Restrictions on Provider Access in Health Plans and Socioeconomic Status

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Objective. To model the socioeconomic determinants of restrictions on provider access and choices in health plans.

Data Sources. Data from the 1996–97 Community Tracking Study are used. Publicly available enrollee data including enrollee reports of health care plan characteristics are linked with restricted use data with insurer reports of health plan characteristics.

Study Design. This is an observational study. A mixed multinomial logit model is used to model the enrollees' choice between health plans, each plan being treated as a bundle of attributes formed from restrictions on provider access.

Principal Findings. There are important differences between the enrollee responses and the insurer reports, which may be due to poor information dissemination on the part of health plans and/or lack of attention on the part of enrollees. There is no evidence of selection into plans with restrictive attributes on the basis of observed health status but there is evidence of selection on the basis of race, ethnicity, gender and other socioeconomic characteristics. Determinants of plan supply, i.e., employment characteristics, are the most important determinants of plan attribute choices.

Conclusion. The finding suggests that plan designs optimized using “objective” knowledge and with the best intentions may not receive favorable reviews from enrollees because enrollees have different perceptions of these plans.

Key Words: Community tracking study, mixed multinomial logit, self-selection, health-plan attributes

Historically, the market for health insurance consisted mostly of indemnity (INDM) plans that paid some fraction of the fees charged by providers for medical services. Such plans, typically known as fee-for-service or, more appropriately, INDM plans, varied mostly along financial dimensions: deductibles, copayments, and caps on out-of-pocket expenditures, but sometimes also varied in the types of services covered and the limits on coverage for some services (e.g., preventive care, prenatal care, mental health care). Generally, there were few or no restrictions on the providers covered under the plans. With the emergence and growth of health maintenance organizations (HMOs)

and other types of managed care plans that combine insurance for and provision of health care, this traditional view of the market has become less important. Managed care plans, in general, and HMOs in particular, place significant restrictions on provider choices and the process of care. Hence, health plan choice is no longer simply a matter of selecting a system for financing medical care, but instead involves choosing a set of providers and system for delivering care. In recent years, the distinction between HMO and non-HMO managed care plans has also become increasingly ambiguous and traditional INDM plans virtually extinct. All types of health insurance plans, including most INDM plans, place restrictions on types and amounts of care and generally manage the process of medical care (Pauly and Nicholson 1999). Moreover, less restrictive forms of HMOs have gained market share, muddying the distinctions further.

In this paper, we use unique data from the 1996 to 1997 Community Tracking Study (CTS) to model the determinants of revealed preferences or attitudes of individuals towards whether plans (1) require enrollees to choose from a list or network of providers; (2) require enrollees to sign up with a primary care provider; and (3) cover any of the costs for going outside of the network. Our study sheds light on the sources of heterogeneity in the individual preferences and valuation of these attributes of health plans. Because brochures describing health plans typically highlight plan attributes, it is reasonable to believe that such attributes, rather than HMO, preferred provider organizations (PPO), point of service (POS), and INDM designations, play the pivotal role in the actual optimization decisions of individuals. From the point of view of health plans, administrative restrictions on access to providers, of which the three described above are among the most widely used, attempt to reduce costs by improving coordination of medical care and limiting unnecessary use of services. Although we do not have data on prices of health plan alternatives, hence making us unable to examine price sensitivities towards such restrictions, the CTS has a rich set of variables measuring health and socioeconomic status, which is the focus of our analysis.

Although there is a substantial empirical literature on health plan choice in which the choice sets analyzed range from choice among a set of HMOs, between HMOs and INDM plans, or choices that include HMOs, PPOs, and INDM plans, there is relatively little empirical literature that directly examines

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consumer choices of health plans as preferences or attitudes towards specific restrictions on providers, access to specialists, and other processes of medical care provision. Scanlon, Chernew, and Lave (1997) provide an extensive review of the literature on plan choices. Barringer and Mitchell (1994), Royalty and Solomon (1999), and Studdert et al. (2002) are more recent studies examining choices between HMO, PPO, and INDM plans. Feldman et al. (1989) is a rare, early study that modeled the existence of restrictive provider networks as an intermediate step in their analysis. Schoenbaum et al. (2001) and Harris (2002) are recent experimental studies that emphasize and directly model network restrictions on provider choice. However, while Schoenbaum et al. (2001) and Harris (2002) provide valuable information regarding individuals attitudes towards provider restrictions along price and information dimensions, they provide little information on how health status, race and other socioeconomic characteristics might affect attitudes towards such restrictions, and are not nationally representative.

Empirically, plans can be grouped using a relatively small number of combinations or bundles of attributes. In addition, plans tend to use only few restrictions for administrative efficiency. Therefore, these restrictions are typically complementary and there is strong association between attributes. Unfortunately, this makes the direct econometric modeling of attributes very complicated, if not infeasible. Consequently, we begin by modeling choices of bundles of attributes using traditional multinomial choice models (Greene 2002). Subsequent to estimation, we take a hedonic approach (Lancaster 1966; Gorman 1980) and provide a method for deducing the revealed preferences of enrollees for each of the three attributes.

The CTS provides, in a supplemental survey, information on health plan attributes as reported by the insurers, that is likely to be more accurate than that reported by the households. In our analysis, we report results from models using both enrollee and insurer reports of health plan attributes for two reasons. First, it is plausible that enrollees perceptions of health plan attributes are at least as important as “true” attributes for issues of access to and satisfaction with care (Cunningham, Denk, and Sinclair 2001; Reschovsky, Hargraves, and Smith 2002). Second, there is evidence that many consumers are misinformed about the characteristics of the plans they choose (Cunningham, Denk, and Sinclair 2001), and a comparative analysis of perceptions and truth may have implications for knowledge dissemination.

The remainder of the paper is organized as follows. The following section describes the CTS data on plan attributes and the issues involved in using it for modeling purposes. The third section describes the implementation of

our econometric methods. We describe our empirical results in the fourth section and conclude in the following section.

DATA

Data for this analysis come from two linked surveys conducted as part of the CTS. The CTS, sponsored by the Robert Wood Johnson Foundation, is a national study designed to provide information about changes in the health care system and the effects of these changes on care delivery on individuals. One component of this study is the CTS Household Survey (HS), a large, nationally representative survey of more than 60,000 individuals. We use data collected in 1996–1997. A total of 60 sites, 51 in metropolitan areas and 9 in nonmetropolitan areas, were randomly selected to form the core of the CTS. The HS was administered to households in the 60 CTS sites and to a supplemental national sample of households. Among many other demographic and health care-related items, survey respondents were asked specific questions about attributes of their health insurance plans. Information was collected also that allowed identification of the insurer and of the product line that covered privately insured respondents. With this information, insurers were contacted and asked to respond to the CTS Insurance Followback Survey (FS), a short questionnaire concerning attributes of the health insurance product. Proxy respondents (e.g., employers) were used when information could not be obtained from insurers. Information from this survey was then matched to HS respondents to describe their insurance coverage.

Our sample consists of nonelderly adults (age 18–64) who are covered by exactly one private health insurance plan, are employees of firms, and for whom we have data in the HS and FB surveys. Thus, our sample excludes individuals who are covered by a health insurance plan (e.g., through their spouse's plan) but are not employed, but includes those who are employed and insured, even if they might be covered through someone else's plan. The sample size, after matching, is 14,885 observations.¹ We do not observe the set of plan choices actually available to an individual, which is an important issue, discussed in more detail in "Mixed Logit" below. It is safe to assume, for example, that unemployed and self-employed individuals have systematically different choice sets than those who are employees of firms, but that choice sets of employees of firms display more similarity.² Therefore, as an attempt to improve sample homogeneity in the choice sets of the households, we have used data on only those individuals who are employees of firms.³ Finally, we have chosen to use the sample of matched individuals to enable a cleaner

comparison between estimates based on enrollee responses and those based on insurer responses. The use of the matched sample means any differences in results must be due to differences in how enrollees and insurers report the attributes, and not due to differences in socioeconomic factors.

Although we have chosen to model the insurance plan choice of individuals, one could argue that models should be based on household-level data because such insurance plan choice decisions are often made at the household level. In addition, in the CTS, all insurance information is obtained from one "household informant." However, it is well known that, in many households, individuals are covered by different plans and in some cases, some individuals are covered while others are not. These features of households make it very difficult to define insurance plan at the household level. It is also difficult to define characteristics of individuals in households in parsimonious ways. Therefore, we choose to model insurance decisions of individuals while controlling for a number of observable household characteristics in addition to individual characteristics. We also take the expected unobserved household effects into account when calculating standard errors of estimates obtained using individual-level data. We note, that Reschovsky, Hargraves, and Smith (2002) find that results of choice models for household informants are not different from those for other family members, but we conduct a similar analysis ourselves.

Restrictions on Provider Choices

Questions about three types of restrictions on provider choices were asked of all respondents in the Household and the FSs. The first restriction is whether plans require enrollees to choose from a list or network of providers (*Network*). This is based on the survey question—*Is there a book, directory, or list of doctors associated with the plan/this product?* The second restriction is whether plans require enrollees to sign up with a primary care provider (*Pepsignup*). This is based on the survey question—*Does your plan/product require you to sign up with a certain primary care doctor, a group of doctors, or clinic, which you must go to for all your routine care?* The third restriction is whether the plan does not cover any of the costs for care received outside the network (*Nooutnet*) and is based on the survey question—*If you do not have a referral, will your plan pay for any of the costs of visits to doctors who are not associated with the plan/Under the product, if enrollees do not have a referral and go to out-of-network doctors, does the plan cover any of the costs for these visits?* Note that a response of "yes" to this question indicates a less restrictive plan. However, for consistency with the other two attributes for

which responses in the affirmative indicate restrictive plans, in our empirical analysis we code Nooutnet = 1 or “yes” if the plan does not cover costs associated with out-of-network care.⁴

Cunningham, Denk, and Sinclair (2001) report that agreement rates are 80, 69, and 73 percent for Network, Pcpsignup, and Nooutnet. This points to the superiority of the quality of information contained in insurer reports from the FS. However, as described earlier, it is plausible that enrollees perceptions of health plan attributes are at least as important as “true” attributes for issues of access to and satisfaction with care so we construct models using both HS and FS measures of health plan attributes.

Table 1 (panels a, b, and c) reports frequencies of attributes by type of respondent. It shows that enrollees of health insurance plans are significantly less likely than the insurer to report that their plan has a network of providers. In 5.3 percent of cases, enrollees report a network restriction when insurers do not. In another 10.9 percent of cases, insurers report a network restriction when enrollees do not. Thus enrollees and insurers disagree in over 16 percent of cases. Enrollees are also significantly more likely than insurers to report that they are required to sign up with a PCP. Enrollees and insurers disagree in 24 percent of cases in this dimension, with enrollees more likely to report having the restriction when insurers do not than vice versa. Finally, enrollees are less likely than the insurer to report that their plan pays for medical care received out-of-network. Along this dimension, disagreement is the greatest at 29 percent. However, unlike for network and signup restrictions, both enrollees and

Table 1: Frequencies of Restrictions by Respondent Type

<i>Enrollee Response</i>	<i>Insurer Response</i>	
	<i>0</i>	<i>1</i>
Network		
0	5.8	10.9
1	5.3	78.0
Pcpsignp		
0	33.1	8.2
1	16.1	42.6
Nooutnet		
0	46.9	13.9
1	15.1	24.1

Notes:

1 denotes the presence of the restriction whereas 0 denotes its absence.

Table 2: Frequencies of Bundles of Restrictions

<i>Bundle #</i>	<i>Network</i>	<i>Pcpsignup</i>	<i>Nooutnet</i>	<i>Common Plan Name</i>	<i>Enrollee Response</i>	<i>Insurer Response</i>
1	0	0	0	INDM	14.7	11.1*
2	1	0	0	PPO	20.5	34.9*
3	1	1	0	POS	24.6	16.0*
4	1	1	1	HMO	32.5	34.8*
5	1	0	1	?	5.6	3.2*
6	0	1	1	?	0.7	0*
7	0	1	0	?	0.9	0*
8	0	0	1	?	0.7	0*

Notes:

1 denotes the presence of the restriction whereas 0 denotes its absence.

*Statistically different from corresponding enrollee response at the 1 percent level of significance.

+ Statistically different from corresponding enrollee response at the 5 percent level of significance.

INDM, indemnity; PPO, preferred provider organizations; POS, point of service; HMO, health maintenance organization.

insurers report this restriction when the other respondent does not in roughly equal numbers of cases.

These three restrictions on provider choice form eight mutually exclusive and exhaustive bundles of attributes. Table 2 shows frequencies of bundles by type of respondent. Bundle 1 has no restrictions, i.e., it is an INDM plan. Insurers responses suggest that 11 percent of individuals with health insurance are in such INDM plans, but these fractions are significantly smaller than those reported by enrollees themselves (15 percent). On the other hand, while insurers report that 35 percent of enrollees are in health plans with a network of providers but that do not require a signup with a PCP and pay for out-of-network services (bundle 2), only 21 percent of enrollees themselves report being in such plans. Bundle 2 is akin to a PPO plan. Enrollees over-report being in plans with physician networks and PCP signup requirements but that do pay for out-of-network services (bundle 3) relative to insurers reports. Most POS plans are likely to be characterized by bundle 3. According to insurers, about 35 percent of individuals are in plans with networks and PCP signup requirements and who do not pay for out-of-network services (bundle 4). Such plans likely include many, but not all or even most, closed model HMOs. Enrollees themselves underreport enrollment in such plans. These four bundles cover over 90 percent of individuals. According to insurers, the remainder of individuals are in bundle 5, plans with networks of providers that do not require PCP signups but do not pay for out-of-network services. Such plans are not easily categorized using standard labels.

Logically, there should be no plans without networks but requiring PCP signups or not paying for out-of-network services, and this is consistent with insurer reports. Nevertheless, a small fraction of enrollees report being in each of three such plans (bundles 6, 7, and 8). Because these do not make much sense to us, and because each of these frequencies is too small to model separately, in our empirical model based on enrollee responses, we combine bundles 5–8 into one choice. As we describe in detail below, for purposes of calculating effects of covariates on each of the three attributes, these bundles 5–8 are, fortunately, no more than of nuisance value.

Although we focus on three attributes (restrictions) of plans, there are obviously other relevant attributes that are not observed. These include the use of prior authorizations, size of networks, menus of covered services, method of cost-sharing (coinsurance and deductibles versus copayments) and so forth. If such data were available, one could create additional bundles and model the choices based on a larger choice set. Unfortunately, they are not so we construct models for the only three attributes available in the household and FSs of the CTS. To the extent that unobserved attributes of plans are correlated with those that we analyze, it makes clean interpretation difficult.

Covariates

The CTS contains detailed information on demographic characteristics, social economic variables, health utilization, health status, and employment of individuals. The covariates we use are defined in Table 3, where we also provide basic summary statistics for the sample of all individuals with insurance in the survey as well as those who are employees of firms. Demographic characteristics of the individual include age, gender (female), years of education, marital status (married) and minority group (Hispanic, black). Household characteristics include family size, and income.⁵ Employees of firms are somewhat younger, on average, than all individuals with health insurance.⁶ They are also slightly less likely to be female. Otherwise, there are no statistically significant differences in demographic characteristics in the two samples.

Health status is captured through two health indices that are measures of general physical and mental health, respectively. Both are scores based on the SF-12 scale which takes into account self-reported health status as well as responses to a list of physical limitation questions. We find that enrollees of health insurance plans who are employees of firms have better physical health, on average, than all individuals with health insurance. This is not surprising

Table 3: Demographic Characteristics by Sample Definition

		<i>All</i>		<i>Employees</i>	
<i>Variable</i>	<i>Definition</i>	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>
<i>N</i>	Sample size	20,786		14,885	
Demographic					
Age	age/10	4.02	1.17	3.94	1.10
Female	= 1 if female	0.53	0.50	0.50	0.50
Black	= 1 if black	0.09	0.28	0.09	0.29
Hispanic	= 1 if Hispanic	0.06	0.24	0.06	0.25
Married	= 1 if married	0.73	0.45	0.68	0.46
Income	Annual household income/10,000	5.88	3.51	5.79	3.36
Education	Years of education/10	1.41	0.24	1.41	0.23
Family size	Number of individuals in the family	2.76	1.39	2.68	1.40
Employment					
Government job	= 1 if employed in the government sector	0.15	0.36	0.22	0.41
Firm size	firm size indicator (1–6)	3.66	2.62	4.94	1.87
HMO and non-HMO offered	= 1 if employer offers HMO and non-HMO plans	0.38	0.49	0.43	0.49
Only HMO offered	= 1 if employer offers an HMO plan only	0.187	0.39	0.25	0.43
Only non-HMO offered	= 1 if employer offers a non-HMO plan only	0.18	0.39	0.25	0.43
Health status					
Physical health status	SF = 12 physical health score (0–100)/10	5.17	0.81	5.23	0.72
Mental health status	SF = 12 mental health score (0–100)/10	5.27	0.84	5.28	0.81

HMO, health maintenance organization.

given that one expects some individuals are not working because of exceptionally poor physical health. The average mental health in the two groups is, on the other hand, not different between employees and all individuals.

We also include some employer characteristics in our econometric model. These include whether the individual works for the government, the size of the firm and whether the firm offers both HMO and non-HMO insurance plans, only HMO plans or only non-HMO plans. By conditioning on these variables we attempt to control for the differences in the choice sets confronting households and individuals. If information were available on the actual choice sets available to each consumer, it would be possible to address this issue more explicitly. Clearly, firm characteristics and sector of work offer

only partial and imperfect control. A more detailed discussion of this limitation follows the description of the econometric model below.

A potentially serious limitation of our dataset is the absence of information on premiums. Such information introduces into the analysis choice specific variables that might be key explanatory variables. Because actuarially fair rates vary by the type and size of the group covered, and because there may be economies of scale in administrative costs associated with plans, larger employers may be able to provide their employees with cheaper health insurance compared with smaller employers. Therefore, our employer characteristic variables will be correlated with the omitted choice specific variables. If such correlation were perfect, the price variables would be redundant. In practice, we expect firm characteristics and sector of work to imperfectly control for plan prices. Clearly this affects the interpretation of the coefficients on firm characteristics and sector of work. A more detailed discussion of limitations due to lack of price data follows the description of the econometric model below.

ECONOMETRIC METHODS

Insurance plans are defined as bundles of relevant attributes based on combinations of Network, Pcpsignup, and Nooutnet. We use five such plans in our econometric model, justification for which was described above. Let $a_m = (0, 1)$, where $m = 1$ (Network), 2 (Pcsignup), 3 (Nooutnet), denote the absence (0) or presence (1) of attribute m in plan d_j . Let $B_j = B(a_1, a_2, a_3)$ denote the mapping from plan attributes to bundles. Thus $B(1, 0, 0)$ means that the first attribute applies to the chosen bundle but the second and third attributes do not. Consumers are plausibly assumed to derive utility from the attributes of the insurance plans rather than from the plans themselves. The latent utility from the choice of bundle j by person i , based on choice theory (Greene 2002; Train 2003) and in the context of demand for health (Grossman 1972), can be written as

$$U_{ji} = \mathbf{x}_i \alpha_j + \mathbf{w}_{ji} \gamma + \varepsilon_{ji} \quad (1)$$

where $\mathbf{X}_i$ consists of individual-specific covariates such as age, education, income, and health status and $\mathbf{w}_{ji}$ consists of alternative-specific covariates such as plan prices (premiums). In addition, the vector $\mathbf{X}_i$ includes interactions of individual-specific covariates and $\mathbf{w}_{ji}$ includes interactions between individual-specific and alternative-specific covariates.⁷ Note that because we are

modeling latent utilities, choice theory dictates that prices (premiums) enter on the right-hand side of the utility representation and that all attributes of plans are subsumed in the definition of the “good.” Also, because the CTS does not have information on plan prices, $w_{ji}\lambda$ is subsumed in a composite error term during estimation. However, we continue to explicitly specify the price term for purposes of discussion.

Mixed Logit

A suitable multinomial model to study the determinants of the choice probability of a bundle based on the utility specification in (1) is the mixed logit model (Greene 2002).⁸ The mixed logit model is a combination of the multinomial logit model, which is explicitly defined for individual-specific covariates (with alternative-specific coefficients) and the conditional logit model, which is explicitly defined for alternative-specific covariates (with common coefficients across alternatives). The choice probability for bundle j by household i given by

$$Pr[B_{ji} = 1 | \mathbf{x}_i, \mathbf{w}_{ji}] = \frac{\exp(\mathbf{x}_i \alpha_j + \mathbf{w}_{ji} \gamma)}{\sum_{k=1}^5 \exp(\mathbf{x}_i \alpha_k + \mathbf{w}_{ki} \gamma)}, \quad i = 1, \dots, N; j = 1, \dots, 5 \quad (2)$$

here B_{ji} equals one if the i th household chooses plan j and zero otherwise. Note, however, that because alternative-specific data are not available, our econometric model collapses to the multinomial logit model.⁹ We adopt the normalization restriction $\alpha_1 = 0$ and $j = 1, \dots, 5$ with the first bundle corresponding to the no restrictions plan (bundle 1), roughly the INDM plan, acting as the benchmark. We have estimated the model parameters and standard errors by maximum likelihood using a custom program in *SAS/IML*.

Like many other large national surveys, the CTS sample design employs stratification, clustering, and oversampling to provide the basis for making national estimates. Normally, if one is interested in population estimates of sample means and percentages, the use of sampling weights is recommended. However, in the regression context, models estimated without sampling weights yield unbiased estimates of parameters in any case (Cameron and Trivedi 2005). When it is not clear which weights are appropriate for the sample of data being analyzed, it is preferable to estimate unweighted models as these are unbiased whereas weighted models with incorrect weights provide inconsistent estimates. In our case, because we use a subsample of employed, insured, nonelderly adults with matched information from the FS, the choice

of which sampling weights to use is not clear at all. Therefore, we adopt the conservative approach and estimate our models without sampling weights.

Regardless of whether sampling weights are used for estimation or not, the clustering in the sample design means that standard errors of estimates calculated using regular formulae would be too small. The user guide to the 1996–1997 CTS HS (Center for Studying Health System Change 2000; chapter 3) reports that, for HS person-level combined national estimates, the average design effect over a representative set of variables is 3.7, i.e., naive standard error estimates are almost twice as large as they should be. To account for design effects, we calculate standard errors using the Eicker–White type robust “sandwich” formula adjusted for clustering at the community level (Cameron and Trivedi 2005). In addition to clustering at the community level, one expects clustering at the household level. Because household-level clustering is embedded in community-level clustering, the formula for calculation of the standard errors takes both levels of clustering into account. In addition, because communities were sampled randomly, with probability in proportion to their 1995 population (Center for Studying Health System Change 2000; chapter 2), one does not expect clustering across communities.

The dataset does not have information on the choice sets available to individuals, so we are forced to assume that each individual has each type of plan available to choose from. We recognize that some individuals work for employers who do not offer any choice of health plans and that, although many plans can be purchased in the individual market, these may be unaffordable. The statistical consequence of assuming that all individuals have all choices set is that the probability of choosing each attribute is necessarily positive. But these probabilities can be arbitrarily small so as to closely approximate nonavailability. To provide a crude check on the validity of this assumption, we examined the observed distribution of choices within each of the 60 sampling sites. If individuals in certain sites never chose a particular bundle, one might reasonably assume they did not have access to that bundle and that the probability of such a choice would be, indeed, equal to zero. The results showed that each of the five bundles of attributes was chosen by more than 2 percent of surveyed enrollees within a site, i.e., there was no site where no enrollee reported choosing a particular bundle. Although these results are encouraging, we cannot, however, rule out the possibility that some individuals may, in fact, not be able to purchase particular types of plans at any prices. Consequently, the impact of this misspecification will depend on the extent to which employees of firms with few or no choices may have choices available through spouses employment, unions or other such organizations, or in the

nongroup market (at much higher prices) and to the extent to which conditioning on whether the individual works for the government, the size of the firm and whether the firm offers both HMO and non-HMO insurance plans, only HMO plans or only non-HMO plans, alleviates this problem statistically by making choice probabilities in such instances close to zero.

Note that one could estimate individual binary choice models for each of the three attributes separately. However, because it is not possible to purchase each attribute separately, rather they are available as bundles of attributes, such separate models are misspecified. In purely statistical terms, the relationships between attributes manifest as the attributes having strong associations with each other. In general, this could be modeled using a multivariate probit model, which we attempted to estimate. However, because only five of the eight possible combinations of attributes are actually present in the data, estimation of the multivariate probit model was infeasible due to singularities. Kemper et al. (2002) also report on the difficulties of modeling attributes of health plans directly. By modeling bundles of attributes, rather than the attributes themselves, we explicitly take into account the empirically relevant features of the data. Correlations between attributes are naturally built into the multinomial logit model.¹⁰ However, we are left with the task of uncovering preferences for attributes from the model for bundles of attributes.

Changes in Relative Risks (RR) of Attributes

We use RR, or ratios of probabilities, to describe preferences for attributes of health plans. We calculate the relative risk of each attribute as

$$\begin{aligned} RR(a_1|\mathbf{x}) &= \frac{Pr[B(1, 0, 0)|\mathbf{x}]}{Pr[B(0, 0, 0)|\mathbf{x}]} \\ RR(a_2|\mathbf{x}) &= \frac{Pr[B(1, 1, 0)|\mathbf{x}]}{Pr[B(1, 0, 0)|\mathbf{x}]} \\ RR(a_3|\mathbf{x}) &= \frac{Pr[B(1, 1, 1)|\mathbf{x}]}{Pr[B(1, 1, 0)|\mathbf{x}]} \end{aligned} \quad (3)$$

all else held constant. So $RR(a_1)$ is the risk of an individual choosing a plan with Network = 1 relative to a plan with Network = 0, with covariates and other attributes of the two health plans being compared being held constant. Note, however, that the choice of values for the other attributes is not unique. We have chosen plans with Pcpsignup = 0 and Nooutnet = 0 because these attributes in combination with Network = 0 or Network = 1 are relatively prevalent in our sample. The RR for Pcpsignup and Nooutnet are constructed

similarly, with values for the other attributes chosen in each case to correspond with commonly observed bundles in our sample. The RR are functions of covariates; we report the sample average of individual RR. Standard errors of the sample averages of individual RR are calculated using a Monte Carlo method.¹¹

Given these “baseline” values, we calculate percentage changes in RR because of changes in covariates, i.e., the change in the probability of choosing a bundle with attribute A, relative to the bundle without attribute A, due to a change in a covariate, given by

$$\frac{\% \Delta RR(a_m)}{\Delta \mathbf{x}_k} = \frac{\Delta RR(a_m) / \Delta \mathbf{x}_k}{RR(a_m)} \times 100$$

where $\Delta \mathbf{x}_k$ denotes a small change in the k th covariate in the vector $\mathbf{x}$, all other covariates held constant. A value greater than 0 indicates a positive impact on preference for the attribute, and a value less than 0 indicates a negative impact. If the predictor is dichotomous, we use discrete variation by setting it to 0 first and then to 1, i.e., $\Delta x_k = 1$. For continuous variables, we calculate the discrete difference analog of a partial derivative with Δx_k taken to be a small number. A very appealing feature of this measure of impact in the context of the mixed logit model, which can be analytically verified, is that it depends linearly on the change in the covariate of interest and is independent of all other covariates, including alternative-specific covariates.¹² Because they only depend on changes in the covariate of interest, their values are constant across observations, and need not be evaluated at any particular sample point or as a sample average. In addition, although there is an analytical formula for the standard errors of these estimates of changes in RR, for simplicity they are calculated using the Monte Carlo method.

It is important to consider the possibility that price effects (premiums), which are not observed in our data, may be confounding our estimates of RR and changes in RR. However, because the percentage change in the relative risk due to a change in a particular individual-specific covariate is independent of the coefficients on other covariates (although the estimates of RR themselves do depend on all coefficients), $\% \Delta RR(a_m) / \Delta x_k$ can be interpreted appropriately regardless of prices of plans. The logic applies to interactions between individual-specific and alternative-specific (price) variables as well. But for socioeconomic groups that have interactions with prices, the effects calculated are averages across groups, i.e., group-specific effects cannot be identified.

Note however, that the lack of price data is not without costs. First, because the price terms are in the error terms, this makes the errors larger and the precision of all coefficients less than they would otherwise be. Second, to the extent that plan prices are correlated with individual-specific attributes, the associated coefficients would be subject to omitted variable bias that would make their interpretation less clear. For example, if firm characteristics are correlated with prices, as we expect them to be, then the coefficients on firm characteristics are estimates of true firm effects contaminated by price effects. Finally, the properties of the measure of impact are algebraically true only for the mixed logit model and for extensions within the logit family. So, if our statistical model is misspecified, the impact of missing prices on the effects of individual-specific covariates on RR will also be biased.

Although we focus on three attributes of plans, there are other relevant attributes that are not observed. If the unobserved attributes of plans are correlated with those that we analyze, it makes clean interpretation difficult. For example, while PCP signup generally distinguishes HMOs and POS plans from PPOs and INDM plans, such plans are also more likely to use copays as the cost-sharing mechanism, rather than deductibles and a coinsurance, which are common mechanisms for PPOs and INDM plans. Clearly the relative risk for PCP signup versus no PCP signup is positively related to the relative risk of copays versus coinsurance. But one cannot determine how much the estimate of the effect of a change in a covariate on the relative risk for PCP signup versus no PCP signup is contaminated by the effect of the covariate on the relative risk of copays versus coinsurance, i.e., it is not easy to determine the sign or the magnitude of possible biases for the marginal effects in such cases, even when the relationship between the observed and missing attribute is known.

RESULTS

We have estimated MNL models for several samples. For brevity, and because the choice sets for such individuals are most homogeneous, we only report results of specifications for samples and subsamples of individuals who have health insurance and are employees of firms. Our interpretation is confined to employed individuals with health insurance. In each case, we report results of models using enrollee and insurer responses of attributes of health plans and for whom data from the HS and FS samples can be matched. Although models based on insurer reports of attributes are likely to be more reliable, models based on enrollee reports, although measured with error, may have policy

relevance as consumers are likely to choose plans using their perceptions of plan attributes, which may or may not be the true attributes, as choice variables.

The baseline model we report, arrived at after experimentation with covariates and functional forms, includes the following variables: female, age, married, education, family size, income, black, Hispanic, physical health status, mental health status, HMO and non-HMO offered, only HMO offered, only non-HMO offered, firm size, and government job. We then consider a number of model variations, comparisons of which with the baseline model are reported in Table 4. We use Akaike's information criterion (AIC) and the

Table 4: Model Selection

<i>Model</i>	<i>N</i>	<i>K</i>	<i>Enrollee Response</i>			<i>Insurer Response</i>		
			<i>log(L)</i>	<i>AIC</i>	<i>BIC</i>	<i>log(L)</i>	<i>AIC</i>	<i>BIC</i>
Baseline interactions	14,885	64	-21,438	43,003	43,490	-19,487	39,102	39,589
Age × gender and race	14,885	76	-21,432	43,015	43,594	-19,477	39,107	39,685
Income × gender and race	14,885	76	-21,433	43,019	43,597	-19,483	39,118	39,696
Health status × gender & race	14,885	88	-21,428	43,032	43,702	-19,480	39,135	39,805
Education × gender and race	14,885	76	-21,432	43,016	43,595	-19,480	39,113	39,691
Sample split								
Small firm jobs	6,488	60	-9,379			-8,382		
Big firm jobs	5,187	56	-7,354			-6,857		
Government jobs	3,210	56	-4,633			-4,151		
Combined jobs	14,885	172	-21,366	43,076	44,385	-19,390	39,124	40,433
Sample split								
Jobs that offer HMO and non-HMO plans	6,390	52	-9,294			-8,572		
Jobs that do not offer both types	8,495	60	-12,091			-10,837		
Combined jobs	14,885	112	-21,385	42,993	43,845	-19,409	39,041	39,893
Sample split								
Family insurance respondents	9,163	64	-13,054			-11,932		
Not a family insurance respondent	5,722	64	-8,320			-7,516		
Combined insurance respondents	14,885	128	-21,374	43,004	43,978	-19,448	39,152	40,126

Notes:

AIC = $-2\log(L) + 2K$.

BIC = $-2\log(L) + K\log(N)$.

Best models by AIC and BIC criteria are in boldface type.

HMO, health maintenance organization; AIC, Akaike's information criterion; BIC, Bayesian information criterion.

Bayesian information criterion (BIC) to compare models. The AIC penalizes fit of the model only as a function of the number of parameters, so it can sometimes inappropriately favor larger models when the sample size is large. The BIC penalizes fit of the model as a function of the number of parameters as well as the number of observations, subtracting larger penalties when sample sizes are larger. Both the AIC and BIC are standard model selection criteria (Greene 2002).

The first set of variations we consider involves sets of interactions between age/income/health status/education and gender/race. The results show that none of these augmented models is preferred to the baseline by either criterion. In addition, we estimated models using a quadratic function for age and its interactions, but these are not reported as such models were never preferred. The second set of models splits the sample in a variety of ways, designed to test whether models for the subsamples have significantly different parameters. In the first case, we split the sample into three parts: those with private sector jobs in small firms, those with private sector jobs in large firms, and those with government jobs. Both the AIC and BIC favor one model for the combined sample (baseline). In the second case, we split the sample according to individuals whose jobs offer both HMO and non-HMO plans and individuals whose jobs do not offer both types of plans. Here, the AIC favors separate models for the two groups, suggesting that availability does affect choice. However, the BIC continues to favor the baseline model. Finally, we split the sample into individuals who are the family insurance respondents and those who are not. This distinction may be especially important for the models using enrollee responses as the responses for those who are not insurance respondents within families may be subject to more measurement error. The results in Table 4 show that both criteria favor the baseline model. Overall, given the large sample size and the large number of parameters, we favor inference from the BIC. Thus, we find consistently that the baseline model is preferred to alternatives, regardless of whether models using enrollee or insurer responses are considered.

Given the findings from the model selection exercises, we proceed by describing results from the baseline model in greater detail. Direct interpretation of the estimated MNL coefficients is difficult and generally uninformative in our context because the outcomes are simply bundles of attributes. Therefore, we do not report these estimates but instead focus on RR and their changes, which evaluate the impacts of covariates on attributes. We note, however, that the MNL models are generally well determined with a majority of the parameter estimates being statistically significant and overall fit as

Table 5: Relative Risks of Attributes

<i>Enrollee Response, N = 14,885</i>			<i>Insurer Response, N = 14,885</i>		
<i>Network</i>	<i>Pcp/signup</i>	<i>Nooutnet</i>	<i>Network</i>	<i>Pcp/signup</i>	<i>Nooutnet</i>
1.51*	1.41*	1.11	2.99*	0.58*	1.94*
(0.13)	(0.09)	(0.08)	(0.55)	(0.05)	(0.24)

Notes:

Standard errors in parentheses.

*Significantly different from 1 at 1 percent.

expected for such cross-sectional models. For both models of enrollee and insurer responses, we find that the models provide relatively more precise predictions for bundles 3 and 4 and relatively imprecise predictions for bundle 5.

Relative Risk Comparisons

Table 5 reports RR of enrollment in plans with specific attributes, i.e., the risk of enrollment in a plan with a particular attribute relative to a plan without that attribute. The first three columns report estimates obtained from models of enrollee responses. We find that an individual is, using the sample average of enrollee responses, 1.6 times more likely to be enrolled in a plan with a network of physicians (*Network* = 1) than one without; this relative risk is statistically greater than 1. This relative risk incorporates price differences in plans with networks and those without so one cannot be sure whether the preference is for networks or lower prices. In the multinomial logit model, the relative risk of two alternatives is proportional to the difference in the values of an alternative-specific variable (for those two alternatives) multiplied by its coefficient.¹³ Therefore, the price of a plan with networks multiplied by the price coefficient (elasticity) would have to be 1.5 times less than the price of a plan without networks multiplied by the price coefficient for the relative risk of networks to be equal to or less than one. Individuals, on average, also report being 1.2 times more likely to be in a plan that does not cover out-of-network care than a plan that does. Reality, or at least plan attributes reported by insurers, paints a different picture. According to insurers, individuals are, on average, 3.2 times more likely to be in a plan with a network than one without, and 2 times more likely to be in a plan that does not cover out-of-network care (*Nooutnet* = 1) than one that does. Note that both RR are substantially larger

than the corresponding values reported by enrollees of such plans. The gap between enrollee and insurer responses is even greater in the context of the question concerning the enrollee being required to sign up with a primary care provider. Enrollees think this is more likely to be the case than not (relative risk of 1.3). Insurers, on the other hand, report that the individuals, on average, are less likely to be in a plan that requires signup with a primary care provider than one without it (the relative risk of 0.5 is significantly less than 1).

This dissonance between perception and reality may arise because of poor understanding of the “language” of medical care (especially managed care) organizations. For example, enrollees in group/staff practices may report not having a network because they perceive the “group” as the entity through which they get their care, while in fact, the plan may have a network (a set of groups), only one of which is relevant for the enrollee. Similarly, enrollees may report requiring sign up with a PCP, when in fact, they only need to sign up with a group. Our data do not allow us to distinguish between this, and other explanations for this dissonance. We can rule out, however, the lack of price information as a source of dissonance. One expects the “distortion” in RR because of systematic differences in bundle prices should be the same for both samples, so although magnitudes of RR are confounded with price effects within each sample, comparisons across estimates based on enrollee and insurer responses are valid and informative. The dissonance between perception and reality may be a reason why enrollees of restrictive plans are found to be unhappy with their plans and providers of medical care (Reschovsky, Hargraves, and Smith 2002).

The analysis of RR clearly points to differences between enrollee and insurer reports of attributes of health plans. Nevertheless, this does not rule out the possibility that the effects of socioeconomic characteristics and health status are similar regardless of which reports are used. If they are similar, this simplifies any policy implications of such findings. If not, even policy implications will be complex. We report percentage changes in these baseline RR for each of the three attributes and for enrollee and insurer reports in Table 6. Note that these estimates are not directly affected by missing price data because each change in relative risk is independent of other covariates and parameters.

One consistent finding, with potentially important policy implications, is that health status generally has little or no association with the choice of plan attributes, both as reported by enrollees and as reported by insurers. All the changes due to changes in the SF-12 physical health index are statistically insignificant, and so are changes due to the mental health index when insurer

Table 6: Changes in Relative Risks Due to Changes in Predictors

	<i>Enrollee Response</i>			<i>Insurer Response</i>		
	<i>Network</i>	<i>Pcpsignup</i>	<i>Nooutnet</i>	<i>Network</i>	<i>Pcpsignup</i>	<i>Nooutnet</i>
Female	5.79 (4.65)	0.09 (4.41)	9.34 [†] (4.61)	-7.31 (4.13)	14.78* (4.85)	4.62 (4.36)
Age	-4.11 (3.24)	-7.21* (2.16)	-3.67 (2.94)	-8.81 [†] (3.47)	0.58 (2.40)	-4.43 [†] (2.21)
Married	-22.83* (8.41)	8.92 (7.49)	6.51 (8.67)	-2.32 (13.52)	3.13 (10.13)	-0.14 (9.01)
Education	31.90 (18.67)	-5.70 (11.70)	-21.73 (12.42)	6.58 (13.32)	54.76* (11.90)	-23.06 (13.75)
Family size	-0.03 (2.77)	2.30 (3.21)	1.34 (3.59)	1.15 (3.99)	-1.48 (3.28)	4.18 (3.02)
Income	2.95 [†] (1.36)	-3.02* (0.99)	-3.36* (0.90)	1.85 (1.54)	1.43 (1.00)	-3.12* (1.17)
Black	29.19 (22.04)	1.85 (12.43)	22.07 (11.37)	43.12 (25.57)	21.84 (14.90)	15.26 (12.65)
Hispanic	65.17 [†] (26.84)	-7.38 (13.53)	36.61* (13.30)	36.72 (44.35)	39.29 [†] (19.74)	38.93 [†] (18.15)
Physical health status	-2.42 (3.47)	-4.39 (3.52)	-3.70 (3.37)	-5.21 (3.29)	-1.75 (5.03)	-0.19 (4.63)
Mental health status	3.98 (4.03)	-6.20 (3.81)	-6.89 [†] (2.75)	-5.56 (4.34)	-4.02 (3.23)	-3.90 (3.11)
HMO & non-HMO offered	89.70* (23.42)	25.99 (15.11)	9.50 (10.95)	21.52 (16.92)	80.94* (19.90)	7.68 (12.90)
Only HMO offered	190.87* (39.18)	115.50* (21.12)	-0.60 (10.29)	79.46* (24.98)	117.23* (27.03)	-17.93 [†] (8.46)
Only non-HMO offered	27.51 (14.40)	-43.64* (5.97)	-42.97* (6.12)	39.36 [†] (18.08)	-36.91* (7.42)	-56.24* (5.31)
Firm size	-7.19* (2.27)	6.39* (2.05)	-0.95 (1.60)	-4.54 (3.03)	8.19* (2.11)	-8.36* (2.09)
Government job	41.15 [†] (19.09)	-38.59* (7.84)	5.51 (9.96)	13.63 (19.22)	-51.30* (8.08)	66.26* (24.40)

Notes:

Standard errors in parenthesis.

*Statistically significant at 1 percent.

[†]Statistically significant at 5 percent.

HMO, health maintenance organization.

responses are used. The only exception is that individuals with higher mental health scores report being less likely to be in plans that do not cover out-of-network services. At first glance, this result appears in conflict with the evidence that there is favorable selection into HMOs, although that evidence is also mixed (Glied 2000; Schaefer and Reschovsky 2002). Note that our

findings are for *employed* individuals with health insurance, a market in which selection on health may be a smaller issue. Note also that there is no evidence that sicker individuals are less likely to choose plans with each restriction taken *separately*, but this does not rule out the possibility that sicker individuals might be less likely to choose plans with all restrictions taken *together* (a characteristic of HMOs). Also, given that our findings are based on a cross-section of data in which causality between health and insurance status cannot be definitively determined, one cannot rule out the possibility that there is selection into health insurance, but in a complex way that does not manifest as a statistical association between the two variables.

Race has no effect on RR of health plan attributes, but ethnicity does. Hispanics are more likely to be in plans that require signups with primary care providers and those that do not cover out-of-network care. Their perceptions do differ somewhat: although the model based on enrollee reports confirms that they are more likely to be in plans that do not cover out-of-network services, they do not report being more likely in plans with signups. Overall, we conjecture these effects are due to historically lower attachment of Hispanics to the medical care system in general, and to specific "family" physicians, in particular. Gender also plays a small role. There is statistically significant evidence that women are more likely to enroll in plans that require signups, although this is not evident when self-reported choice is used. Using enrollee reports, it appears that women are more likely to be in plans that do not cover out-of-network services. Older enrollees are less likely to choose plans with networks and physician signups, perhaps because they are more likely to be attached to particular physicians from the premanaged care era. They also report being less likely to choose plans with required PCP signups, but this evidence is not supported by evidence from insurer reports. Marital status and family size do not have significant effects on choice of attributes. More educated individuals are more likely to enroll in plans that require PCP signups, but this is not consistent with their perception. Higher income individuals are significantly less likely to enroll in plans that do not cover care received out-of-network. Although such individuals also report being less likely to be enrolled in plans requiring signups with primary care providers and more likely to be in plans with networks, the model based on insurer responses does not support these findings.

Five variables serve as proxies for supply of health plans. These are the most important determinants of choices of attributes, regardless of whether the model is based on enrollee or insurer reports. We find that enrollees who work for firms that only offer HMO plans, relative to firms that offer no plans, are

more likely to be in plans that have networks and require signups. Analogously, we find that enrollees who work for firms that only offer non-HMO plans are less likely to select plans that require signups and those that do not cover out-of-network services. When enrollees work for firms that offer both HMO and non-HMO plans they are more likely to choose plans with signups. Unlike in the first two cases, we observe a dissonance here. According to enrollees, if they work in such firms they are not significantly more likely to choose plans with signups, instead they are more likely to choose plans with provider networks. Conditional on the types of plans offered by firms, those who work in the government sector are less likely to enroll in plans that require signups and more likely to choose plans that do not pay for out-of-network services. Those who work in larger firms are more likely to be enrolled in plans that require signups, but less likely to be in plans that do not pay for out-of-network services. This suggests either that the supply of health plans in the government sector is substantially different from those offered in private sector jobs or that individuals who work in the private sector have different preferences compared with those who work in the government sector. Interestingly, results based on enrollee and insurer reports are more harmonized along these supply dimensions than among demand-side determinants.

CONCLUSIONS

In this paper, we provide some evidence on the effects of socioeconomic and health status on choices of attributes of health plans that restrict choices of medical plans. This is not a straightforward task because it is virtually impossible to model choices of attributes directly as they only appear in the data in a small number of bundles. We use insights from the literature on hedonic models to uncover preferences for attributes implicit in preferences for bundles.

Conditional on being an employee of a firm and on availability of HMO and non-HMO plans offered by the firm, we find no evidence of selection into restrictive plans on the basis of observed health status. However, we do find evidence of selection on the basis of ethnicity, gender, and other socioeconomic characteristics. To the extent that these characteristics are correlated with health status, this may indicate selection on the basis of health status. If not, the significance of these characteristics indicates selection into plans with specific attributes on the basis of differences in information on health plans, providers and quality of care, expectations of future use of medical care, or

other attitudes towards health or health care across different socioeconomic strata. We find that determinants of plan supply, i.e., employment characteristics, are the most important determinants of plan attribute choices.

We find that enrollee and insurer reports of the attributes of enrollees health plans are quite different, suggesting a dissonance arising, perhaps, from poor information dissemination on the part of health plans and/or lack of attention on the part of enrollees. Note that the use of the matched sample means any differences in results must be due to differences in how enrollees and insurers report the attributes, and not due to differences in socioeconomic factors. This finding is somewhat troubling because it suggests that plan designs optimized using “objective” knowledge and with the best intentions may not receive favorable reviews from enrollees because enrollees have different perceptions of these plans. This calls for better dissemination of information on the part of plan providers. But if these information gaps are persistent, client dissatisfaction with plans with restrictions on provider choices may be inevitable unless plan design explicitly takes into enrollees perceptions of plans into account. Moreover, it is plausible to believe that dissatisfaction with health plans might spill over to dissatisfaction with employers.

Because the CTS provides matched enrollee-insurer responses, it might be possible to examine whether there is real information to be conveyed when there is a difference in perception between the enrollee and the insurer. In other words, it might be possible to combine information from actual (insurer reports) attributes of health plans and perceived (enrollee reports) attributes of the same plans to draw out additional information on determinants of plan choices and on the reasons for the incongruence. A study of these issues requires the development of computationally complex models of which the building blocks have been described in Walker and Ben-Akiva (2002). This is likely to be a fruitful path as it will illuminate important areas of relative darkness in models of health plan choice, but is clearly beyond the scope of this paper.

We focus on the choices that individuals make from the options available to them taking their choice sets as given. Given the data, we cannot examine how employers choose which plans to offer or what might be offered elsewhere in the private market. Clearly, these are extremely important issues. Moreover, our model assumes that each individual can choose from plans with each of the five bundles of attributes. As we do not observe actual choice sets, the impact of this misspecification will depend on the extent to which employees of firms with few or no choices may have choices available through spouses employment, unions or other such organizations, or in the nongroup

market (at much higher prices) and to the extent to which conditioning on firms offerings of health plans alleviates this problem statistically. In addition, we do not have information on plan premiums. These financial variables are clearly important determinants of preferences for plan choices and are likely important determinants of preferences for plan attributes. Finally, although we focus on three attributes of plans, there are other relevant attributes that are not observed, especially financial attributes such as whether plans have cost sharing by deductibles/coinsurance or copayments. Unfortunately, even when the relationship between the observed and missing attribute is known, it is not easy to determine the sign or the magnitude of possible biases for the marginal effects in such cases.

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NOTES

1. We have estimated our models on a variety of alternative samples, and they generally provide qualitatively similar results. These results are available upon request.
2. Restricting our attention to just employees might be overly conservative as we know that some individuals who are not employees have access to employee insurance plans through their spouses or parents. But this conservative approach ensures that we do not include individuals who may not have the same choices as an employed individual in the same family, a detail we do not observe in the data.
3. We are not restricting our sample to just policy holders although that would clearly be an alternative approach.
4. In the HS and FS, there is a fourth attribute that we do not model because they are not the same in both datasets, hence not comparable. In the HS, the question asks whether referrals are needed to see specialists (*Under your plan, do you need approval or referral to see a specialist or get special care?*). In the FS, the question refers to costs of seeing out-of-network providers (*If enrollees do not have a referral and go to in-network specialists, does the plan cover any of the costs for these visits?*).
5. Unlike some other work using data from the CTS (e.g., Kemper et al. 2002; Reschovsky, Hargraves, and Smith 2002), we do not include subjective preferences for risk or stated willingness to trade-off costs for provider choice because they are unlikely to be exogenous in models of revealed health plan choices.

6. Note that both samples are defined for the 18–64 age group.
7. Evidence of interaction effects among observables is given in Remler and Atherly (2003), while evidence of interaction effects between observables and unobservables is given in Deb and Trivedi (2002).
8. Unfortunately, this term is not universally accepted (Train 2003).
9. Lacking alternative-specific data, it is not possible to extend the multinomial logit model (e.g., multinomial probit) to allow for possible correlations between the error terms of alternatives because the correlation parameters are not identified.
10. Bundles are, however, not correlated through errors.
11. In this procedure, multinomial logit model parameters are drawn randomly from a multivariate normal distribution with mean given by the maximum likelihood estimates and covariance given by the cluster-corrected, estimates of the covariance matrix of parameters (Cameron and Trivedi 2005, chapter 24). For each draw, the sample averages of relative risks are calculated and this process is repeated 500 times. The standard error of each average relative risk is calculated as the sample standard deviation of the 500 estimates.
12. A proof of this proposition is available from the authors on request.
13. A proof of this proposition is available from the authors on request.

REFERENCES

- Barringer, M. W., and O. S. Mitchell. 1994. "Workers' Preferences among Company Provided Health Insurance Plans." *Industrial and Labor Relations Review* 48: 141–52.
- Cameron, A. C., and P. K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. Cambridge, UK: Cambridge University Press.
- Center for Studying Health System Change. 2000. "Community Tracking Study Household Survey Public Use File: User's Guide" (Round One, Release 3), *Technical Publication* 7: 1–302.
- Cunningham, P. J., C. Denk, and M. Sinclair. 2001. "Do Consumers Know How Their Health Plan Works?" *Health Affairs* 20: 159–66.
- Deb, P., and P. K. Trivedi. 2002. "The Structure of Demand for Health Care: Latent Class versus Two-Part Models." *Journal of Health Economics* 21: 601–25.
- Feldman, R., M. Finch, B. Dowd, and S. Cassou. 1989. "The Demand for Employment-Based Health Insurance Plans." *Journal of Human Resources* 24: 115–42.
- Glied, S. 2000. "Managed Care." In *Handbook of Health Economics*, Vol. 1A, edited by A. J. Culyer and J. P. Newhouse, pp 707–45. Amsterdam: Elsevier.
- Gorman, W. M. 1980. "A Possible Procedure for Analysing Quality Differentials in the Egg Market." *Review of Economic Studies* 47: 843–56.
- Greene, W. H. 2002. *Econometric Analysis*, 5th edition. Englewood Cliffs, NJ: Prentice-Hall.
- Grossman, M. 1972. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy* 82: 223–55.

- Harris, K. M. 2002. "Can High Quality Overcome Consumer Resistance to Restricted Provider Access? Evidence from a Health Plan Choice Experiment." *Health Services Research* 37: 551-7.
- Kemper, P., H. T. Tu, J. D. Reschovsky, and E. Schaefer. 2002. "Insurance Product Design and Its Effects: Trade-Offs along the Managed Care Continuum." *Inquiry* 39: 101-17.
- Lancaster, K. 1966. "A New Approach to Consumer Theory." *Journal of Political Economy* 74: 132-57.
- Pauly, M., and S. Nicholson. 1999. "Adverse Consequences of Adverse Selection." *Journal of Health Politics, Policy and Law* 24: 921-30.
- Remler, D. K., and A. J. Atherly. 2003. "Health Status and Heterogeneity of Cost-Sharing Responsiveness: How Do Sick People Respond to Cost-Sharing?" *Health Economics* 12: 269-80.
- Reschovsky, J. D., J. L. Hargraves, and A. F. Smith. 2002. "Consumer Beliefs and Health Plan Performance: It's Not Whether You Are in an HMO but Whether You Think You Are." *Journal of Health Politics, Policy and Law* 27: 353-77.
- Royalty, A., and N. Solomon. 1999. "Health Plan Choice: Price Elasticities in a Managed Competition Setting." *Journal of Human Resources* 34: 1-41.
- Scanlon, D. P., M. Chernew, and J. R. Lave. 1997. "Consumer Health Plan Choice: Current Knowledge and Future Directions." *Annual Review of Public Health* 18: 507-28.
- Schaefer, E., and J. D. Reschovsky. 2002. "Are HMO Enrollees Healthier than Others? Results from the Community Tracking Study." *Health Affairs* 21: 239-58.
- Schoenbaum, M., M. Spranca, M. Elliott, J. Bhattacharya, and P. Farley Short. 2001. "Health Plan Choice and Information about Out-of-pocket Costs: An Experimental Analysis." *Inquiry* 38: 35-48.
- Studdert, D. M., J. Bhattacharya, M. Schoenbaum, B. Warren, and J. J. Escarce. 2002. "Personal Choices of Health Plans by Managed Care Experts." *Medical Care* 40: 375-86.
- Train, K. 2003. *Discrete Choice Analysis by Simulation Methods*. Cambridge: Cambridge University Press.
- Walker, J., and M. Ben-Akiva. 2002. "Generalized Random Utility Model." *Mathematical Social Sciences* 43: 303-4.