Adverse Selection, Welfare and Optimal Pricing of Employer-Sponsored Health Plans

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October 2008

Revision in Process – Comments Welcome

**Abstract**

We assess the welfare impact of adverse selection in health insurance choices using detailed panel data on health plan choices and complete health care utilization. Our estimates suggest that adverse selection plays an important role in explaining cost differentials across plans and much of the selection occurs along difficult to contract upon dimensions. Interestingly, the distortionary consequences of the asymmetric information are very modest because individuals are very premium inelastic in our data. Our findings show that the presence of significant adverse selection need not cause meaningful welfare loss.

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We have received helpful comments from seminar participants at International Health Economics Association Conference in Copenhagen, Cornell University and the University of Minnesota. We thank Bryan Down, Roger Feldman, Thomas Holmes, Sam Kortum and Dean Lillard for their comments. Support provided by AHRQ Dissertation Grant HS015527.
1. Introduction

It is a mantra of economics: adverse selection can wreak havoc on health insurance market outcomes. This distortion can manifest along two related dimensions. First, selection may affect whether insurance is available and if it is available the structure of contracts offered to consumers (Rothschild and Stiglitz, 1976). Second, since the health plan’s average and marginal costs are a function of the identity of its enrollees, for a given set of health insurance plans, administrators and/or the market equilibrium will have difficulty setting premiums optimally (Akerlof, 1970; Newhouse, 1996; Cutler and Reber, 1998). Distorted relative prices induce welfare loss as the enrollees do not sort into plans that generate the largest net private surplus. The importance of adverse selection likely becomes more acute in the presence of significant health plan cost heterogeneity. Depending on the premium setting strategies employed by the sponsors of the insurance, small initial health plan cost differentials can be magnified by adverse selection into inefficiently large premium differentials. Furthermore, health plans’ cost heterogeneity may differ by individual health status. Some plans may use more resources treating the healthier enrollees while other plans may provide care to the relatively sick at lower cost. The presence of health plan heterogeneity thus complicates the welfare assessment of adverse selection.

In this paper, we assess the welfare impact of adverse selection in the health insurance choices of employees working for a large organization. The focus here is on the role that adverse selection plays in distorting premiums -- a welfare consequence of asymmetric information that dates to Akerlof (1970). In the simplest model, if adverse selection is present, the average and marginal cost (as a function of premium) curves diverge. Optimal sorting of enrollees into plans requires premiums to be set equal to the cost of the marginal enrollee. However, in a competitive equilibrium and in many employer-sponsored settings, premiums will equal average cost of the
plan and not the cost of marginal enrollee. This distortion implies that that the plans attracting higher cost enrollees with be priced too high.\footnote{Under different premium setting mechanisms the low-cost plan’s premium could be set too high relative to the optimum. If this is the case, the logic of the subsequence sentence holds substituting ‘low-cost’ for ‘high-cost’ and vice versa.} Welfare loss is a consequence of enrollees who value the high cost plan more than their marginal cost of joining in it failing to enroll in that plan because of the premium distortion.

We possess detailed information on both the actual health insurance choices and the complete health care utilization experience of a large number of individuals over multiple years. Our data also allow us to formulate rich measures of the employee’s health status that are based upon actual medical care utilization and previous diagnoses. In order to assess welfare implications of adverse selection, it is necessary to account for both individual and health plan expenditure heterogeneity, and these data provide sufficient detail to cleanly model these dimensions. Furthermore, the health status information that is available using the claims data allows us to decompose adverse selection into easily observable (to the insurer) demographic variables and more difficulty to observe health status dimensions. It is well known that identifying adverse selection from moral hazard can be difficult (Chiappori and Salanie, 2000).

As we use claims information from the previous year to construct individual-specific health status measures in conjunction with plan fixed effects, exogenous premium variation enable us to isolate the role of adverse selection in explaining cost differentials across health plans.

To examine the role of adverse selection, we construct a utility-maximizing model of health insurance choice in which individuals assess the quality of the health plan, their estimated health status, premiums, and expected level and variance out-of-pocket expenses when selecting a plan. Here we exploit the detailed data and formulate measures of the health status and expected out-of-pocket expenditures that reflect actual enrollee medical care utilization across
different plans. In the choice model, potentially risk-averse individuals can act upon their health status in selecting a plan.

We estimate utility parameters using an autoregressive, multinomial probit choice model (Geweke, Keane and Runkle, 1997). The probit model allows complete freedom in the correlation structure of the choice-specific errors. Our implementation also allows the unobserved choice-specific error term to be autocorrelated and the autocorrelation parameter can vary across health plans. Individuals tend to remain in the same health plan for multiple years suggesting that incorporating unobserved autocorrelated heterogeneity into the model may be important. Statistical inference is generated using Bayesian methods (Gelfand and Smith, 1990) as classical approaches to estimating the model are too computationally intensive to implement and convergence using classical methods is often problematic. This model removes many of the unappealing implications (and potential biases) of the literature’s workhorse empirical model, the iid, multinomial (or nested) logit.

In order to assess the welfare consequences of adverse selection, using the detailed claims data information, we estimate the parameters of a set of health expenditure equations allowing for individual- and plan-specific heterogeneity. In keeping with the spirit of the choice model estimation, inference is done within a Bayesian framework. The model allows for individual-specific random effects and allows nonlinear plan-specific relationships between costs and health status. The estimates from the expenditure equation enable us to decompose cost differentials across plans into differences that are a consequence of selection and plan heterogeneity in costs. Differences in plan costs may be a consequence of paying higher prices to providers (Cutler, McClellan and Newhouse, 2000) and/or differences in the ability to control utilization in the presence of potential moral hazard. For all but one plan, conditional on health status, health care
utilization does not differ across plans. This suggests that differences in costs are driven primarily by differential prices paid to providers and not moral hazard.\textsuperscript{2}

Our estimates from the expenditure analysis suggest that adverse selection plays an important role in explaining average cost differentials across plans. That is, the magnitude of health status selection can adversely affect welfare. In addition, the estimates from the expenditure model indicate that there is significant variation in health plan costs and these differences vary by the health status of an enrollee. Some plans provide health care coverage for enrollees cheaper than the other plans but the ranking of plans differs by the health status of enrollees.

The estimates from the choice model indicate that adverse selection manifests along both the relatively easy to observe demographic variables and the much more difficult to observe health status dimension. That is, information that individuals use to make health plan choice is private and unlikely to be contractible and is correlated with their expected cost. Furthermore, our estimates also suggest that the use of the multinomial logit choice models leads to erroneous conclusions over several important dimensions of health plan choice. We also find that unobserved heterogeneity in plan preference is extremely persistent and failure to account for this inertia leads to biased estimates of premium elasticities and other important factors that influence health plan choice. Finally, our results suggest that individuals are extremely risk-adverse in making health plan decisions.

To explore the welfare consequences of adverse selection, we perform several premium experiments via simulation. In these simulations we adjust premiums according to commonly used risk adjustment rules and we also calculate an optimal premium structure. While there is adverse selection in our data, the distortionary consequences of the asymmetric information are

\textsuperscript{2} While there is substantial overlap in provider panels between the plans, some group practices are excluded from the HMO and the Point-of-Service plans.
modest. The welfare gain from using optimal premium structures or the more easily computed risk adjusted premiums lead to very small gains in welfare. The reason adverse selection does not greatly affect welfare in our context is because plan choices are relatively insensitive to changes in premiums. Large changes in premiums marginally affect the average health status of a given plan’s population.

The remainder of the paper has the following structure. We provide an overview of the relevant literature in Section 2. The data on which the analysis rests is described in Section 3, and the model is laid out in detail in Section 4, with details of the Bayesian estimation strategy used in quantifying the model provided in Appendices. The results of the model estimation are presented in Section 5, and the results of the employer pricing policy experiments shown in Section 6. Section 7 concludes.

2. Background

Theoretical concerns over adverse selection in health insurance markets date back at least to Rothschild and Stigliz (1976) where they show that non-contractible heterogeneity in health risk can lead to a suboptimal set of contracts being offered. Newhouse (1996) furthers this idea arguing that there is an important trade-off between competition and adverse selection in healthcare and health insurance markets. Newhouse notes that the introduction of competitive forces into health insurance markets induces premium reductions but also gives insurers greater incentive to attract favorable risks. The premium reduction effect increases welfare but the rise in adverse selection that may accompany competition decrease welfare. Cutler and Reber (1998) and Einav, Finkelstein and Cullen (2008) highlight how the use of market-like incentives in
health insurance choice in the presence of adverse selection and health plan cost heterogeneity can lead to inefficient premium setting.\textsuperscript{3}

Given that it is well-known that adverse selection can have deleterious impacts on health insurance outcomes, it is not surprising that a large literature has arisen examining the prevalence of selection-driven cost differentials by health plan.\textsuperscript{4} The typical research in this line of analysis studies differential demographic or cost experience between some form of managed care and a less restrictive health insurance product (e.g. a preferred provider organization or fee-for-service plan) in a particular context.\textsuperscript{5} While there are a number of studies that find no selection, the typical study finds that the more restrictive the provider network or the more managed the care, the more favorable is the health plan risk selection. Sicker enrollees have a greater willingness to pay for broad provider access and less insurer involvement in their care.

In this literature, the strategy of inferring adverse selection through use of explicit risk measures embedded within choice models is atypical, however several papers of note use this approach. Strombom, Buchmueller and Feldstein (2002) acquire data on hospitalizations and cancer diagnoses around the time of plan enrollment and include this information as regressors in a choice model. Others use chronic illness indicators or paid claims information by participant (Parente, Feldman and Christianson, 2004; Atherly, Dowd and Feldman 2004; Harris, Schultz and Feldman, 2002; Cardon and Hendel, 2001; Royalty and Solomon, 1999).\textsuperscript{6} But in general,

\begin{itemize}
  \item \textsuperscript{3} See, also, Pauly and Herring (2000).
  \item \textsuperscript{5} There is a modest but important body of work that examines adverse selection in the non-health insurance context. An incomplete list of papers in this literature include Cawley and Philipson (1999), Chiappori and Salanie (2000), Finkelstein and Poterba (2004) and Einov, Finkelstein and Schrimpf (2007).
  \item \textsuperscript{6} Parente, Feldman and Christianson (2004) use data from a similar setting to ours, supplemented with an employee survey to examine the profile of those who enroll in a Consumer Directed Health Plan (CDHP). Using a MNL approach, they find the CDHP plan enrolled wealthier employees and the CDHP was not more attractive to the young and healthy.
\end{itemize}
there is little attempt in the literature to adjust choice for differences in health status, with the exception of differences inherent in employee age and gender.

Cardon and Hendel (2001) use data from the 1987 National Medical Expenditure Survey aggregating many different health plans into three choice categories to quantify the influence of information asymmetries on health plan selection. Their work is noteworthy for the integration of individual expected health care expenditures into the choice equation in an internally consistent manner. Cardon and Hendel model informational asymmetries as correlations between errors in the expenditure and choice equations. In their view, the observable factors of age, gender, race and geographic region that are correlated with both health care expenditures and plan choice are observable by health plans and hence contractible. The cross-equation correlation coefficients are small and not significantly different from zero and therefore they conclude that there is no adverse selection in health insurance choice.

In spite of the potential importance of adverse selection in affecting health insurance market outcomes, very few estimates of the impact of adverse selection on welfare exist. Cutler and Reber’s (1998) provide the first econometrically sophisticated estimates. Cutler and Reber study the health plan choices of Harvard employees after the implementation of a fixed employer premium contribution policy. They show that under such a premium setting strategy the premium differentials between plans is likely to be too high resulting in welfare loss. Specifically, they note that the optimal premium differences between plans should be based solely upon the cost differential of treating the marginal enrollee. However, in most settings the premium differentials will reflect the average efficiency differential as well as the average health status of the enrollees. If sicker enrollees prefer plans that offer a broader choice of providers and choice is more costly to offer, the premium differentials will be too high relative to the optimum. Cutler and Reber estimate the parameters and utility functions using multinomial logit methods and estimates of
costs using other data sources to conclude that adverse selection resulted in a welfare loss of 4% of gross premiums. However, it is uncommon for employers to risk adjust premiums (Kennen et al., 2001). Thus, their findings introduce a puzzle that our paper addresses. If the welfare loss from adverse selection in health insurance is so large, why do not more employers risk-adjust their premiums?

Two other papers have recently estimated the welfare loss from adverse selection in employer-sponsored health insurance. Einav, Finkelstein and Cullen (2008) note that the demand and cost curves can be separately identified from premium variation alone. This observation along with linearity and premium exogeneity assumptions makes estimating welfare loss a simple OLS problem. Using cross-sectional data from a large employer and focusing on two plans, they find evidence of modest welfare loss from adverse selection of $9.55 per employee per year. Bundorf, Levin and Mohoney (2008) use data from a single health insurance broker to analyze the welfare gains from individually risk-adjusting the out-of-pocket premium to enrollees. The underlying idea is that risk adjusting the out-of-pocket premium is better sort enrollees to plans thereby increasing net surplus.

This paper seeks to advance the welfare analysis of adverse selection on two fronts. First, we have detailed medical care claims information for our enrollees and, with the exception of Einav, Finkelstein and Cullen (2008), other analyses rely on aggregate or estimates of costs or use other sources to impute costs. These detail data enable us to formulate individual measures of health status. Second, we use a rich choice model that explicitly accounts for individual heterogeneity and in the context of the panel structure of the data. Our estimates suggest that cross-sectional estimates of health plan demand can lead to biased inference. We also estimate cost
There is a literature modeling health plan choice for Medicare and employer-based plans which is also relevant to our work. The aim of much of this literature is to estimate premium elasticities or adverse selection. An incomplete list of the papers in this literature includes Feldman, et al. (1989), Dowd and Feldman (1994-1995), Cutler and Reber (1998), Royalty and Solomon (1999), Buchmueller (2000), Scanlon, et al. (2002), Strombom, Buchmueller and Feldstein (2002), Dowd and Feldman (2003) and Atherly, Dowd and Feldman (2004). None of these papers include direct measures of out-of-pocket expenditures, and they all rely on the restrictive iid, logit family of choice models to estimate the parameters of interest. These papers estimate premium elasticities for health insurance that range from the moderately elastic to the very inelastic.

3. Data and Institutional Setting

The data are detailed employee health care claims and health plan enrollment history for a very large, self-insured employer. Linked, but de-identified, enrollment history is available for 2002-2005 and claims history is available for 2002-2004, with six months of claims run-out paid in 2005. As the employer is self-insured, all covered medical care rendered to an employee will have an associated claim and we have access to all of the employer’s health care claims information. A claim contains all information needed to process an insurance payment and thus includes valuable information such as primary and secondary diagnosis codes, procedure codes and identification of provider. The claim also contains information on the amount paid by the organization and by the enrollee. For each enrollee we aggregate all their health care claims throughout the year to formulate a precise measure of both the total claims paid by the organization and the total out-of-pocket expenditures incurred by the enrollee for covered medical care.

7 The only paper that we are aware of that includes measures of the expected mean and variance of out-of-pocket medical expenditures in a utility maximizing model of health plan choice is Cardon and Hendel (2001).
The employer offers health insurance coverage for individuals, individual and spouse/domestic partner and families. Information about the spouse/domestic partner employment-based benefits choices are not available -- we do not know what the exact choice set is in this case, as the partner may have insurance benefits at another firm. For this reason our analysis focuses solely on individuals continuously enrolled in single coverage over the three years. While single coverage does not equate to single marital status, we hope the approximation introduces little error. In addition, employees outside the metropolitan service area have a different health insurance choice set and they were eliminated from the analysis sample. This leaves 3,578 employees for the estimation.

Employee demographics information is gathered from several sources. Age and gender are taken directly from the encrypted plan enrollment files. Employee earnings was imputed from a separate accounting file, provided directly from the employer, based on birth date, gender, home zip code, work location and job classification. The demographic information is merged with health plan choice files and health status and expenditure data culled from the claims files. Plan characteristics (provider panel structure, out-of-pocket limitation, employee contribution levels) are drawn from the employer’s open enrollment materials.

The employer offered a total of four plans in 2002 through 2005. The employer contracts with the plans to access their provider network and specifies the benefit design. The plans charge the employer a fee for accessing their network and processing the claims while the employer pays the medical care claim net of enrollee out-of-pocket payments. The plans include one closed-panel health maintenance organization (HMO), two point-of-service (POS) plans, and a Consumer-Driven Health Plan (CDHP).

The HMO is a restricted provider network plan in which enrollees incur a modest co-pay for any within-network utilization, however the plan does not cover any out-of-network medical
care. The organization offered two POS plans with differing provider networks both across and within the plans. One of the POS plans (POS 1) has three tiers, each with different premiums levels; the tiers corresponding to successively broader provider networks. Tier 2 includes all the providers in Tier 1 as well as offering enrollees access to additional, potentially higher cost providers. Likewise, Tier 3 includes all the providers in Tier 2 in addition to other higher-cost providers. The other POS plan (POS 2) has only one option. The POS plans charge higher co-pays than the HMO but allow out-of-network care (with a higher co-pay).

The CDHP is a recently developed health insurance product that combines a catastrophic indemnity plan matched with an employer-funded medical spending account. In the CDHP a single enrollee is given an account of $750 (2003 and 2004) or $600 (2005) to draw upon for medical care. Once the account is exhausted the enrollee pays the balance of the $1500 deductible out of pocket. After the enrollee utilizes more than $1,500 of medical care, there is no additional copayment for in-network health care. In sum, there are a total of six health plan choices available to the employee: HMO, POS 1/tier 1, POS 1/ tier 2, POS 1/ tier 3, POS 2, CDHP.

Table 1 presents the annualized premiums and enrollment shares for the plans in our data. The out-of-pocket premiums vary across plans and time. The organization spends considerable resources attempting to inform employees of their health plan options, thus enrollees are well informed of the premiums and benefit differences across the plans when making their plan selections. During the open enrollment period, brochures and emails are distributed to all employees detailing the premiums (and changes in premiums from the previous year as well as the plan benefit structures and provider panels. In addition, the detailed plan information is available on the organizations human resources web site.

\[8\] While the Tiers were advertised as differing in the prices paid to providers, as we discuss in Section 5 we found little cost differential between the tiers in POS 1.
The temporal variation in out-of-pocket premiums is driven by two types of changes in the employer’s premium-setting strategy. First, the employer used a defined contribution strategy and the formula used to construct the premiums changed over time. For 2002-2003 the employee share for single coverage was set to zero for the base plan. Employee share for other plans was simply the excess of other plan total premium over base plan total premium. For 2004-2005 the employee share was set at 10% of the base plan premium. Employee share for other plans was 10% of this base amount plus the excess of other plan total premium over base plan total premium. These changes were driven by the organization drive to push more of the cost of health care onto employees. The second change was that the employer moved from a strategy of no risk-adjustment in 2002 to one of risk-adjustment “light” by the end of our data. Importantly, we have discussed the premium setting strategy with the human resource personnel and they assured us that the changes in the relative premiums do not reflect specific changes in the plan characteristics but changes in the premium-setting strategy of the organization. Thus, to the best of our understanding, time varying differences in premiums are exogenous.

The most popular plan is the HMO, and it is also the cheapest plan. Another noteworthy pattern in Table 1 is that while the premiums of the plans shifted considerably, the shares did not. This pattern suggests that controlling for autocorrelation in enrollee preferences is likely to be important.

**Measuring Health Status**

An important feature of this study is that we are able to use past claims information to formulate health status measures that are incorporated into the choice model. In order to do this we need to map the thousands of ICD-9CM codes (and millions of potential combinations of codes) into a parsimonious representation of future health status. To do this we rely on commercial algorithms that are designed to forecast future morbidity and health care
expenditures for the purposes of risk adjustment in the evaluation of provider performance, forecasting healthcare utilization and setting payment rates.

The health status indicators are constructed for individual enrollees through the use of the Johns Hopkins University ACG Case-Mix System (v. 6) developed by the Health Services Research and Development Center. The ACG Case-Mix System uses a combination of clinical assessments and grouping of diagnoses and procedures along with extensive regression fitting to take the thousands of ICD-9CM codes that are embedded in the claims to construct simple measures of health status. The predictive modeling feature of the ACG software produces the concurrent weight (CW). The CW is a summary measure of the current individual health status and resource utilization. The CW is constructed so that the national average is 1.0 with higher values denoting poorer health and likely higher expenditures.

A potential concern with our measure of health status is that is based on the previous year’s health care utilization which, in turn, is potentially a function of the characteristics of the plan. That is, our measure of health status may incorporate aspects of moral hazard. To investigate this possibility we regess the logarithm of CW on plan and individual fixed effects. Since we are controlling for time-invariant, individual differences in CW, if the plan coefficients are insignificant it strongly suggests (but is not dispositive) that our measure of health status does not include a moral hazard component. The plan fixed effects are all individually insignificant and the joint test of their significance does not reject the hypothesis that they are equal to zero suggesting that, in fact, CW varies only with the health status of the individual. These findings do not imply that moral hazard is not present, but only that its influence on our measure of health status is, at best, modest.

Table 2 provides summary statistics of our estimation sample. The organization has a high percentage of female employees and the average health status of the employees is poorer than the
national average as measured by the CW. Interestingly, there are important differences in the mean demographic and health status measures across the plans, however the health status measures display much greater across-plan variance than the demographic variables. This suggests that relying solely on demographic variables to measure risk variation may underestimate the true magnitude of adverse selection.

The simple summary statistics in Table 2 show that health plans differ in both demographics and in measured health status and this is *prima facie* evidence of adverse selection. The HMO attracts a younger, more male, lower-paid and healthier population than the other plans. The plan that garners the least favorable selection is the POS 2 plan—the mean age and CW is significantly higher than the HMO. The CDHP enrolls an older population with a higher salary, and a higher CW than the HMO but a lower CW than the other plans.

From these summary statistics it is difficult to decompose the dimensions of the selection into the parts that can be easily contracted upon (age and gender) and those dimensions that are more difficult to contract upon – the non-age and non-gender components of health status. One of our goals is to understand the welfare loss from adverse selection. For these reasons we estimate structural parameters from a model of health plan choice.

4. Empirical Approach

To measure the welfare consequences of adverse selection we first must accomplish two tasks: 1) estimate the expected out-of-pocket expenditures that individuals would incur if they were to enroll in any of the available plans; and 2) estimate the parameters of an indirect utility function. Theoretically, if individuals are risk adverse, utility from health plan enrollment should be a function of both the expected mean and variance of the enrollees’ out-of-pocket expenditure. The Monte Carlo estimation methods allow us to construct measures of these variables and include them in the choice model.
Medical Care Cost Model

To predict total health care expenditures and patient out-of-pocket (OOP) expenses, we face three important modeling challenges. First, we need to account for unobserved individual heterogeneity. Second, much of the data is censored at zero. Third, OOP and total claims expenditure are determined jointly with plan-specific rules placing nonlinear restrictions on the OOP realizations. To implement a framework that accounts for these features of the data, we use a two-part, three-equation censored regression model building upon the work of Cowles, Carlin and Connet (1996). The first equation in the model is an indicator of whether the patient receives care. Conditional on the threshold being breached, these other two equations of the model predict total claims expenditure, denoted $Clm_{it}$, and total out-of-pocket expenditure, $OOP_{it}$.

More specifically, the variable $T_{it}$ is a zero-one indicator of non-zero claims, and is a function of the latent variable $T^*_{it}$ in the following way:

$$T_{it} = \begin{cases} 
0 & \text{if } T^*_{it} \leq 0 \\
1 & \text{if } T^*_{it} > 0 
\end{cases}$$

Positive values of claims and out-of-pocket expenditures are observed only when this threshold is met. Letting the $^*$ denote latent values, the process guiding the realized data for $Clm_{it}$ and $OOP_{it}$ is given by

$$Clm_{it} = \begin{cases} 
0 & \text{if } T^*_{it} \leq 0 \\
Clm^*_{it} & \text{if } T^*_{it} > 0 
\end{cases}$$

and letting $I_j$ denote the set of plan $j$’s enrollees:

$$OOP_{it} = \begin{cases} 
0 & \text{if } OOP^*_{it} \leq 0 \text{ or } T^*_{it} \leq 0 \\
OOP^*_{it} & \text{if } 0 < OOP^*_{it} < OOPLim_{jt}, (i, t) \in I_j, \text{ and } T^*_{it} > 0 \\
OOPLim_{jt} & \text{if } OOP^*_{it} \geq OOPLim_{jt}, \text{ where } (i, t) \in I_j, \text{ and } T^*_{it} > 0 
\end{cases}$$
Each plan places explicit limits on the total OOP expenditures incurred by an enrollee in a year, and this institutional feature is modeled by capping out-of-pocket expenditures by $OOP\text{Lim}_{jt}$.

We model the latent variables as functions of demographics and health status (and higher order health status terms); the impact of these variables can differ across plans. The inclusion of CW controls for health status, and allows the costs of the plans to be functions of health status. Cost differentials across plans (conditional on health status) may be driven by different prices paid by the plan to providers, differentials in the networks of providers who will have heterogeneous contract prices and differential patient incentives to access care. Importantly, we allow for individual-specific, unobserved, time-invariant shocks that differ across equations. The system of latent variables is simply:

$$
T_{it}^* = x_i' \beta_{t}^{th} + b_{it}^{th} + \xi_{it}^{th},
$$

$$
Clm_{it}^* = x_i' \beta_{t}^{c} + b_{it}^{c} + \xi_{it}^{c},
$$

$$
OOP_{it}^* = x_i' \beta_{t}^{o} + b_{it}^{o} + \xi_{it}^{o},
$$

where $b_{i} = [b_{it}^{th} b_{it}^{c} b_{it}^{o}]'$ are the time-invariant, individual-specific intercepts. In the language of frequentist econometrics the $b_{i}$’s are random effects. The iid error vector is assumed to be normally distributed: $\xi_{it} = [\xi_{it}^{th} \xi_{it}^{c} \xi_{it}^{o}]' \sim N(0,\Sigma_{j})$ for $(i,t) \in I_{j}$. Note that the covariance matrix, $\Sigma_{j}$, is plan-specific, as we expect different correlations between the threshold, claims and OOP expense across the plans.

In order to flexibly model health plan costs, the vector of explanatory variables, $x_{it}$, includes the demographic and health status variables, higher order and interactions of those variables. Specifically, $x_{it}$ includes age, age squared, female indicator, age interacted with female, both measures of health status and their squares and interaction with female status. We
estimate plan-specific parameters for all of the explanatory variables. In this way, we allow for the possibility that some plans may be more efficient at treating enrollees with relatively good health status while others may be more efficient in providing care for sicker enrollees.

Bayesian inference is used to formulate our estimates of the parameters of interest. The aim in Bayesian estimation is to construct the posterior distribution of the parameters given assumptions on the prior distribution of the parameters and the data. We simulate the posterior distribution of the parameters using Monte Carlo Markov Chain (MCMC) methods. Specifically, we use the Gibbs sampler (Gelfand and Smith, 1990) and data augmentation techniques (Tanner and Wong, 1987). The details of the estimation algorithm are described in Appendix A.

Our estimates will be unbiased as long as residual, unobserved health status is uncorrelated with plan choice. We believe this is a reasonable assumption in this application as we include in the set of regressors health status measures based on very detailed information on prior diagnoses and procedures. With some notable exceptions, the health status measure is based on much of the same information the enrollee has access to when selecting a health plan.\(^9\)

The most important kinds of information the enrollee possess that we cannot incorporate into the analysis are known genetic predispositions for which the disease is not manifest, maternity plans (a relatively uncommon outcome in our data as we focus on single coverage enrollees), the presence of symptoms for which the enrollee does not seek care and, perhaps most importantly, illness severity within a diagnosis that is not captured by diagnosis and procedure codes and is known and acted upon by the patient. With the exception of genetic predispositions, these effects

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\(^9\) There is a sense in which we have better health status information than the enrollee as we are running their claims histories through a sophisticated algorithm constructed for the purposed of predicting future health care expenditures.
are generally time varying and thus would cause concern if there is a lot of plan switching in the data. Only 7% of employees in the data switch plans in any given year.  

While we believe that that the institutional setting and the quality of our data make it unlikely that conditional on our measure of health status, enrollees are cognizant of health status information that affects their choice of plan, it is clearly still a possibility. However, we perform two indirect tests for the presence of unobservable health status information that is correlated with plan choice. To implement this test we first construct a predictive cost residual -- the difference between actual and our cost model’s predicted expenditures. In the first test we include the year $t$ cost residual interacted with the plan indicator variables in the plan choice model. If individuals anticipate future health status and they use that to inform their choice of plan, then the parameters on the contemporaneous residual/plan dummy interaction should be different than zero. For all parameters, at least 10% of the estimated posterior distribution cross zero indicating that the residual/plan dummy interactions do not significantly explain plan choice.

In the related second test, we use a probit framework to regress an indicator for whether the individual switch plans between year $t$ and $t-1$ on this expenditure residual in year $t$ interacted with an indicator for the plan they enrolled in the previous year and its square controlling for demographic variables, $CW_{t-1}$ interacted with plan indicators and year indicators. If individuals posses more information about their future health expenditures than is captured by our measures of health status and use it to inform plan selection, then the residual should predict switching behavior. The coefficient estimates on the residual interacted with the incumbent plan indicators

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10 In addition, others have argued (and tested) that the type of risk adjustment we employ corrects for unobserved selection bias in an environment where unobservable health status is more likely to bias the results (Shea, et al., 2007). Pietz and Peterson (2007) find that other measures of self-reported health status beyond the diagnostic information in claims do not help predict mortality.
are all different from zero at traditional levels of confidence.\textsuperscript{11} In sum, these tests suggest that enrollees do not possess information that is not embodied in the CW and other demographic variables when selecting a health plan.

Once the cost model is estimated, we construct estimates of the expected $Clm$ and $OOP$, and the variance of the $OOP$ expenses for each individual (in logarithm scale) across all plans including the plan actually selected by the individual. Both the mean and the variance of $OOP$ measures are used to capture aversion to out of pocket expenditures and risk in the health plan choice model. Because the Gibbs Sampler method results in a sample from the posterior distribution of the parameters, including the latent expenditure variables, we can use this sample to calculate both a sample mean and sample variance estimate of OOP expenses for each individual, in each plan.

**Health Plan Choice Model**

We model health plan choice using a multinomial probit with autocorrelated errors. In our model the unobservable components of plan choice are allowed to be freely correlated across plans and autocorrelated over time. Most analyses of health plan choice rely upon the iid logit model or the heteroskedastic but independent nested logit model. Our results suggest that this assumption may lead to biased inference. In addition, as we noted above, only 7\% of the enrollees switch plans in any given year, suggesting that plan preferences are likely to be correlated over time and our framework explicitly accounts for this autocorrelation. We are unaware of any analysis of health plan choice that allows for both full freedom in cross-plan correlation, and correlation of unobserved preferences across time.

In selecting their health plan, we assume enrollees observe their health status and formulate consistent estimates of both the mean and variance of their out-of-pocket expenditures

\textsuperscript{11} The largest t-statistic (in magnitude) is 1.41 for the residual interacted with the POS plan. The joint test of all of the plan interactions is also insignificant.
across all plans. Given these estimates they select the plan that maximizes their utility. Let $\tilde{U}_{ijt}$ be the indirect utility of the $i^{th}$ person ($i = 1, ..., N$) for the $j^{th}$ plan ($j = 1, ..., J$) at time $t$ ($t = 1, ..., T$). It is well known that $\tilde{U}_{ijt}$ is not identifiable because level and scale are irrelevant to the maximization problem. The $J^{th}$ plan is used to normalize the level of utility so that $W_{ijt} = U_{ijt} - U_{ijt}$. The CDHP is used as the baseline choice because of its distinct plan design. We normalize for scale by setting the variance of the unobserved preferences for the HMO to 1.

It is assumed that $\tilde{W}_{ijt}$ is linearly related to the characteristics of the individuals and the choices ($x_{ijt}$, where it is understood that the elements of $x$’s are distinct from those used in the cost model), so $\tilde{W}_{ijt} = x_{ijt}\tilde{\beta} + \tilde{\epsilon}_{ijt}$, where $\tilde{\epsilon}_{ijt}$ is the unobservable component of utility. Stacking the choices into matrix form, we have the relationship $W_{it} = X_{it}\beta + \epsilon_{it}$. The errors are assumed to be normally distributed: $\epsilon_{it} \sim N(0, \Sigma)$. In a slight modification of Geweke, Keane and Runkle (1997), the “stickiness” of plan choice across time is captured via an AR(1) relationship in the error terms. Specifically, $\epsilon_{it} = \rho_{i,t-1}\epsilon_{i,t-1} + \eta_{it}$, with $\eta_{it}$ iid $N(0, T)$. The variance matrix $T$ is a diagonal matrix, whose diagonal elements $\tau_j^2$ are plan-specific variances. The AR(1) coefficient, $\rho_{i,t-1}$, is a plan-specific parameter, based on the plan individual $i$ is in at time $t - 1$, when the time $t$ plan election is made. Given the apparent persistence in plan market shares, we anticipate the estimated values of $\rho$ closer to one than to zero.

It is awkward and perhaps computationally infeasible to estimate the autoregressive multinomial probit parameters of interest using a classical maximum likelihood approach. However, the parameter can be estimated using Bayesian methods. As in the cost model, we specify a diffuse prior distribution for the parameters and simulate the posterior distribution
using MCMC methods. Specifically, we use the Gibbs sampler and simulate the latent variables using data augmentation techniques. Appendix B describes the likelihood function and the Gibbs algorithm in detail.

The $x_{gt}$ vector includes the following plan invariant variables: age, female indicator, age interacted with female, the CW (the measure of health status in the year the enrollment election is made). The parameters on these variables can vary by plan. The $x_{gt}$ vector also includes the following variables that vary across plan and time: logarithm of net salary, $\log(salary_{t} - premium_{t})$, and the expected value of the logarithm of out-of-pocket expenditure and the variance in the logarithm of out-of-pocket expenditure, as predicted by the cost model.\(^\text{12}\)

Our model imposes fewer restrictions than traditionally used approaches. In so far as the implied elasticity estimates from our model differ from the MNL, it is instructive to decompose the source of those differences into the importance of capturing heteroskedasticity and modeling persistence in health plan preferences. Specifically, we wish to decompose differences into the importance of accounting for serial correlation and cross-plan correlation in the residuals. For comparison purposes we use frequentist methods to estimate a multinomial logit model, a nest-logit model and a static multinomial probit. We use a Bayesian approach to estimate a homoskedastic autoregressive model—this model is the same as our base model except the off-diagonals of the variance-covariance matrix are constrained to be zero.

\(^{12}\) We have estimated models with different specification over
5. Results

Cost Model

For the cost model, the Monte Carlo chains converge well after the initial burn-in of 2000 iterations.\textsuperscript{13} Given the space constraints, the cost model contains too many parameters (over 70) to report here. However, the posterior distributions for the parameters look sensible. Costs are increasing in age, female and CW. We decided to combine all the POS 1 tiers into one plan as there did not appear to be meaningful cost differences across the tiers. The model also does a nice job of fitting the data and replicating the realized distribution of costs, primarily because the panel data allows the estimation of individual-specific intercepts. The $R^2$ is 0.41 for claims and 0.58 for out-of-pocket expenses. In Figure 1 we present the actual and fitted distributions of total expenditures and out-of-pocket costs. The model under-predicts the number of zeros but otherwise does capture the skewness of both the total cost and OOP distributions.

The results of the cost model imply that there are significant cost differentials across the plans. This is not surprising as the plans have different provider networks ranging from the restrictive HMO network to the open access CDHP plan. The plans also impose different out-of-pocket payment structures that also can (and are designed to) affect marginal utilization. For example, the HMO generally has constant co-payments for a doctor visit while the CDHP will have very low effective out-of-pocket expenditures for both low and high utilization and high out-of-pocket in the doughnut hole.

To get a sense of the mean cost differentials we perform the following experiments. We take the entire sample population and estimate their mean expenditures (the total of expenditures paid out-of-pocket and by the plan) as if they were all to enroll in each plan. We also take the

\textsuperscript{13} Details on the convergence of the MCMC chains and estimated parameters are available in Carlin (2006).
enrollees of each plan and estimate the costs of the enrolling that population in the other plans. This latter exercise provides a sense of the differential selection into each plan.

Table 3 presents the results of this exercise. The results in Table 3 show that adverse selection is present in our data and economically important. The realized HMO costs are predicted to be 13\% lower than if they had to treat the entire enrollment. In contrast, the per-capita costs for the POS 1 are 25\% higher, the POS 2 plan is 47\% higher and the CDHP plan is 20\% higher if they enrolled the entire population. These results imply that it is important to note that these cost figures are total cost differentials and do not breakout the adverse selection into easily observable and hence contractible and non-contractible components.

Not surprisingly, the HMO is the cheapest plan and the CDHP plan is the most expensive. Using the estimated per-capita cost of the entire sample as the comparison, the HMO has 28\%, 20\% and 45\% lower cost than the POS 1, POS 2 and the CDHP plan, respectively. These results raise an obvious question: what is the source of these cost differentials?

The results presented in Table 3 also suggest that the relative costs of the plans differ by health status. For example, the cost differential between the HMO and the POS 1 plans depends upon comparison populations. The cost of the POS 1 plan is 26\% higher than the HMO for those who enrolled in the HMO but is 18\% higher for those who enrolled in the POS 1 plan.

Figure 2 highlights this phenomenon. It graphs the estimated logarithm of costs (plan payment plus out-of-pocket expense) for a 47-year old woman as a function of the logarithm of the CW for each plan. Interestingly, the CDHP plan is the second lowest cost plan for the very healthy but is the most expensive plan for the sick. This result is likely due to moral hazard and the fact that the CDHP likely pays providers more for a given service. The CDHP imposes real costs on the marginal use of care at low utilization levels but at high utilization levels the
marginal cost falls to zero and since the plan has a broad network it pays higher prices to providers.

Figure 3 graphs the expected logarithm of out-of-pocket expenditures for a 47-year old woman as a function of the logarithm of the CW for each plan. This figure gives a sense of the variation across plans and CW in OOP that is used to identify the parameters on the expected logarithm of OOP in the choice model. Not surprisingly, OOP is monotonically increasing in the CW for each plan; however, there are interesting patterns across the plans in both the level and the slope of OOP as a function of CW. The HMO plan design has the lowest co-payments (for within-network utilization) and this is reflected in Figure 3 as the HMO has the lowest OOP for all CW levels. Conversely, the CDHP plan has the highest expected OOP expenditures for all but the lowest CW levels. For low CW values, the POS1 plan has lower OOP than POS2 but the marginal effect of CW is higher for POS1 than POS2 so that by for those with CW greater than 1 (Log(CW) = 0), the OOP for POS1 and 2 are virtually identical.

Figure 4 graphs the expected variance in the logarithm of out-of-pocket expenditures for a 47-year old woman as a function of the logarithm of the CW for each plan. As in the level of OOP, there is significant variation across plans and CW in the expected variance in the logarithm of OOP. The patterns in the expected OOP variance are quite interesting. For all plans but the CDHP, the variance gradually increases in OOP. However, for the CDHP the variance declines as health status worsens until the CDHP plan has the lowest expected variance in OOP for the sickest two-thirds of the distribution. This reflects the benefit design structure of the CDHP for which there can be significant OOP variation for modest utilization levels but very little variation in OOP expenditures at high utilization levels where nearly all enrollees would have met their catastrophic deductible.
Evidence on the Importance of Moral Hazard

The large cost differentials for treating a patient with similar health status characteristics across plans raise an obvious question: Are these cost differences driven by differences in moral hazard or differences in the prices paid to providers? The plans differ significantly in their benefits structure with the HMO being the lowest cost option with modest co-pays for most in-network provider visits to the CDHP plan having a large deductible (with a health spending account attached to it). As Figure 3 shows and we discussed above these differences in benefit structures result in significant difference in out-of-pocket payments for enrollees.

To better understand the source of the cost differences across plans we estimate the impact of plan enrollment on the number of physician office visits. There are a large number of zeros in the data thus we estimate the parameters using a negative binomial hurdle regression (Cameron and Trivedi, 2006). If there is no difference in the coefficients on the plan indicators it suggests that moral hazard is not responsible for the differences in health care costs across plans.

The estimates of this procedure indicate that there is little difference in utilization across the HMO, the three PPO 1 plans and PPO 2. However, the estimates indicate that conditional on having at least one office visit, CDHP enrollees visit the physician office more frequently. However, the magnitude of the differential is modest. The estimates indicate that 47-year old female enrollee with a CW of 2 who enrollees in the CDHP will visit the doctor 1.2 (10%) more times per year relative to the HMO plan. However, the claims expenditure of the CHDP is over 60% more than the HMO suggesting that while moral hazard is present it does not account for the large differences in costs across plans. That is, the plan cost differentials are primarily driven by differences in the prices paid to providers.

14 Because of space constraints we do not present the parameter estimates here. However, they are available from the authors upon request.
Health Plan Choice Model

The statistics of the posterior distribution of the parameters for the choice model are presented in Table 4. The estimation relies heavily on the data augmentation process of sampling the unobserved latent utilities, thus the convergence of the Monte Carlo process is somewhat slower than in the cost model, taking 7,000-10,000 iterations before the variance parameters appear to converge. We used a 10,000 iteration burn-in in our analysis. For comparison purposes, Table 4 also presents the results of a multinomial logit model.\textsuperscript{15} The MNL model is estimated using maximum likelihood.\textsuperscript{16}

The results of the MNP model indicate: 1) Adverse selection is present both on easily observed demographics of age and gender and on the more difficult to observe health status dimensions. Interestingly, the significant health status dimension is not the current health status, but the probability that the enrollee will be high cost next year, indicating sophisticated health risk measures are needed. The selection patterns are complex and selection on one dimension does not imply selection on another dimension; 2) Enrollees are premium inelastic, particularly for the HMO and POS 2 plans; 3) There is significant autocorrelation in the unobservable dimensions of health plan choice and this autocorrelation is unrelated to health status; and 4) Many of these conclusions would be reversed if one relied on the estimates of the MNL model.\textsuperscript{17}

\textsuperscript{15} We have also estimated models that relax the strict IIA assumption of the MNL. Specifically, we estimated a nested logit model (with four nests: HMO, POS 1, POS 2 and the CDHP) and a mixed MNL model (Train, 2003). The nested logit results are qualitatively similar to the MNL findings. The mixed logit estimates are closer to estimates we present here but there are nonetheless meaningful differences in statistical inference. We have also estimated a static multinomial probit model using frequentist methods, however there were difficulties with convergence unless we dropped some explanatory variables; when the model did coverage the Hessian was not invertible. These results are available upon request.

\textsuperscript{16} To estimate the logit model we follow a common practice in the literature to control for autocorrelation and include in the estimation sample only one observation per individual where the observation is randomly drawn from the three possible years.

\textsuperscript{17} The autoregressive, MNP appears to fit the data well. An R\textsuperscript{2} calculation based on the squared differences between 0/1 indicators of plan election and the probability of electing each plan gives a statistic of 0.50, in contrast to an R\textsuperscript{2} of 0.42 for the MNL model. Not surprisingly, this autoregressive, MNP model R\textsuperscript{2} jumps to 0.81 when the 2005 enrollment is predicted conditional on the 2004 actual enrollment.
Our principal focus in this analysis is on the role of adverse selection in health plan choice. Recall that the coefficient estimates measure the influence of the variables relative to CDHP. The estimates in Table 4 indicate that the HMO attracts a lower-cost pool than the CDHP (and most other plans). The HMO enrolls a younger and more male population. Women, on average, are more expensive to insure than men. Furthermore, the HMO also attracts an enrollment that is less likely to have high expenditures than the other plans, but there is no difference in the impact of the health status measures on enrollment between the HMO and the CDHP.

The patterns of adverse selection are more complicated for the POS plans. All else equal, relative to the CDHP, the POS 1 plans attract a younger population, but they also are more popular with those who have a higher PHC in the next year. Said somewhat differently, on the basis of easily observed demographics, the POS 1 plan looks to get a better selection than the CDHP, however examining only the health status measures the POS 1 plan appears to get adverse selection. The lesson we take from these estimates is that adverse selection may occur along multiple dimensions and simple approaches to risk adjustment may be incomplete and potentially magnify the impact of adverse selection.\(^\text{18}\)

One of the most important functions of health insurance (if not its most important function) is to reduce an individual’s exposure to financial risk. The estimates in Table 4 do indeed indicate that between-plan risk reduction is valued. The mean of the posterior distribution for the coefficient on the expected variance is negative and virtually none of the distribution overlaps zero. This is the second study to estimate a risk aversion parameter in the context of health plan choice and the first to find that enrollees are extremely risk averse.\(^\text{19}\)

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\(^{18}\) Finkelstein and Poterba (2004) draw a similar conclusion using data from annuities markets.

\(^{19}\) Cardon and Hendel (2001) also estimate a risk aversion parameter which is insignificantly different from zero. In our work, we calculate an estimate of the coefficient of absolute risk aversion and rough calculation implies that it is
Table 5 presents the distributions of the posterior for the autocorrelation parameters and the variance-covariance terms from the MNP. As expected, there is significant persistence in unobserved preferences towards health plans. In Table 5a, the sample means of the posterior distribution for the autocorrelation parameters are all above 0.50. Interestingly, the errors associated with the HMO plan have a significantly lower autocorrelation than the non-HMO plans. The mean of the posterior distribution of the HMO autocorrelation parameter is .58 while the mean of the posterior distribution for the other plans in excess of .90.

The variance-covariance terms are presented in the Table 5b, with the implied correlation coefficients shown in Table 5c. These estimates look quite sensible. Many of the cross health plan covariances are significantly different from zero, with 4 of the implied correlation coefficients in excess of 0.20. This finding, in conjunction with the AR(1) estimates, convincingly rejects the MNL assumption of iid, homoskedastic errors. The error terms from the POS 1 plans are all positively correlated with the plans which are closest substitutes (Tier 1 / Tier 2 and Tier 2 / Tier 3). It is also noteworthy that there is a high correlation between the errors in the HMO and POS 2, suggesting that they are closer substitutes than one might infer given that they have very different provider networks.

We now turn our attention to the estimates of the premium sensitivity of health plan enrollees. In Table 4 the parameter estimate on $ln(Salary_i - Premium)$ is positive and none of the posterior sample crosses zero. Increases in premiums lead to decreases in enrollment. This is true for both the AR-MNP and the MNL models. Table 6 quantifies the magnitudes of the parameter estimates by presenting the own- and cross-premium elasticity estimates from our base

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20 An order of magnitude larger than the levels generally seen in the literature. An exact calculation is difficult due to the truncated nature of the out-of-pocket payment variable.

20 We explored alternative functional forms for the relationship between premium, salary and plan choice including allowing the coefficient on premiums to vary by salary. All of these specifications did not fit the data as well as the current specification and often generated parameter estimates that were not sensible.
specification. For comparison purposes, Table 6 also presents the implied elasticity estimates from several other estimation strategies: Classical, MNL, classical nested logit (the nests being the POS 1 plans and the other plans), Baysian AR(1) probit with a diagonal covariance matrix, and a Bayesian multinomial probit.  

The implied price elasticities (from the enrollee’s perspective) from our base model are low and somewhat lower than previous estimates. The estimated average enrollee price elasticities is -.05. An examination of the plan-specific elasticities reveals that the low estimated average elasticities are driven by a strong enrollee loyalty towards the HMO and POS 2 plans. The own price elasticities for these plans are approximately -0.01 and -0.08, respectively, while the plan-specific elasticities for the other plans are approximately -0.11 to -0.15. The plan-perspective elasticities are much larger than the enrollee perspective elasticities ranging from -0.10 for the HMO to -0.68 for the CDHP. The cross-premium elasticity estimates reveal some interesting asymmetric substitution patterns. The POS 1 plan is the closest substitute for all the other plans. The CDHP is the closest substitute to the POS 1 plan.

The MNL model generates much larger price elasticities than those implied by our primary model. The mean price elasticity across plans and enrollees from this model is -.14 with non-HMO plan elasticities ranging from -.26 to -.36. Our results reject the underlying assumptions of the MNL model in this population; in so far as this finding is generalizable, it suggests that the widespread use of the iid, MNL model may be inflating health plan elasticity estimates significantly. Estimated elasticities from the nested MNL are approximately half as large as the MNL. The multinomial probit generates nonsensical positive own-price elasticity estimates. Interestingly, the implied own-price elasticities estimates from the AR(1) probit

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21 We combine all the POS 1 tiers in this analysis.

models with the constrained variance matrix imply elasticity estimates that are closer to our primary model than the logit models. Not surprisingly, the cross-price elasticities from the constrained this model differ from our base specification. The fact that the AR models generate similar own-price elasticities that are significantly smaller in magnitude than all the static models suggests that the bias in the own price estimates is a consequence of a failure to account for persistence in unobserved plan choice preferences.

The estimated cross-price elasticities (and their economic implications) implied by the MNL and nested MNL models are very different from those implied by the AR-MNP, highlighting again that the functional form assumptions of these MNL can drive the estimates. For example, the MNL estimates suggest that the HMO is the closest substitute for all of the plans because it has the largest share. The AR-MNP estimates imply that the HMO is not the closest substitute for any of the other plans.

We can decompose the premium elasticities across different segments of our sample. In particular, we can examine the elasticity of demand by age, gender and health status. There is a literature that argues that the healthy are more premium sensitive than the sick and these differential elasticities affect the dynamic stability of health plan premium setting. In general, our results are not consistent with this view. We have calculated elasticities by health status quartile and by age / gender cells. There are no differences in the elasticities by gender and modest differences by age. The mean elasticity for the non-HMO plans for enrollees 30 years and younger is -.16 while for those enrollees who are 45 years of age and older the corresponding elasticity is -.10. There are virtually no differences in the elasticities across health status quartiles. The lowest CW score quartile has an elasticity of -.11 for the non-HMO plans while the highest risk quartile has an elasticity of -.10.
A related question is whether plan preference “stickiness” differs by health status. Strombom, Buchmueller and Feldstein (2002) find that plan enrollees with a previous admission or cancer diagnoses are less likely to switch plans. In order to investigate whether enrollees in our data displayed similar patterns in plan choice we divide the sample into four quartiles based on health status (CW) and allowed the AR parameters to vary across the quartiles. In this model, the AR(1) coefficients were held constant across plans.

Table 7 presents the coefficient estimates from this exercise. The results indicate that there are statistically significant differences between the healthy and the sick in the autoregressive coefficient, but the magnitudes are not economically important. Thus, our estimates do not provide much support for the notion that the healthy are more premium sensitive and experience less health plan inertia than the sick.

The results from the cost and health plan choice models suggest that there is both adverse selection and employees are relatively premium insensitive when selecting a plan. Thus, the importance of adverse selection on welfare is unclear. Clearly, the presence of differential selection opens up the possibility that it may result in large premium distortions as suggested by Culter and Reber (1998). However, the low premium response of enrollees mitigates the impact of these premium distortions on plan selection and total welfare. To investigate the direction and magnitude of the welfare consequences requires simulating the impact of alternative premiums setting strategies on enrollee wellbeing and that is the subject of the next section.


The influential Jackson Hole group sought to bring the beneficial effects of market forces to the health care sector, and one important feature of its managed competition strategy was to force employees to face the cost differential between different health plans (Enthoven and Kronick, 1989a and 1989b). However, as noted by Newhouse (1996), Cutler and Reber (1998),
and Cutler and Zeckhauser (2000), unless the premium setting strategy accounts for adverse selection, managed competition can lead to inefficient premiums. Cutler and Reber (1998) argue that, in fact, Harvard University’s implementation of this managed competition approach to premium setting led to significant adverse selection induced welfare loss.

In order to measure the welfare harm associated with suboptimal premium setting, we calculate the impact of alternative premium setting strategies on the compensating variation of employees. In our context, the welfare harm arises because the individuals sort into plans where the relative (to other plans) cost of their enrollment is greater than the relative utility of that plan. We consider a partial equilibrium analysis within this organization by treating the self-insured organization’s health care budget as fixed.23 The optimal set of premiums will maximize the utility of enrollees given this fixed budget.

As we have estimated the structural indirect utility parameters, it is straightforward to perform counterfactual premium experiments via simulation. In each of these experiments we calculate the expected utility from alternative premium strategies and then find the change in salary for each individual in our data that would make them indifferent between the new premium vector and the old premium vector.

More formally, letting $P_{ij}$ denote the probability of individual $i$ of selecting plan $j$, and letting $W_{ij}$ denote the estimated expected utility of individual $i$ enrolling in plan $j$ conditional on choosing plan $j$, we find the compensating variation, CV, such that:

$$\sum_{j=1}^{J} P_{ij}(\text{Old prem}_j, \text{salary}_i) \cdot W_{ij}(\text{Old prem}_j, \text{salary}_i)$$

23 If the cost differentials between plans are solely a consequence of differential prices paid to providers and not moral hazard then our approach would still capture the welfare loss as the cost differentials still lead to distorted plan choices given those costs.
\[ \sum_{j=1}^{J} P_j \left( \text{Newprem}_j, \text{salary}_i + CV_i \right) \cdot W_j \left( \text{Newprem}_j, \text{salary}_i + CV_i \right). \]

Here, \( \text{Oldprem} \) and \( \text{Newprem} \) are the base level premium and the new premium in the experiment, respectively. In the risk adjustment experiments, we use the 2005 data and employer’s actual 2005 premium level as the comparison point. We explored the welfare impact of shifting to four possible premium setting scenarios.\(^{24}\) The first three of these scenarios are strategies that are used by employers, with the first two being the most common. The third strategy is a modestly sophisticated risk adjustment approach that requires the analysis of previous claims data. The fourth strategy is the optimal strategy modified from Cutler and Reber (1998). In each of the scenarios below, \( E(c_j|\text{premiums}) \) is the expected average cost of plan \( j \) conditional on the resulting employee premiums (and the characteristics of the plan \( j \)’s enrollees). In addition, in each of the four scenarios, employee premiums were set so that the average employer contribution remained at $1,916, the actual 2005 average employer contribution.

1. **Fixed percent of premium**: \( \text{premium}_j = \theta \cdot E(c_j|\text{premiums}) \) where \( \theta \in [0,1] \) is chosen to meet the target employer contribution.
2. **Fixed dollar contribution with no risk adjustment**: \( \text{premium}_j = E(c_j|\text{premiums}) - F \) where \( F \) is set equal to the target employer contribution.
3. **Fixed dollar contribution adjusted to the average population risk**: \( \text{premium}_j = \left( \frac{\overline{CW}}{CW_j} \right) E(c_j|\text{premiums}) - F \) where \( \overline{CW} \) is the average concurrent weight across all employees and \( CW_j \) is the concurrent weight of plan \( j \). Here the nominal \( F \) is adjusted so that the actual average employer contribution matches the target.
4. **Optimal Premiums**: The differential between the premium for plan \( j \) and the HMO is set equal to the weighted difference in plan costs across employees, where the weight is the marginal probability of enrollment for each individual:

\(^{24}\)An obvious strategy to explore is the Nash premium outcome. However, because our estimated plan perspective elasticities are low at the current premiums, the Nash equilibrium would result in equilibrium premiums an order of magnitude larger than our the current premiums and thus seems to be of little practical relevance.
\[ \Delta \text{premium}_j = \frac{\sum_{i=1}^{N} \frac{\partial \text{Pr}_i(\text{plan } j)}{\partial \text{Prem}_j} (E(c_j | \text{premiums}) - E(c_{HMO} | \text{premiums}))}{\sum_{i=1}^{N} \frac{\partial \text{Pr}_i(\text{plan } j)}{\partial \text{Prem}_j}} \]

The HMO premium, on which all other plan premiums are based is then selected so that the average employer contribution matches the target. This is a generalization of the optimal premium setting strategy as characterized by Cutler and Reber (1998), to a setting with more than two plan options in a random utility environment.

The fixed percent of premiums strategy can be viewed as a crude mechanism to risk adjust premiums as individuals do not fully incur the cost differential of enrolling in high cost plans. The fixed dollar contribution is a strategy that promotes the efficient allocation of enrollees across plans; the high cost plans are not subsidized for higher health care risk, and enrollees join high cost plans if the utility of those plans exceeds the increased cost. The risk adjusted, fixed dollar premium is the strategy promoted by the early advocates of managed competition and attempts to maintain the efficiency aspects of the fixed dollar approach while mitigating the impact of adverse selection. The optimal premium difference between plans is given by the difference in the marginal cost of the plans for the marginal enrollee. This is the approach we take in implementing the optimal premium in this experiment.

As mentioned above, by 2005 this employer partially risk adjusted the premiums using an ad hoc approach. So the baseline premiums which we use to compare the results of the experiments should not be viewed as representing a state “no risk adjustment,” but rather are crudely risk adjusted using an ad hoc risk approach.

The results of this simulation are presented in Table 8. The premiums based on fixed employer contribution, with and without risk adjustment, are very different from the baseline premiums levels. The HMO becomes significantly cheaper and the CDHP plan is much more expensive. All of the premium setting strategies yield welfare improvements. However, despite the large changes in premiums, the magnitudes of the increases are very modest. The best performing strategies are the nearly identical third and fourth scenarios, which result in a
compensating variation decrease of approximately $13, or 0.5% of average total health care expenditures. It is significant that the optimal strategy can be achieved using a fairly simple risk adjustment methodology when historical health claims data are available.

In order to get a sense of the importance of underlying model is affecting welfare conclusions, we also calculate the welfare using the estimates from the Multinomial Logit model. The implied estimated improvement in welfare is significantly higher for the MNL. The welfare gain from the optimal premium is $190 or 6% of total expenditures – 14.6 times the estimates from our base model. So not only does it appear that the MNL approach (and its static cousins) yield biased estimates of the elasticities, it also affects welfare inferences.

In Table 9 we analyze the distributional impact of the different premium setting strategies. Relative to baseline premiums, those with poorer health status and higher salaries are better off with the percent of premium strategy. This is because these individuals are more likely to enroll in high cost plans and the percent of premium strategy lowers the relative cost of those plans. The use of fixed contribution strategies and the optimal premiums benefits healthier employees and those at the lower end of the pay scale.

Cutler and Reber (1998) found that moving to a fixed contribution setting from one that subsidized high cost plans at Harvard University induced adverse selection welfare loss between 2 to 4 percent of baseline spending. To compare our results to Cutler and Reber’s, simply difference the compensating variation values of scenarios (2) and (1) in Table 8. Our results indicate that a change in premium setting strategy such as the one that occurred at Harvard would induce an adverse selection welfare loss of $2.35 -- a much smaller relative value than the Cutler and Reber figure. Our results differ from Cutler and Reber’s, in part, because of the difference in the estimated premium elasticities. Cutler and Reber estimate the average out-of-pocket premium elasticity between -.3 and -.6 a figure that is seven to fifteen times larger than our estimates. The
lower the price sensitivity, the lower the welfare loss due to adverse selection as premium distortions do translate into distortions in the distribution of enrollees across health plans. Our welfare loss magnitudes are much closer to those in Einav, Finkelstein and Cullen (2008). They estimate the welfare loss from adverse selection to be $9.55 per year for enrollees in a large multinational firm.

In sum, for the employer we examine there is significant adverse selection in health plan choice. The magnitude of the adverse selection can be seen by examining the differences in the risk-adjusted premiums verses the premiums actually set by the employer. However, the welfare impact of the adverse selection is small. This finding highlights that most economists’ intuitive reaction that adverse selection must lead to market distortions is not necessarily correct. The welfare loss will be a function of both the degree of adverse selection, the price elasticity of demand and the cost-differentials across plans.

7. Conclusion

Using flexible models of health insurance choice and medical care expenditures that remove many of the unappealing assumptions of traditional approaches, we estimate the welfare impact of adverse selection. Our estimates suggest that adverse selection is present and economically important -- there are significant mean cost differences across plans as a consequence of differential enrollee health status. Importantly, this adverse selection does not translate into significant welfare loss induced by pricing distortions and the implementation of risk-adjusted premiums only improves welfare marginally. This finding highlights the tension between health insurance competition, adverse selection and efficiency. Welfare loss due to

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25 There are two likely reasons for the differential elasticity estimates. First, the employees in our organization are very loyal to the HMO and POS 2 plans, and Harvard employees did not display similar loyalty to their health plans. Second, we estimate a choice model that imposes fewer ad hoc restrictions and our results suggest that elasticities implied by our model are about half as large as those from the MNL – the model Cutler and Reber use.
adverse selection is low because premium elasticities are low. However, since estimated premium elasticities are low it suggests that market-based health plan competition will not result in premiums near marginal cost. The standard prescription to resolve these conflicting incentives induced by health plan competition is to risk-adjust premiums. While this strategy can certainly solve the adverse selection problem, risk adjustment is often difficult to implement and is the exception in employment-based health insurance (Kennen et al., 2001). Our results suggest why this is the case.
References


### Table 1
Annual premiums and health plan shares 2002-2005

<table>
<thead>
<tr>
<th>Plan</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
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<tbody>
<tr>
<td></td>
<td>Share Premium ($)</td>
<td>Share Premium ($)</td>
<td>Share Premium ($)</td>
<td>Share Premium ($)</td>
</tr>
<tr>
<td>HMO</td>
<td>.622 0.00</td>
<td>.688 0.00</td>
<td>.688 382</td>
<td>.686 408</td>
</tr>
<tr>
<td>Tier 1</td>
<td>.077 0.00</td>
<td>.044 21</td>
<td>.040 741</td>
<td>.047 770</td>
</tr>
<tr>
<td>Tier 2</td>
<td>.096 242</td>
<td>.082 247</td>
<td>.080 1,064</td>
<td>.072 1,074</td>
</tr>
<tr>
<td>Tier 3</td>
<td>.073 522</td>
<td>.095 512</td>
<td>.050 1,474</td>
<td>.031 1,721</td>
</tr>
<tr>
<td>POS 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POS 2</td>
<td>.090 1,346</td>
<td>.060 1,258</td>
<td>.064 1,463</td>
<td>.086 783</td>
</tr>
<tr>
<td>CDHP</td>
<td>.041 329</td>
<td>.061 194</td>
<td>.074 670</td>
<td>.073 793</td>
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</table>
Table 2
Demographics and health status by plan
(standard deviations in parentheses)

<table>
<thead>
<tr>
<th></th>
<th>All Enrollees</th>
<th>HMO</th>
<th>POS</th>
<th>POS2</th>
<th>CDHP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Tier 1</td>
<td>Tier 2</td>
<td>Tier 3</td>
</tr>
<tr>
<td>Age</td>
<td>46.0</td>
<td>44.3</td>
<td>47.5</td>
<td>48.7</td>
<td>48.5</td>
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<tr>
<td></td>
<td>(11.4)</td>
<td>(11.4)</td>
<td>(9.8)</td>
<td>(10.2)</td>
<td>(10.0)</td>
</tr>
<tr>
<td>Percent Female</td>
<td>62.5</td>
<td>59.2</td>
<td>76.0</td>
<td>71.6</td>
<td>64.2</td>
</tr>
<tr>
<td></td>
<td>(48.4)</td>
<td>(49.1)</td>
<td>(42.7)</td>
<td>(45.1)</td>
<td>(48.0)</td>
</tr>
<tr>
<td>Salary ($)</td>
<td>48,810</td>
<td>45,249</td>
<td>51,489</td>
<td>49,149</td>
<td>53,772</td>
</tr>
<tr>
<td></td>
<td>(25,127)</td>
<td>(21,920)</td>
<td>(25,197)</td>
<td>(21,950)</td>
<td>(29,127)</td>
</tr>
<tr>
<td>Concurrent Weight</td>
<td>1.78</td>
<td>1.47</td>
<td>2.59</td>
<td>2.22</td>
<td>2.41</td>
</tr>
<tr>
<td></td>
<td>(3.30)</td>
<td>(2.76)</td>
<td>(4.42)</td>
<td>(3.26)</td>
<td>(2.76)</td>
</tr>
</tbody>
</table>
Table 3
Estimated per enrollee cost of alternative enrollments

<table>
<thead>
<tr>
<th>Currently Enrolled in Plan</th>
<th>HMO</th>
<th>POS 1</th>
<th>POS 2</th>
<th>CDHP</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMO</td>
<td>1,958</td>
<td>2,743</td>
<td>2,469</td>
<td>3,546</td>
</tr>
<tr>
<td>POS 1</td>
<td>2,842</td>
<td>3,895</td>
<td>3,376</td>
<td>4,961</td>
</tr>
<tr>
<td>POS 2</td>
<td>3,226</td>
<td>4,366</td>
<td>4,136</td>
<td>6,087</td>
</tr>
<tr>
<td>CDHP</td>
<td>2,561</td>
<td>3,410</td>
<td>3,390</td>
<td>4,887</td>
</tr>
<tr>
<td>All in One Plan</td>
<td>2,246</td>
<td>3,107</td>
<td>2,819</td>
<td>4,079</td>
</tr>
</tbody>
</table>
### Table 4

**Posterior means and coefficient point estimates for choice models**

(standard deviations of posterior in parentheses)

[standard errors in brackets]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Bayesian AR(1) Probit</th>
<th>MNL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>***</td>
</tr>
<tr>
<td>HMO Intercept</td>
<td>1.2863</td>
<td>5.7896</td>
</tr>
<tr>
<td></td>
<td>(0.1434)</td>
<td>[0.6771]</td>
</tr>
<tr>
<td>POS 1, Tier 1 Intercept</td>
<td>0.0360</td>
<td>1.6798</td>
</tr>
<tr>
<td></td>
<td>(0.1192)</td>
<td>[0.8956]</td>
</tr>
<tr>
<td>POS 1, Tier 2 Intercept</td>
<td>-0.1034</td>
<td>2.1391</td>
</tr>
<tr>
<td></td>
<td>(0.1035)</td>
<td>[0.7765]</td>
</tr>
<tr>
<td>POS 1, Tier 3 Intercept</td>
<td>-0.1366</td>
<td>1.9270</td>
</tr>
<tr>
<td></td>
<td>(0.1038)</td>
<td>[0.8021]</td>
</tr>
<tr>
<td>POS 2 Intercept</td>
<td>-0.4232 ***</td>
<td>0.9675</td>
</tr>
<tr>
<td></td>
<td>(0.1348)</td>
<td>[0.9010]</td>
</tr>
<tr>
<td>HMO Age</td>
<td>-0.0136 ***</td>
<td>-0.0608 +++</td>
</tr>
<tr>
<td></td>
<td>(0.0026)</td>
<td>[0.0101]</td>
</tr>
<tr>
<td>POS 1, Tier 1 Age</td>
<td>-0.0071 ***</td>
<td>-0.0410 ++</td>
</tr>
<tr>
<td></td>
<td>(0.0022)</td>
<td>[0.0167]</td>
</tr>
<tr>
<td>POS 1, Tier 2 Age</td>
<td>-0.0043 **</td>
<td>-0.0311 ++</td>
</tr>
<tr>
<td></td>
<td>(0.0020)</td>
<td>[0.0136]</td>
</tr>
<tr>
<td>POS 1, Tier 3 Age</td>
<td>-0.0026</td>
<td>-0.0255 +</td>
</tr>
<tr>
<td></td>
<td>(0.0019)</td>
<td>[0.0138]</td>
</tr>
<tr>
<td>POS 2 Age</td>
<td>0.0027</td>
<td>-0.0112</td>
</tr>
<tr>
<td></td>
<td>(0.0023)</td>
<td>[0.0150]</td>
</tr>
<tr>
<td>HMO Female</td>
<td>-0.3237 **</td>
<td>-1.4108 ++</td>
</tr>
<tr>
<td></td>
<td>(0.1404)</td>
<td>[0.6523]</td>
</tr>
<tr>
<td>POS 1, Tier 1 Female</td>
<td>-0.1432</td>
<td>-0.3688</td>
</tr>
<tr>
<td></td>
<td>(0.1332)</td>
<td>[1.0036]</td>
</tr>
<tr>
<td>POS 1, Tier 2 Female</td>
<td>-0.1280</td>
<td>-0.7279</td>
</tr>
<tr>
<td></td>
<td>(0.1240)</td>
<td>[0.8666]</td>
</tr>
<tr>
<td>POS 1, Tier 3 Female</td>
<td>-0.0548</td>
<td>-0.1430</td>
</tr>
<tr>
<td></td>
<td>(0.1211)</td>
<td>[0.9016]</td>
</tr>
<tr>
<td>POS 2 Female</td>
<td>-0.0708</td>
<td>-0.6144</td>
</tr>
<tr>
<td></td>
<td>(0.1500)</td>
<td>[0.9739]</td>
</tr>
<tr>
<td>HMO log(Health Status)</td>
<td>0.0055 *</td>
<td>0.0273 ++</td>
</tr>
<tr>
<td></td>
<td>(0.0029)</td>
<td>[0.0126]</td>
</tr>
<tr>
<td>POS 1, Tier 1 log(Health Status)</td>
<td>0.0042</td>
<td>0.0176</td>
</tr>
<tr>
<td></td>
<td>(0.0027)</td>
<td>[0.0200]</td>
</tr>
<tr>
<td>POS 1, Tier 2 log(Health Status)</td>
<td>0.0040</td>
<td>0.0218</td>
</tr>
<tr>
<td></td>
<td>(0.0026)</td>
<td>[0.0169]</td>
</tr>
<tr>
<td>POS 1, Tier 3 log(Health Status)</td>
<td>0.0009</td>
<td>0.0023</td>
</tr>
<tr>
<td></td>
<td>(0.0025)</td>
<td>[0.0176]</td>
</tr>
<tr>
<td>POS 2 log(Health Status)</td>
<td>0.0028</td>
<td>0.0249</td>
</tr>
<tr>
<td></td>
<td>(0.0030)</td>
<td>[0.0185]</td>
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</tbody>
</table>
Table 4, continued
Posterior means and coefficient point estimates for choice models
(standard deviations of posterior in parentheses)
[standard errors in brackets]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Bayesian AR(1) Probit</th>
<th>Classical MNL</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMO Female x Age</td>
<td>0.0095 (0.0085)</td>
<td>-0.6522 [1.0372]</td>
</tr>
<tr>
<td>POS 1, Tier 1 Female x Age</td>
<td>0.0322 (0.0091) ***</td>
<td>0.6815 [1.2695]</td>
</tr>
<tr>
<td>POS 1, Tier 2 Female x Age</td>
<td>0.0323 (0.0085) ***</td>
<td>-0.9221 [1.2253]</td>
</tr>
<tr>
<td>POS 1, Tier 3 Female x Age</td>
<td>0.0394 (0.0089) ***</td>
<td>0.0321 [1.2235]</td>
</tr>
<tr>
<td>POS 2 Female x Age</td>
<td>0.0374 (0.0095) ***</td>
<td>0.2926 [1.1775]</td>
</tr>
<tr>
<td>log(Salaryi-Premiumj)</td>
<td>1.6287 (0.6865) ***</td>
<td>17.4481 [3.7362] +++</td>
</tr>
<tr>
<td>E(logOOP)</td>
<td>-0.1257 (0.0204) ***</td>
<td>0.0745 [0.1566]</td>
</tr>
<tr>
<td>Var(logOOP)</td>
<td>-0.1936 (0.0336) ***</td>
<td>-1.6245 [0.2808]+++</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* 90% Bayesian confidence interval excludes zero.
+ 90% classical confidence interval excludes zero.
** 95% Bayesian confidence interval excludes zero.
++ 95% classical confidence interval excludes zero.
*** 99% Bayesian confidence interval excludes zero.
+++ 99% classical confidence interval excludes zero.
Table 5
Estimated parameters of variance matrix

Table 5a – AR(1) parameters

<table>
<thead>
<tr>
<th>AR(1) Model</th>
<th>HMO</th>
<th>POS 1, Tier 1</th>
<th>POS 1, Tier 2</th>
<th>POS 1, Tier 3</th>
<th>POS 2</th>
<th>CDHP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rho</td>
<td>0.5765 ***</td>
<td>0.9869 ***</td>
<td>0.9659 ***</td>
<td>0.9335 ***</td>
<td>0.9960 ***</td>
<td>0.9960 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0291)</td>
<td>(0.0112)</td>
<td>(0.0192)</td>
<td>(0.0267)</td>
<td>(0.0039)</td>
<td>(0.0039)</td>
</tr>
<tr>
<td>Tau2</td>
<td>0.0866 ***</td>
<td>0.1042 ***</td>
<td>0.1049 ***</td>
<td>0.0959 ***</td>
<td>0.1099 ***</td>
<td>0.1099 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0093)</td>
<td>(0.0123)</td>
<td>(0.0127)</td>
<td>(0.0113)</td>
<td>(0.0137)</td>
<td>(0.0137)</td>
</tr>
</tbody>
</table>

Table 5b – Across-plan variance/covariance matrix

<table>
<thead>
<tr>
<th>Across-Plan Variance-Covariance Matrix (std dev)</th>
<th>HMO</th>
<th>POS 1, Tier 1</th>
<th>POS 1, Tier 2</th>
<th>POS 1, Tier 3</th>
<th>POS 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMO</td>
<td>1.0000 ***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POS 1, Tier 1</td>
<td>0.2243 ***</td>
<td>0.1874 ***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0376)</td>
<td>(0.0271)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POS 1, Tier 2</td>
<td>0.0386</td>
<td>0.0219</td>
<td>0.1501 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0327)</td>
<td>(0.0148)</td>
<td>(0.0325)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>POS 1, Tier 3</td>
<td>0.0631</td>
<td>-0.0056</td>
<td>0.0523 ***</td>
<td>0.1767 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0334)</td>
<td>(0.0135)</td>
<td>(0.0217)</td>
<td>(0.0388)</td>
<td></td>
</tr>
<tr>
<td>POS 2</td>
<td>0.2170 ***</td>
<td>0.0395</td>
<td>-0.0278 *</td>
<td>0.0092</td>
<td>0.2627 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0409)</td>
<td>(0.0209)</td>
<td>(0.0173)</td>
<td>(0.0191)</td>
<td>(0.0522)</td>
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</table>
**Table 5c – Across-plan implied correlation coefficients**

<table>
<thead>
<tr>
<th>Implied Across-Plan Correlation Coefficients</th>
<th>POS 1, Tier 1</th>
<th>POS 1, Tier 2</th>
<th>POS 1, Tier 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMO</td>
<td>0.5182</td>
<td>0.0996</td>
<td>0.1306</td>
</tr>
<tr>
<td>POS 1, Tier 1</td>
<td></td>
<td>0.1306</td>
<td></td>
</tr>
<tr>
<td>POS 1, Tier 2</td>
<td>0.1502</td>
<td>-0.0306</td>
<td>0.3214</td>
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<td>POS 1, Tier 3</td>
<td>0.4234</td>
<td>0.1779</td>
<td>-0.1399</td>
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</tbody>
</table>

* 90% Bayesian confidence interval excludes zero.
** 95% Bayesian confidence interval excludes zero.
*** 99% Bayesian confidence interval excludes zero.
Table 6
Own- and Cross-Price Elasticities

<table>
<thead>
<tr>
<th></th>
<th>AR(1) Multinomial Probit Elasticities: Unconstrained Covariance Matrix (Base Model)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HMO</td>
</tr>
<tr>
<td>HMO</td>
<td>-0.009</td>
</tr>
<tr>
<td>POS 1</td>
<td>0.016</td>
</tr>
<tr>
<td>POS 2</td>
<td>0.004</td>
</tr>
<tr>
<td>CDHP</td>
<td>0.002</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>Multinomial Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HMO</td>
</tr>
<tr>
<td>HMO</td>
<td>-0.091</td>
</tr>
<tr>
<td>POS 1</td>
<td>0.574</td>
</tr>
<tr>
<td>POS 2</td>
<td>0.043</td>
</tr>
<tr>
<td>CDHP</td>
<td>0.012</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Nested Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HMO</td>
</tr>
<tr>
<td>HMO</td>
<td>-0.053</td>
</tr>
<tr>
<td>POS 1</td>
<td>0.071</td>
</tr>
<tr>
<td>POS 2</td>
<td>0.024</td>
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<tr>
<td>CDHP</td>
<td>0.022</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>AR(1) Multinomial Probit Elasticities: Diagonal Covariance Matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HMO</td>
</tr>
<tr>
<td>HMO</td>
<td>-0.011</td>
</tr>
<tr>
<td>POS 1</td>
<td>0.018</td>
</tr>
<tr>
<td>POS 2</td>
<td>0.004</td>
</tr>
<tr>
<td>CDHP</td>
<td>0.004</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Multinomial Probit Elasticities: Unconstrained Covariance Matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HMO</td>
</tr>
<tr>
<td>HMO</td>
<td>0.001</td>
</tr>
<tr>
<td>POS 1</td>
<td>-0.003</td>
</tr>
<tr>
<td>POS 2</td>
<td>0.001</td>
</tr>
<tr>
<td>CDHP</td>
<td>0.001</td>
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</table>
Table 7
AR(1) coefficients by risk group

<table>
<thead>
<tr>
<th>Risk Group</th>
<th>AR Coefficient Sample Mean (std dev) of Posterior</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthiest Quartile</td>
<td>0.8564 *** (0.0189)</td>
</tr>
<tr>
<td>2nd Quartile</td>
<td>0.8442 *** (0.0177)</td>
</tr>
<tr>
<td>3rd Quartile</td>
<td>0.9226 *** (0.0221)</td>
</tr>
<tr>
<td>Sickest Quartile</td>
<td>0.9152 *** (0.0190)</td>
</tr>
</tbody>
</table>

*** 99% Bayesian confidence interval excludes zero.
## Table 8
**Employer pricing scenarios – impact on welfare and claims cost**

<table>
<thead>
<tr>
<th></th>
<th>Annual Employee Contribution</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
<td>% of Premium</td>
<td>Fixed $, no Risk Adj</td>
<td>Fixed $, w/ Risk Adj</td>
<td>Optimal Premium</td>
</tr>
<tr>
<td>HMO</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tier 1</td>
<td>$408.20</td>
<td>$469.82</td>
<td>$59.02</td>
<td>$246.22</td>
<td>$214.24</td>
</tr>
<tr>
<td>Tier 2</td>
<td>$769.60</td>
<td>$838.76</td>
<td>$1,607.32</td>
<td>$1,301.30</td>
<td>$1,456.52</td>
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<tr>
<td>POS 1</td>
<td>$1,073.80</td>
<td>$787.54</td>
<td>$1,399.32</td>
<td>$1,277.38</td>
<td>$1,284.14</td>
</tr>
<tr>
<td>Tier 3</td>
<td>$1,721.20</td>
<td>$829.14</td>
<td>$1,575.34</td>
<td>$1,213.94</td>
<td>$1,285.96</td>
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<tr>
<td>POS 2</td>
<td>$782.60</td>
<td>$803.66</td>
<td>$1,470.82</td>
<td>$696.28</td>
<td>$799.50</td>
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<td>CDHP</td>
<td>$793.00</td>
<td>$1,091.22</td>
<td>$2,741.18</td>
<td>$2,139.28</td>
<td>$2,208.70</td>
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<tr>
<td>Compensating Variation</td>
<td></td>
<td>($8.24)</td>
<td>($5.32)</td>
<td>($13.66)</td>
<td>($13.24)</td>
</tr>
<tr>
<td>std dev</td>
<td></td>
<td></td>
<td>17.4</td>
<td>87.2</td>
<td>46.6</td>
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</table>

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</thead>
<tbody>
<tr>
<td></td>
<td>Break-Down of Average Annual Per-Capita Costs</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Employer Contribution</td>
<td>$1,916</td>
<td>$1,916</td>
<td>$1,916</td>
<td>$1,916</td>
<td>$1,916</td>
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<tr>
<td>Employee Contribution</td>
<td>$603</td>
<td>$600</td>
<td>$570</td>
<td>$580</td>
<td>$578</td>
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<tr>
<td>Plan Cost</td>
<td>$2,518</td>
<td>$2,515</td>
<td>$2,485</td>
<td>$2,495</td>
<td>$2,493</td>
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<tr>
<td>Ave Employee OOP Cost</td>
<td>$370</td>
<td>$367</td>
<td>$360</td>
<td>$363</td>
<td>$362</td>
</tr>
<tr>
<td>Total Claims Cost</td>
<td>$2,888</td>
<td>$2,883</td>
<td>$2,845</td>
<td>$2,858</td>
<td>$2,856</td>
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Table 9
Employer pricing scenarios – distribution of welfare

<table>
<thead>
<tr>
<th></th>
<th>Count</th>
<th>Ave Age</th>
<th>% Female</th>
<th>Ave cwt</th>
<th>Average pr(high)</th>
<th>Average Income</th>
<th>Average Compensating Variation</th>
</tr>
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<tbody>
<tr>
<td>Current Premiums</td>
<td>3578</td>
<td>47.0</td>
<td>62%</td>
<td>1.857</td>
<td>9.9%</td>
<td>$49,299</td>
<td>---</td>
</tr>
<tr>
<td>% of Premium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benefit/Same</td>
<td>2503</td>
<td>48.6</td>
<td>72%</td>
<td>2.276</td>
<td>11.8%</td>
<td>$51,299</td>
<td>($16.71)</td>
</tr>
<tr>
<td>Harmed</td>
<td>1075</td>
<td>43.4</td>
<td>39%</td>
<td>0.881</td>
<td>5.5%</td>
<td>$44,643</td>
<td>$9.32</td>
</tr>
<tr>
<td>Total</td>
<td>3578</td>
<td>47.0</td>
<td>62%</td>
<td>1.857</td>
<td>9.9%</td>
<td>$49,299</td>
<td>($8.89)</td>
</tr>
<tr>
<td>Fixed $, no Risk</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjustment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benefit/Same</td>
<td>1911</td>
<td>39.6</td>
<td>54%</td>
<td>1.074</td>
<td>6.9%</td>
<td>$44,935</td>
<td>($54.68)</td>
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<tr>
<td>Harmed</td>
<td>1667</td>
<td>55.5</td>
<td>73%</td>
<td>2.755</td>
<td>13.3%</td>
<td>$54,302</td>
<td>$48.64</td>
</tr>
<tr>
<td>Total</td>
<td>3578</td>
<td>47.0</td>
<td>62%</td>
<td>1.857</td>
<td>9.9%</td>
<td>$49,299</td>
<td>($6.54)</td>
</tr>
<tr>
<td>Fixed $, with Risk</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjustment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benefit/Same</td>
<td>2473</td>
<td>43.6</td>
<td>62%</td>
<td>1.638</td>
<td>9.4%</td>
<td>$47,586</td>
<td>($30.32)</td>
</tr>
<tr>
<td>Harmed</td>
<td>1105</td>
<td>54.7</td>
<td>63%</td>
<td>2.346</td>
<td>11.1%</td>
<td>$53,134</td>
<td>$24.44</td>
</tr>
<tr>
<td>Total</td>
<td>3578</td>
<td>47.0</td>
<td>62%</td>
<td>1.857</td>
<td>9.9%</td>
<td>$49,299</td>
<td>($13.41)</td>
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<tr>
<td>Optimal Premium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benefit/Same</td>
<td>2460</td>
<td>43.3</td>
<td>61%</td>
<td>1.584</td>
<td>9.2%</td>
<td>$47,694</td>
<td>($30.48)</td>
</tr>
<tr>
<td>Harmed</td>
<td>1118</td>
<td>55.2</td>
<td>65%</td>
<td>2.458</td>
<td>11.5%</td>
<td>$52,832</td>
<td>$24.26</td>
</tr>
<tr>
<td>Total</td>
<td>3578</td>
<td>47.0</td>
<td>62%</td>
<td>1.857</td>
<td>9.9%</td>
<td>$49,299</td>
<td>($13.38)</td>
</tr>
</tbody>
</table>
Figure 1
Comparison of actual and predicted claims and out-of-pocket payments
Figure 2
Logarithm of estimated claims for 47-year old female by health status and plan
Figure 3
Logarithm of estimated OOP for 47-year old female by health status and plan
Figure 4
Estimated variance of logarithm of OOP for 47-year old female by health status and plan
Appendix A: Bayesian inference for cost model

Prior Specifications for the Cost Model

The likelihood for the latent values of allowed charges and OOP expenses:

\[ L(T^*, Clm^*, OOP^* | b, \beta_t^b, \beta_c^e, \beta_o^o, \Sigma, T, Clm, OOP) \]

\[ \propto \prod_{j=1}^{P} \left[ \Sigma_j \right]^{N_j/2} \exp \left\{ -\frac{1}{2} \sum_{(i,j) \in P_j} \left( SampErr_i^j \Sigma_j^{-1} SampErr_i^j \right) \right\} , \]

where \( N_j \) is the number of times in the panel a patient is enrolled in plan \( j \).

This likelihood is conditional on five sets of parameters, which are assumed to have the following prior distributions:

- The set of individual-specific, time-invariant intercepts, \( b = \left[ b_t^b \ b_c^e \ b_o^o \right]^T \). \( D \) is to be estimated.
- The parameter vectors for the overall means of \( T^*_u \), \( Clm^*_u \) and \( OOP^*_u \): \( \beta_t^b \), \( \beta_c^e \) and \( \beta_o^o \).
  \[ \beta_t^b \sim N(0, A_t^{-1}) \]
  \[ \beta_c^e \sim N(0, A_c^{-1}) \]
  \[ \beta_o^o \sim N(0, A_o^{-1}) \]
- The covariance matrices, \( \Sigma_j \), for the period-specific random error terms \( \xi_u = \left[ \xi_t^b \xi_c^e \xi_o^o \right]^T \) for individuals enrolled in plan \( j \).
  \( \Sigma_j \sim IW(b, W) \), \( j = 1, \ldots, P \)
- And finally, the covariance matrix, \( D \), for the distribution of \( b_i \).
  \( D \sim IW(a, V) \)

Gibbs Iterations

Combining these prior specifications with the likelihood results in the posterior

\[ P(b, \beta_t^b, \beta_c^e, \beta_o^o, D, \Sigma | T^*, Clm^*, OOP^*, T, Clm, OOP) \]
\[ \varepsilon L(T^*, Clm^*, OOP^* | b, \beta^h, \beta^c, \Sigma, D, T, Clm, OOP^*) : \prod_{i=1}^{N} P(b_i) \cdot P(\beta^h) \cdot P(\beta^c) \cdot P(D) \cdot \prod_{j=1}^{P} P(\Sigma) \]

\[ \varepsilon \prod_{j=1}^{P} \left[ \exp \left( -\frac{1}{2} \sum_{(i,j) \in P_j} \left( SampErr_i' \Sigma^{-1} SampErr_i \right) \right) \right] \cdot \left| D \right|^{-N/2} \exp \left( -\frac{1}{2} \sum_{i=1}^{N} b_i' D^{-1} b_i \right) \cdot |A_{nh}|^{1/2} \exp \left( -\frac{1}{2} \beta^h' A_{nh} \beta^h \right) \cdot |A_{o}|^{1/2} \exp \left( -\frac{1}{2} \beta^c' A_{o} \beta^c \right) \cdot \left| D \right|^{-(a+3)/2} \exp \left( -\frac{1}{2} \text{tr}(VD^{-1}) \right) \cdot \prod_{j=1}^{P} \left( \left| \Sigma_j \right|^{-(b+3)/2} \exp \left( -\frac{1}{2} \text{tr}(W \Sigma_j^{-1}) \right) \right), \]

where [X] is partitioned so that \( \Sigma_{11}^j \) is a 1x1 matrix from the upper left and \( \Sigma_{22}^j \) is a 2x2 matrix from the lower right.

From this, we can isolate the conditional distributions to be used in the Gibbs iterations. Details of this derivation can be obtained from the corresponding author.

1. Draw \( T_u^{(k)} | b_i^{(k-1)}, \beta^h, \beta^c, \Sigma, x \)

In this data augmentation step, \( T_u^{*} \) is generated for all observations, constrained to be positive if claims are observed, negative if not.

a. \( T_u = 0 \)

The threshold variable is drawn from a univariate normal distribution, constrained to be less than or equal to zero:

\[ T_u^{(k)} | b_i^{(k-1)}, \beta^h, \Sigma, x \sim N \left[ x_i^h \beta^h + b_i^h, \Sigma_i - \Sigma_i \Sigma_{11}^j (\Sigma_{12}^j)^{-1} \Sigma_{12}^j \right], \]

where \( \Sigma_i \) is partitioned so that \( \Sigma_{11}^j \) is a 1x1 matrix from the upper left and \( \Sigma_{22}^j \) is a 2x2 matrix from the lower right.

b. \( T_u = 1 \)

The threshold variable is drawn from a univariate normal distribution, constrained to be positive:

\[ T_u^{(k)} | Clm_u^{*}, OOP_u^{*}, b_i, \beta^h, \beta^c, \Sigma, x \sim \]

\[ N \left[ x_i^h \beta^h + b_i^h + \Sigma_i^j (\Sigma_{21}^j)^{-1} \left( Clm_u^{*} - x_i^h \beta^c - b_i^c \right), \Sigma_i + \Sigma_i^j (\Sigma_{22}^j)^{-1} \Sigma_{12}^j \right], \]

where \( \Sigma_i \) is partitioned as above.

2. Draw \( OOP_u^{(k)} | b_i^{(k-1)}, \beta^h, \beta^c, \Sigma, \Sigma, x \)

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We set \( Clm^*_i = Clm_i \), if \( T^*_i > 0 \), and set \( OOP^*_i = OOP_i \) if \( T^*_i > 0 \) and \( 0 < OOP_i < OOP_{Lim} \), where \( (i,t) \in P_j \). If claims are observed, but the OOP payments are not in this range, we use data augmentation to sample \( OOP^*_i \).

a. \( T^*_i > 0 \) and \( OOP^*_i = 0 \)

\( OOP^*_i \) is drawn from the normal distribution below, truncated such that \( OOP^*_i < 0 \).

\[
OOP^*_i | T^*_i, Clm^*_i, T_{it}, OOP^*_i, b_i, \beta^h, \beta^c, \Sigma, x \sim N \left( x'_i \beta^o + b'_i + \Sigma_{12}^{j} \left( \Sigma_{11}^{j} \right)^{-1} \left( T^*_i - x'_i \beta^h - b^h_i \right) \right),
\]

where \( \Sigma' \) is partitioned so that \( \Sigma_{11}^{j} \) is a 2x2 matrix from the upper left and \( \Sigma_{22}^{j} \) is a 1x1 matrix from the lower right.

b. \( T^*_i > 0 \) and \( 0 < OOP^*_i < OOP_{Lim} \)

\( Clm^*_i = Clm_i \), and \( OOP^*_i = OOP_i \), and no data augmentation is needed.

c. \( T^*_i > 0 \) and \( OOP^*_i = OOP_{Lim} \)

\( OOP^*_i \) is drawn from the normal distribution below, truncated such that \( OOP^*_i > OOP_{Lim} \).

\[
OOP^*_i | T^*_i, Clm^*_i, T_{it}, OOP^*_i, b_i, \beta^h, \beta^c, \Sigma, x \sim N \left( x'_i \beta^o + b'_i + \Sigma_{12}^{j} \left( \Sigma_{11}^{j} \right)^{-1} \left( T^*_i - x'_i \beta^h - b^h_i \right) \right),
\]

where \( \Sigma' \) is partitioned so that \( \Sigma_{11}^{j} \) is a 2x2 matrix from the upper left and \( \Sigma_{22}^{j} \) is a 1x1 matrix from the lower right.

3. For each individual, draw \( b^{(k)}_i | T^{(k)}_i, Clm^{(k)}_i, OOP^{(k)}_i, \beta^{h(k-1)}, \beta^{c(k-1)}, \beta^{o(k-1)}, \Sigma^{(k-1)}, D^{(k-1)}, x \)

\[
b^{(k)}_i | T^{(k)}_i, Clm^{(k)}_i, OOP^{(k)}_i, \beta^{h(k-1)}, \beta^{c(k-1)}, \beta^{o(k-1)}, \Sigma, D, x \sim N \left( D^{-1} + \sum_{j=1}^{r} \Sigma^{-1}_{j(j)}, \sum_{j=1}^{r} \Sigma^{-1}_{j(j)} SampErr_{it} \right), \left( D^{-1} + \sum_{j=1}^{r} \Sigma^{-1}_{j(j)} \right)^{-1} \right], \text{ where}
\]

\[
SampErr_{it} = Clm^{(k)}_i - x^{(k)}_i \beta^{h(k-1)}
\]

unobserved, and \( j(t) \) indicates the plan selected by the individual in year \( t \).

4. Draw \( D^{(k)} | b^{(k)} \)

\[
D^{(k)} \sim IW \left[ N + a, V + \sum_{j=1}^{r} \sum_{j} b^{(k)}_j \right]
\]
We constrain the (1,1) element of \( D \) to be T+1 (where T is the length of the panel, not \( T^* \)), in order to normalize \( T^* \) for scale. This constraint, along with the constraint on the (1,1) element of \( \Sigma_j \), is chosen to force the posterior of \( b_i^{th} \) to have a large enough variance to allow the Gibbs sampler to move across the probability space.

5. For each \( j \), draw \( \Sigma_j \left[ \beta^{(k)} \right| T^{*(k)}_n, Clm^{*(k)}_n, OOP^{*(k)}_n, b^{(k)}, \beta^{(k-1)}, \beta^{(k-1)} \right], x \). Let \( N_j \) be the number of times out of the \( N \cdot T \) total plan elections that plan \( j \) is selected.

\[
\Sigma_j \left[ \beta^{(k)} \right| T^{*(k)}_n, Clm^{*(k)}_n, OOP^{*(k)}_n, b^{(k)}, \beta^{(k-1)}, \beta^{(k-1)} \right], x \sim IW \left[ N_j + b, W + \sum_{(i,t) \in P_j} \text{SampErr} \right],
\]

where

\[
\text{SampErr} = \begin{bmatrix}
T_n^* - x_n^i b^{th} - b_i^\cdot \\
Clm^{*}_n - x_n^i \beta^c - b_i^c \\
OOP^{*}_n - x_n^i \beta^c - b_i^c
\end{bmatrix},
\]

with the OOP and/or claim elements set to zero if they are unobserved. Again, we constrain the (1,1) element of \( \Sigma_j \) to be T+1, in order to normalize \( T^* \) for scale.

6. Draw \( \beta^{(k)} \left| T^{*(k)}_n, Clm^{*(k)}_n, OOP^{*(k)}_n, b^{(k)}, \Sigma^{(k)}, \beta^{(k-1)}, \beta^{(k-1)} \right], x \)

\[
\sim N \left[ \hat{\beta}^{th} \left( A_{th} + \sum_{j=1}^{p} \sum_{(i,t) \in P_j} (i \sigma)^j_1 x_n^i x_n^t \right)^{-1} \right],
\]

where \((i \sigma)^j_1\) is the \((k,l)\) element of \( \Sigma^{-1} \) and

\[
\hat{\beta}^{th} = \left( A_{th} + \sum_{j=1}^{p} \sum_{(i,t) \in P_j} (i \sigma)^j_1 x_n^i x_n^t \right)^{-1} \sum_{j=1}^{p} \sum_{(i,t) \in P_j} (i \sigma)^j_1 \left( T_n^* - b_i^{th} \right) + (i \sigma)^j_1 (Clm^{*}_n - b_i^c - x_n^i \beta^c) + (i \sigma)^j_1 (OOP^{*}_n - b_i^c - x_n^i \beta^c) \right].
\]

If claims and OOP payments are unobserved, the terms involving \((i \sigma)^j_2\) and \((i \sigma)^j_3\) drop out for that \((i,j)\) combination.

7. Draw \( \beta^{(k)} \left| T^{*(k)}_n, Clm^{*(k)}_n, OOP^{*(k)}_n, b^{(k)}, \Sigma^{(k)}, \beta^{(k-1)}, \beta^{(k-1)} \right], x \)

\[
\sim N \left[ \hat{\beta}^c \left( A_c + \sum_{j=1}^{p} \sum_{(i,t) \in P_j \& Clm \text{ observed}} (i \sigma)^j_2 x_n^i x_n^t \right)^{-1} \right],
\]

where \((i \sigma)^j_2\) is the \((k,l)\) element of \( \Sigma^{-1} \) and

\[
\hat{\beta}^c = \left( A_c + \sum_{j=1}^{p} \sum_{(i,t) \in P_j \& Clm \text{ observed}} (i \sigma)^j_2 x_n^i x_n^t \right)^{-1} \sum_{j=1}^{p} \sum_{(i,t) \in P_j \& Clm \text{ observed}} x_n^i \left( (i \sigma)^j_2 (Clm^{*}_n - b_i^c) \right) + \]

60
\begin{align*}
&\left(i\sigma\right)_{21}^j \left(T_{it}^* - b_{ith}^* - x_{ith}^' \beta_{ith}\right) + \left(i\sigma\right)_{23}^j \left(OOP_{it}^* - b_{i}^o - x_{iti}^' \beta_{i}^o\right) \\
8. \text{ Draw } &\beta^{(k)} \mid T_{it}^*, Clm_{it}^*, OOP_{it}^*, b^{(k)}, \Sigma^{(k)}, \beta^{th(k)}, \beta^{c(k)}, x \\
&\sim N \left(\beta^0, \left(A_o + \sum_{j=1}^p \sum_{(i,t) \in P_j} (i\sigma)_{33}^j x_{iti} x_{iti}' \right)^{-1} \right), \text{ where } (i\sigma)_{kl}^j \text{ is the } (k,l) \text{ element of } \Sigma^{-1} \text{ and} \\
&\hat{\beta}^o = \left(A_o + \sum_{j=1}^p \sum_{(i,t) \in P_j} (i\sigma)_{33}^j x_{iti} x_{iti}' \right)^{-1} \sum_{j=1}^p \sum_{(i,t) \in P_j} x_{iti} \left[(i\sigma)_{33}^j \left(OOP_{it}^* - b_{i}^o\right) + \left(i\sigma\right)_{31}^j \left(T_{it}^* - b_{ith}^* - x_{ith}^' \beta_{ith}\right) + \left(i\sigma\right)_{32}^j \left(Clm_{it}^* - b_{i}^c - x_{iti}^' \beta_{i}^c\right) \right]
\end{align*}
Appendix B: Bayesian inference for choice model

We assume that $\tilde{W}_{ijt}$ is linearly related to the characteristics of the individuals and the choices (\(x_{ijt}\), where it is understood these \(x\)'s are distinct from those used in the cost model), so $\tilde{W}_{ijt} = \tilde{x}_{ijt}'\tilde{\beta} + \tilde{\epsilon}_{ijt}$. Stacking the choices into matrix form, we get the relationship $W_{it} = X_{it}'\tilde{\beta} + \epsilon_{it}$. We assume $\tilde{\epsilon}_{it} \sim N(0, \tilde{\Sigma})$. Note the length of the vectors and the dimension of $\tilde{\Sigma}$ are $P - 1$. In order to capture the inertia, or "stickiness," of plan choice across time, we also assume that errors have an AR(1) relationship, so that $\tilde{\epsilon}_{it} = \rho_{it-1}\tilde{\epsilon}_{it-1} + \eta_{it}$, with $\tilde{\eta}_{it}$ iid $N(0, \tilde{T})$. The variance matrix $\tilde{T}$ is a diagonal matrix, whose diagonal elements $\tilde{\tau}^2_j$ are plan-specific variances. The AR(1) coefficient, $\rho_{it-1}$, is a plan-specific parameter, based on the plan individual $i$ is in at time $t - 1$, when the time $t$ plan election is made. Note that at the time of enrollment, the variance of the AR(1) error term, $\tilde{\tau}^2$, is specific to the new plan, and the AR(1) coefficient, $\rho_{i,t-1}$, is specific to the old plan.

Following the work by Geweke, Keene and Runkle (1997) in modeling a multiperiod multinomial probit model, we stack the years to get a model partitioned by year:

$$\tilde{W}_i = \begin{bmatrix} \tilde{W}_{i1} \\ \tilde{W}_{i2} \\ \vdots \\ \tilde{W}_{iT} \end{bmatrix}, \quad \tilde{X}_i = \begin{bmatrix} \tilde{X}_{i1} \\ \tilde{X}_{i2} \\ \vdots \\ \tilde{X}_{iT} \end{bmatrix}, \quad \text{and} \quad \tilde{\epsilon}_i = \begin{bmatrix} \tilde{\epsilon}_{i1} \\ \tilde{\epsilon}_{i2} \\ \vdots \\ \tilde{\epsilon}_{iT} \end{bmatrix}.$$ Now we can write $W_i = X_i'\tilde{\beta} + \tilde{\epsilon}_i$, where $\tilde{\epsilon}_i \sim N(0, \tilde{\Omega}_i)$, with $\tilde{\Omega}_i$ a combination of $\tilde{\Sigma}, \rho$ and $\tilde{\tau}^2$, specific to individual $i$'s enrollment pattern.

We can now specify the likelihood for the latent variables $\tilde{W}_i$, constrained by the observed choices:

$$L(W | \tilde{\beta}, \tilde{\Sigma}, \rho, \tilde{\tau}^2, data) \propto \prod_{i=1}^{N} \tilde{\Omega}_i^{-\frac{1}{2}} \exp\left[-\frac{1}{2} (\tilde{W}_i - X_i\tilde{\beta})'\tilde{\Omega}_i^{-1}(\tilde{W}_i - X_i\tilde{\beta}) \right] \cdot I_i,$$

where $I_i$ is an indicator value constraining the multivariate normal distribution on $\tilde{W}_i$ to the cone consistent with the observed choice pattern. Again, we will have to use data augmentation strategies for $\tilde{W}_i$ to estimate the parameters in this likelihood, as discussed in Section 5.

An expansion of the $\tilde{\Omega}_i$ matrix can be derived by compounding the impact of the AR(1) relationship to get

$$\tilde{\epsilon}_i = \begin{bmatrix} \tilde{\epsilon}_{i1} \\ \tilde{\epsilon}_{i2} \\ \vdots \\ \tilde{\epsilon}_{iT} \end{bmatrix} = \begin{bmatrix} \rho_{i,i-1}\tilde{\epsilon}_{i1} + \tilde{\eta}_{i1} \\ \vdots \\ \left(\prod_{\tau=1}^{i-1} \rho_{\tau}\right)\tilde{\epsilon}_{i1} + \sum_{\tau=1}^{i-1} \left(\prod_{\rho=1}^{\tau-1} \rho_{\rho}\right)\tilde{\eta}_{i1} \end{bmatrix},$$

and evaluating $E[\tilde{\epsilon}_i'\tilde{\epsilon}_i]$. We find
that this gives $\tilde{\Omega}_i$ in the form

$$
\tilde{\Omega}_i = \begin{bmatrix}
\tilde{\Sigma} & A' \\
A & B
\end{bmatrix}
$$

Where the $m^{th}$ of the $T-1$ partitions in $A$ can be written as

$$
A_m = \left( \prod_{r=1}^{m} \rho_{ir} \right) \tilde{\Sigma},
$$

And the $(m,n)^{th}$ partition of the matrix $B$ can be written as

$$
B_{mn} = \left( \prod_{r=1}^{m} \rho_{ir} \right) \left( \prod_{s=1}^{n} \rho_{is} \right) \tilde{\Sigma} + \left[ \sum_{t=2}^{\min(m,n)+1} \left( \prod_{r=1}^{t} \rho_{ir} \right) \left( \prod_{s=1}^{t} \rho_{is} \right) \right] \tilde{\Sigma}.
$$

Because we have normalized the utilities for level, but not yet normalized $\tilde{W}_i$ for scale, the model is not yet identifiable. We can normalize for scale and make our parameters identifiable by dividing $\tilde{W}_i$ by $\sqrt{\alpha^2}$, where $\alpha^2$ is the (1,1) element of $\Sigma$. Now $W_i = X\beta + \epsilon_i$, where $\epsilon_i \sim N(0,\Omega)$. The following relationships result:

$$
\Sigma = \frac{\tilde{\Sigma}}{\alpha^2},
$$

$$
\beta = \frac{\tilde{\beta}}{\sqrt{\alpha^2}},
$$

$$
\tau^2 = \frac{\tilde{\tau}^2}{\alpha^2}, \text{ and}
$$

$$
\Omega_i = \frac{\tilde{\Omega}_i}{\alpha^2}.
$$

It is these identifiable parameters, $W_i$, $\Sigma$, $\rho$, $\tau^2$ and $\beta$, that form our Markov chain in the Gibbs sampler, with $\alpha^2$ drawn and then discarded in a data augmentation step.

McCulloch and Rossi (1994) were the first to devise a practical method of using data augmentation to sample the latent utilities in a multinomial probit model, allowing Bayesian inference using the Gibbs sampler for this model. Recognizing that utility vectors for each individual, $W_i$, were independent, they used standard probability theory (Greene 1999, Theorem B.7) to derive the univariate normal distribution of the utility for one choice of an individual, conditional on the utilities for the other choices of that individual. These distributions are truncated to ensure that the utility of the plan selected is greatest. This greatly expands the number of draws in each iteration, adding $(J-1)$ draws for each individual in the data for each iteration. We have the additional complication of a multiperiod model, so that we have $(J-1) \cdot T$
draws for each individual. In our notation, this means that we sample from the univariate normal distribution $P\left(W_{ij} \mid W_{i(-j)}, \beta, \Sigma, \rho, \tau^2, X\right)$.

With so many latent variables involved, the resulting model has can converge quite slowly. In evaluating this model, improvement in convergence results when we draw each individual’s non-selected latent utilities (within a year) as a block, using the conditional multivariate normal distribution, and a rejection algorithm to assure these utilities are less than that of the plan selected. In other words, when plan $j$ is selected, we first sample from the univariate normal distribution $P\left(W_{ij} \mid W_{i(-j)}, \beta, \Sigma, \rho, \tau^2, X\right)$, truncated so that $W_{ij} > \max\left\{W_{i(-j)}\right\}$. Next we sample from the multivariate normal distribution $P\left(W_{i(-j)} \mid W_{ij}, W_{i(-j)}, \beta, \Sigma, \rho, \tau^2, X\right)$, truncated so that all elements of $W_{i(-j)}$ are less than the $W_{ij}$ drawn in the previous step.

Still more improvement in convergence can be achieved using the additional data augmentation technique described in Imai and Van Dyk (2005). They followed McCulloch and Rossi (1994) in the sampling of the latent utilities, and then converted these identifiable utilities to the unidentifiable version by multiplying by $\sqrt{\alpha^2}$, or in our notation, calculated $\tilde{W}_i = \sqrt{\alpha^2} \cdot W_i$. This was achieved using a value for $\alpha^2$ drawn from a prior distribution for $\alpha^2 | \Sigma$, isolated from the prior for $\tilde{\Sigma}$. These updated values of $\tilde{W}_i$ are then used to redraw $\alpha^2$ from its posterior distribution. Alternatively, we could use the $\alpha^2$ from the prior iteration to convert $W_i$ to $\tilde{W}_i$.

Imai and Van Dyk compared these two data augmentation schemes, and found improved convergence using an $\alpha^2$ drawn from the prior to effect this conversion. Our testing found similar improvements in convergence.

**Prior Specifications and Posterior Distribution**

The likelihood for the choice model is:

$$L(\tilde{W} | \tilde{\beta}, \tilde{\Sigma}, \rho, \tilde{\tau}^2, \text{data}) \propto \prod_{i=1}^{N} \frac{1}{2} \exp \left[-\frac{1}{2} \left(\tilde{W}_i - X_i \tilde{\beta}\right)^\prime \tilde{\Omega}_i^{-1} \left(\tilde{W}_i - X_i \tilde{\beta}\right)\right] \cdot I_i,$$

where $I_i$ is an indicator value constraining the multivariate normal distribution on $\tilde{W}_i$ to the cone consistent with the observed choice pattern, and $\tilde{\Omega}_i$ is a function of $\tilde{\Sigma}$, $\rho$ and $\tilde{\tau}^2$.

We must then specify priors for the four parameters:

- The parameter vector in the utilities’ means, $\tilde{\beta}$:
  $$\tilde{\beta} \mid \tilde{\Sigma} \sim \mathcal{N}(0, \alpha^2 A^{-1})$$, where $\alpha^2 = \tilde{\sigma}_{11}$, the (1,1) element of $\tilde{\Sigma}$

- The covariance matrix, $\tilde{\Sigma}$, for the multivariate normal error $\varepsilon_i$. 
\[
\hat{\Sigma} \sim IW(v, \tilde{S})
\]

- The \( P \) plan-specific coefficient for the AR(1) distribution, \( \rho^j \).
- \( \rho^j \sim N(\rho_0, \gamma) \cdot I(\left| \rho^j \right| < 1) \), where \( I(\left| \rho^j \right| < 1) = 1 \) if \( \left| \rho^j \right| < 1 \), 0 otherwise
- The \( P-1 \) variances of the normal error for the AR(1) distribution, \( \tilde{\tau}_j^2 \).
- \( \tilde{\sigma}_j^2 \sim IG(n, m) \)

We can combine these priors with the likelihood for \( \tilde{W}_i \) to get the posterior distribution

\[
P(\beta, \hat{\Sigma}, \tilde{\sigma}^2, \rho, W_i | data) \propto L(\tilde{W} | \beta, \hat{\Sigma}, \tilde{\sigma}^2, data) \cdot P(\tilde{\beta} | \hat{\Sigma}) \cdot P(\hat{\Sigma}) \cdot P(\rho) \cdot P(\tilde{\sigma}^2) \\
\propto \prod_{i=1}^{N} \left[ \frac{1}{2} \exp \left[ -\frac{1}{2} \text{tr}(\tilde{S} \hat{\Sigma}^{-1}) \right] \cdot \left[ \frac{1}{2} \exp \left[ -\frac{1}{2} \tilde{\beta}' \tilde{\sigma}^{-1} \tilde{\beta} \right] \right] \cdot \prod_{j=1}^{P} \left[ \exp \left[ -\frac{1}{2} \gamma \left( \rho^j - \rho_0 \right)^2 I(\left| \rho^j \right| < 1) \right] \cdot \prod_{j=1}^{P-1} \left( \tilde{\tau}_j^2 \right)^{-\gamma(n+1)} \exp \left[ -\frac{1}{m \tilde{\tau}_j^2} \right] \right]
\]

**Gibbs Iterations**

The full conditionals resulting from this posterior are summarized below. Details on the derivation of these conditionals are available from the corresponding author.

1. Following our modification of McCulloch and Rossi (1994), iterate through subvectors in the \( W_i \) vectors, given the values of the other elements of \( W_i \) for that individual. Details of these conditional distributions are spelled out in Appendix B. The specifics of the sampling depend on the index of the plan selected by the employee:

   - If the base plan \( J \) was chosen at time \( t \), \( W_{gi} \) must be negative for all values of \( j \).
     Draw \( W_{gi} \), the vector of utilities for person \( i \), time \( t \), from a multivariate normal distribution truncated above at zero for all elements. This distribution is conditional on the values of \( W_i \) for the other years.
   - If plan \( k \) is chosen at time \( t \), first draw \( W_{ki} \) from a univariate normal, conditional on the other utilities in time \( t \), and the utilities for other years. This normal distribution is truncated below at \( \max(0, W_{i(-k)t}) \). Next, draw \( W_{i(-k)t} \) from a multivariate normal
2. In this data augmentation step, draw from the prior of $\alpha^2$:

$$\alpha^2 \Sigma \sim IG \left( \frac{v(P-1)}{2}, \left( \frac{1}{2} tr(S\Sigma^{-1}) \right)^{-1} \right).$$

Use this to calculate $W_f = \sqrt{\alpha^2} \cdot W_i$, and then resample $\alpha^2$ from its posterior distribution, $\alpha^2 | \tilde{W}^{(k)}, \beta^{(k-1)}, \rho^{(k-1)}, \tau^{(k-1)}, \Sigma^{(k-1)}, X$

$$\sim IG \left( \frac{(NT + v + 2n)(P-1) - 1}{2}, \right.$$

$$\left. \left[ \frac{1}{2} \sum_{i=1}^{N} (\tilde{W}_i - X_i \hat{\beta})'\Omega_i (\tilde{W}_i - X_i \hat{\beta}) + \frac{1}{2} \hat{\beta}'\Sigma \hat{\beta} + \frac{1}{2} tr(S\Sigma^{-1}) + \frac{1}{m} \sum_{j=1}^{m} \frac{1}{\tau_j^2} \right]^{-1} \right).$$

where $\hat{\beta} = \left[ A + \sum_{i=1}^{N} X_i \Omega_i^{-1} X_i \right]^{-1} \sum_{i=1}^{N} X_i \Omega_i^{-1} \tilde{W}_i$.  

3. Draw $\beta^{(k)} | \alpha^{2(k)}, \tilde{W}^{(k)}, \Sigma^{(k-1)}, \tau^{(k-1)}, \rho^{(k-1)}, X$

$$\sim N \left( \hat{\beta}, \alpha^2 \left[ A + \sum_{i=1}^{N} X_i \Omega_i^{-1} X_i \right]^{-1} \right).$$

where again, $\beta' = \left[ A + \sum_{i=1}^{N} X_i \Omega_i^{-1} X_i \right]^{-1} \sum_{i=1}^{N} X_i \Omega_i^{-1} W_i$.

4. Draw $\gamma^{(k)} | W^{(k)}, \delta^{(k)}, \rho^{(k-1)}, X$

$$\sim IG \left( \frac{N(T-1)}{2} + n, \left[ \frac{1}{m} + \frac{1}{2} \sum_{k=1}^{N} \sum_{i=1}^{T-1} \left( \rho_i \tilde{\epsilon}_{i,k} - \tilde{\epsilon}_{i,k+1} \right)^2 \cdot I(Plan_{it} = k) \right]^{-1} \right),$$

where $\gamma'_{it} = W_{it} - X_{it} \beta$.

5. Draw $\rho^{(k)} | \delta^{(k)}, \beta^{(k)}, W^{(k)}, X$

$$\sim N \left( \frac{\sum_{i=1}^{N} \sum_{t=1}^{T-1} \tilde{\epsilon}_{i,t}^2 \cdot \tilde{\epsilon}_{i,t+1}^2 \cdot I_{it} + \rho_0}{\sum_{i=1}^{N} \sum_{t=1}^{T-1} \tilde{\epsilon}_{i,t}^2 \cdot I_{it} + \frac{1}{\gamma} \sum_{i=1}^{N} \sum_{t=1}^{T-1} \tilde{\epsilon}_{i,t}^2 \cdot I_{it} + \frac{1}{\gamma}}, \frac{1}{\gamma} \right) \cdot I(|\rho'| < 1),$$

where $\rho_{it}' = W_{it} - X_{it} \beta$ and $I_{it} = I(Plan_{it} = j)$.  

distribution, conditional on $W_{it}$ and the individual’s utilities in other years. This is truncated above at $W_{it}$ for all elements.
6. Draw $\Sigma^{(k)}|\tilde{\beta}^{(k)}, X$

$$\sim IW\left(N + v, \tilde{S} + \sum_{i=1}^{N} (\tilde{W}_n - X_n\tilde{\beta})(\tilde{W}_n - X_n\tilde{\beta})'\right).$$

7. Calculate $\Sigma = \tilde{S}/\alpha^2$, $\beta = \tilde{\beta}/\sqrt{\alpha^2}$, and $\tau^2 = \tilde{\tau}_j^2/\alpha^2$. Retain these values, along with the values of $W_i$ and $\rho^j$ previously calculated, for the next iteration of the Gibbs sampler.