reid, BC, Macek, MD (2004). Dental Insurance Visits and Expenditures Among Older Adults. *American Journal of Public Health*, 94(5), 759–764.

Melkersson, M, Olssen, C (1999). Is visiting the dentist a good habit? Analyzing count data with excess zeros and excess ones. Umea Economic Studies 492. Umea University.

Mueller, CD, Monheit, AC (1988). Insurance Coverage and the Demand for Dental Care: Results for Non-aged White Adults. *Journal of Health Economics*, 7(1), 59-72

Munkin, M.K. and P.K. Trivedi (2007). Bayesian Analysis of the Ordered Probit Model with Endogenous Selection. *Journal of Econometrics*, forthcoming.

Olson, C. (2002). Do Workers Accept Lower Wages in Exchange for Health Benefits? *Journal of Labor Economics*, 20, S91-S114.

Olssen, C. (1999). Visiting a dentist: is dental insurance important? Umea Economic Studies 490. Umea University.

Papapanou PN., (1999). Epidemiology of periodontal diseases: an update. *J Int Acad Periodontol*, 1(4), 110-6.

Rosenqvist, G, Arinen, S., Sintonen, H. (1995). Modified count data models with an application to dental care. Working paper # 293. Swedish School of Economics and Business Administration, Helsinki.

Sintonen, H, Linnosmaa, I. (2000). Economics of Dental Services. In Newhouse J. and Culyer, A. Eds., Handbook of Health Economics. Volume 1B. 2000, 1251-96. Amsterdam: Elsevier

Sintonen, H, Maljanen, T (1995). Explaining utilization of dental care: experiences from Finnish dental care market. *Health Economics*, 4, 453-456.

Table 1: Summary statistics.

Utilization			
GDVIS	Number of general dentist visits	1.763	1.272
Insurance			
DENTAL	= 1 if dental insurance	0.580	0.494
PRIVATE	= 1 if private medical insurance	0.774	0.418
Demographic characteristics			
FAMSIZE	family size	3.185	1.571
AGE	age/10	4.100	0.978
EDUC	years of schooling	12.713	2.916
INCOME	$ income/1000	41.041	34.151
FEMALE	= 1 if female	0.474	0.499
BLACK	= 1 if black	0.132	0.338
HISPANIC	= 1 if Hispanic	0.210	0.407
MARRIED	= 1 if married	0.660	0.474
NOREAST	= 1 if northeast	0.177	0.382
MIDWEST	= 1 if midwest	0.220	0.414
SOUTH	= 1 if south	0.363	0.481
MSA	= 1 if metropolitan statistical area	0.810	0.393
AGEX2	= AGE*AGE	17.768	8.432
AGEXFEM	= AGE*FEMALE	1.950	2.160
Age dummies			
AGE35	= 1 if 30<AGE⩽35	0.173	0.378
AGE40	= 1 if 35<AGE⩽40	0.178	0.383
AGE45	= 1 if 40<AGE⩽45	0.155	0.362
AGE50	= 1 if 45<AGE⩽50	0.131	0.337
AGE55	= 1 if 50<AGE⩽55	0.101	0.301
AGE60	= 1 if 55<AGE⩽60	0.062	0.241
AGE65	= 1 if 60<AGE<65	0.031	0.174
Employment characteristic (exclusion restriction)			
FIRMSIZE	firm size	14.248	18.181
Health characteristics			
VEGOOD	= 1 if very good health	0.338	0.473
GOOD	= 1 if good health	0.267	0.443
FAIRPOOR	= 1 if fair or poor health	0.088	0.284
PHYSLIM	= 1 if physical limitation	0.058	0.234
TOTCHR	number of chronic conditions	0.500	0.777
Year dummies			
YEAR97	= 1 if year 1997	0.167	0.373
YEAR98	= 1 if year 1998	0.184	0.388
YEAR99	= 1 if year 1999	0.197	0.398
YEAR00	= 1 if year 2000	0.153	0.360

Table 2. Utilization patterns.

	GDVIS		GDVIS by insurance	
Frequencies	Actual	Predicted	DENTAL=1	DENTAL=0
Cells				
0	62.38	62.49	53.40	74.78
1	17.49	17.52	21.05	12.57
2	10.54	10.40	13.39	6.60
3	4.71	4.62	5.85	3.13
4	2.29	2.27	3.05	1.24
5	1.10	1.12	1.39	0.71
$\geqslant 6$	1.49	1.58	1.87	0.97

Table 3. Health status by insurance.

Insurance plan	Health status			
	Excellent	Vegood	Good	Fairpoor
DENTAL=1	32.98	35.25	24.61	7.17
DENTAL=0	27.53	31.72	29.66	11.09

Table 4. Posterior means and standard deviations of parameters.

	Insurance	Visits		Insurance	Visits
CONST	−1.521	−2.526	AGE35	0.100	
	0.086	0.179		0.032	
FAMSIZE	−0.071	−0.036	AGE40	0.098	
	0.008	0.007		0.031	
EDUCYR	0.058	0.047	AGE45	0.054	
	0.004	0.004		0.033	
FEMALE	0.166	0.487	AGE50	0.102	
	0.021	0.079		0.035	
BLACK	0.079	−0.402	AGE55	0.074	
	0.029	0.030		0.040	
HISPANIC	−0.204	−0.193	AGE60	−0.134	
	0.028	0.026		0.045	
MARRIED	0.443	0.070	AGE65	−0.148	
	0.023	0.025		0.058	
NOREAST	−0.114	0.095	AGE		0.392
	0.032	0.028			0.081
MIDWEST	0.001	0.082	AGEX2		−0.033
	0.030	0.027			0.009
SOUTH	−0.126	−0.066	AGEXFEM		−0.049
	0.027	0.025			0.018
MSA	0.193	0.023	INCOME		0.0015
	0.025	0.025			0.0003
PHYSLIM	0.029	0.008	FIRMSIZE	0.016	
	0.045	0.040		0.001	
TOTCHR	0.047	0.071	DENTAL		0.783
	0.014	0.011			0.069
VEGOOD	−0.017	0.029	covariance (δ)		−0.272
	0.024	0.022			0.042
GOOD	−0.097	−0.011	τ_1		0.587
	0.026	0.025			0.010
FAIRPOOR	−0.146	−0.023	τ_2		1.104
	0.039	0.038			0.014
YEAR97	−0.085	−0.010	τ_3		1.483
	0.028	0.027			0.017
YEAR98	−0.136	0.045	τ_4		1.791
	0.028	0.028			0.020
YEAR99	0.036	−0.038	τ_5		2.035
	0.028	0.026			0.024
YEAR00	0.067	−0.099	η	1.04×10^{-6}	
	0.031	0.028		1.29×10^{-7}	

Figure 1. The effects of income dummies on dental coverage. Spline regression.
(the dotted error bounds correspond to two standard deviations).

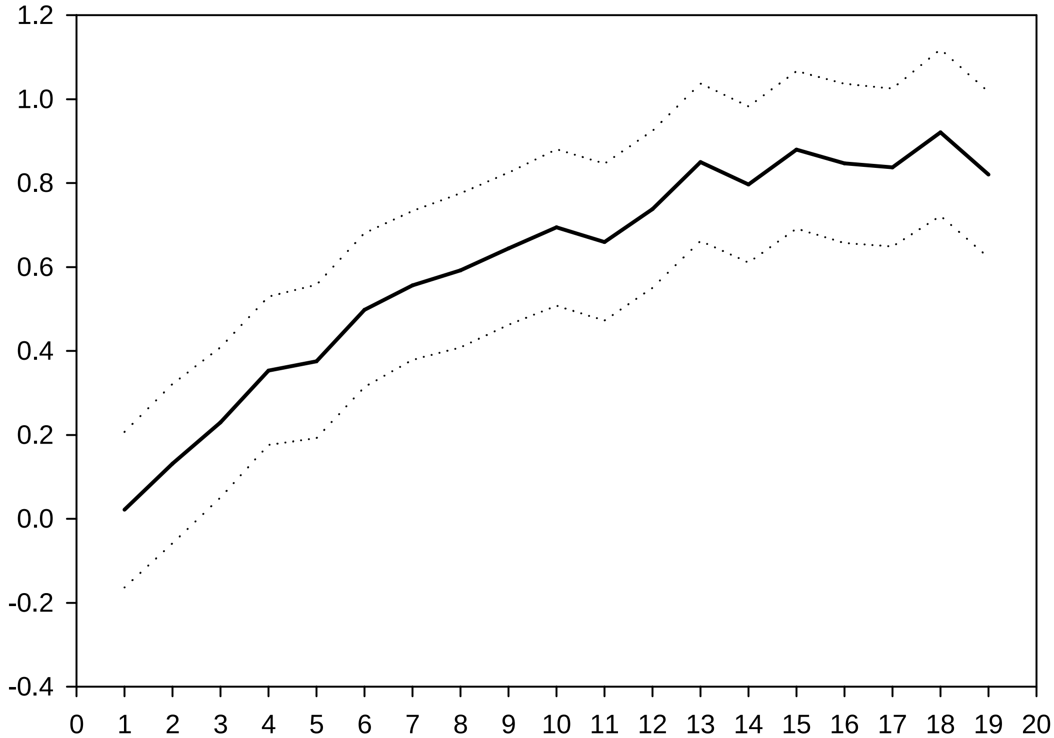

Figure 2. The effects of income on dental coverage. Nonparametric estimates. (k=254)
(the dotted error bounds correspond to two standard deviations).

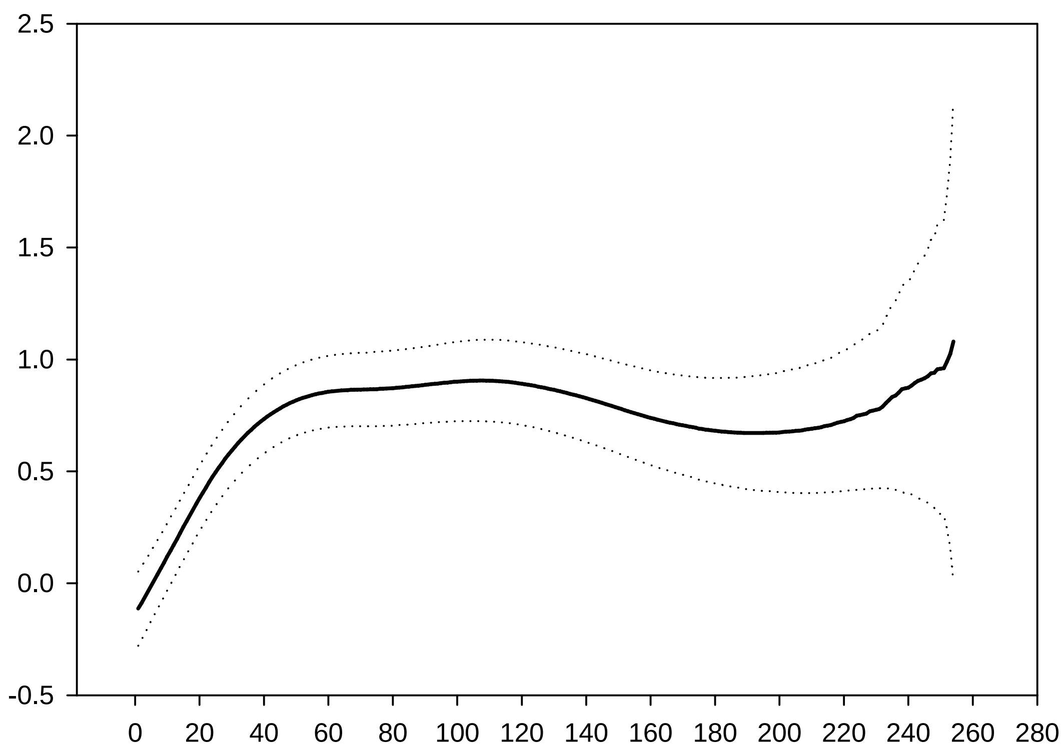

Figure 3. The effects of income on dental coverage. Nonparametric estimates. (k=1626
(the dotted error bounds correspond to two standard deviations).

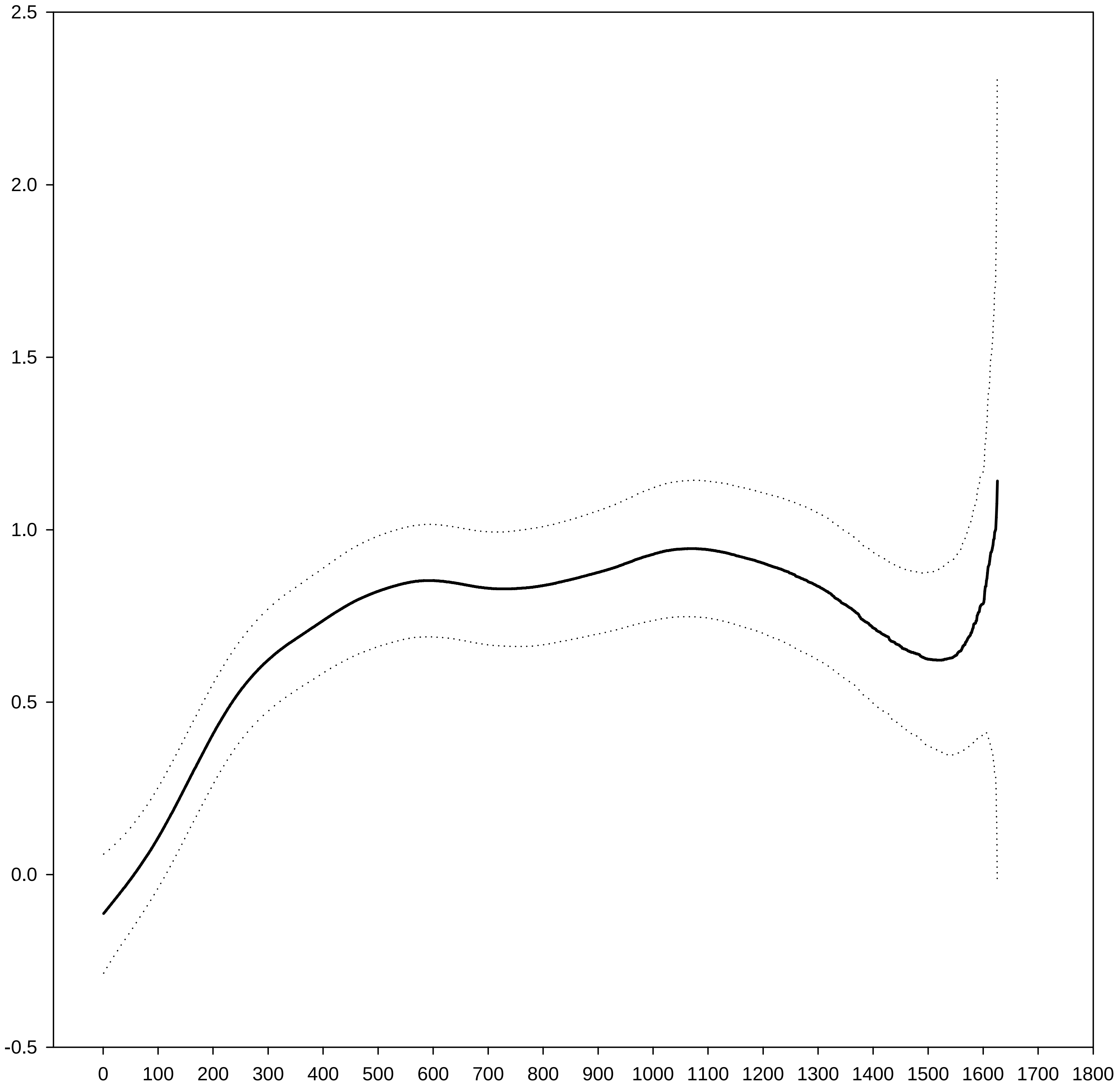

Figure 4. The effects of income on general medical insurance coverage.
Nonparametric estimates. (k=254)
(the dotted error bounds correspond to two standard deviations).

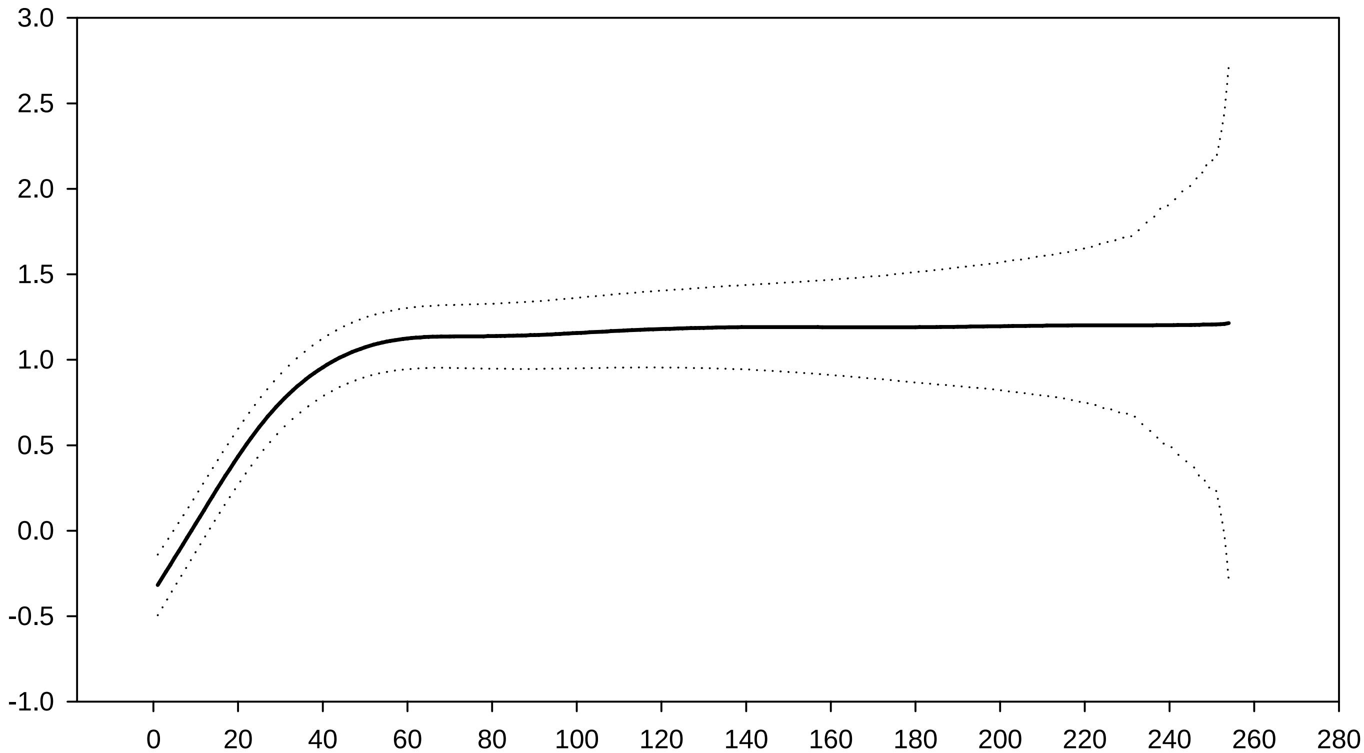

Figure 5. The effects of income on general medical insurance coverage.
Nonparametric estimates. (k=1626)
(the dotted error bounds correspond to two standard deviations).