An Analysis of Selectivity Bias in the Medicare AAPCC

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Using econometric models of endogenous sample selection, we examine possible payment bias to Medicare Tax Equity and Fiscal Responsibility Act of 1982 (TEFRA)-risk health maintenance organizations (HMOs) in the Twin Cities in 1988. We do not find statistically significant evidence of favorable HMO selection. In fact, the sign of the selection term indicates adverse selection into HMOs. This finding is interesting, in view of the fact that three of the five risk HMOs in the study have since converted to non-risk contracts.

BACKGROUND

The current method of paying risk-contracting HMOs for the care of aged and disabled Medicare beneficiaries is based on the principle that the Health Care Financing Administration (HCFA) should pay no more than 95 percent of the estimated costs for the HMO enrollee had he or she remained in the fee-for-service (FFS) sector. Estimates of FFS costs are calculated for each of 30 cells: 5 age groups, 2 sex categories, and 3 institutional-status groups (institutionalized, welfare recipient not institutionalized, and neither). The formula by which these estimates are applied to determine the payments for each HMO is known as the AAPCC, or adjusted average per capita cost.[1] The purpose of the AAPCC payment system to is adjust the HMO's payment rate for the demographic mix of its Medicare enrollees.

Numerous studies of both the Medicare and non-Medicare populations have shown that HMO enrollees differ significantly from those who choose to remain in the FFS sector. Many of the variables related to HMO enrollment (e.g., health status, prior use of services, income, and education) are also possible determinants of health care expenditures. Failure to include these additional variables in the AAPCC payment formula may result in a payment bias within the AAPCC rate cells. The objective of this research is to determine whether such within-cell bias exists.

The setting for the research is the seven-county metropolitan statistical area of Minneapolis-St. Paul (hereafter referred to as the Twin Cities), a large metropolitan area with a mature capitated delivery system for both Medicare and non-Medicare populations. The data were collected in calendar years 1988-89. This period is of particular interest because five TEFRA-risk HMOs operated in the Twin Cities at that time and had enrolled more than one-half of the Medicare beneficiaries in the market area.

Bias in the AAPCC

Biased selection could arise if enrollees within each cell of the AAPCC have different risks, and the high-risk types within a cell tend to be found in either the HMO or FFS sector. For example, if HMO enrollees

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[1]See Palsbo (1991) for a detailed description of the AAPCC calculation. Since our study was completed, an adjustment has been added for the working aged.

within each AAPCC cell tend to be lower risks, then Medicare payment rates, which are based on the average risk of FFS enrollees in each cell, would overstate the expected FFS expenditures of HMO enrollees. As a consequence, including HMOs in the Medicare program will increase total Medicare costs unless there are other, offsetting effects of including HMOs.[2] To produce selection bias, the variables omitted from the AAPCC also must affect, or be correlated with, the beneficiary's choice of health plan and his or her subsequent health care expenditures. Variables that affect only choice but not cost will not cause bias. Similarly, variables that affect cost but not health-plan choice will not be a source of bias in the AAPCC, because those variables will be randomly distributed across health plans.

The literature on health-plan choice and biased selection, reviewed by Dowd and Feldman (1985), Wilensky and Rossiter (1986), Hellinger (1987, 1995), and Dowd et al. (1994), has generally found evidence of favorable selection into group-practice HMOs but not into independent practice associations (IPAs).[3] Evidence of favorable selection into HMOs is more conclusive for Medicare beneficiaries than for the employed population. Eggers (1980) compared FFS expenditures of future HMO enrollees with those of continuing FFS beneficiaries. After controlling for variables included in the AAPCC payment formula, he found that future HMO enrollees used fewer services and had lower FFS payments than continuing FFS beneficiaries. Eggers and Prihoda (1982) found that pre-enrollment payments for enrollees in two HMOs were 20 percent lower than for their comparison groups.

Garfinkel et al. (1986) found that three Minneapolis HMOs participating in the Medicare Capitation Demonstration experienced favorable selection of enrollees with few chronic conditions. HMOs in Marshfield, Wisconsin, and Worcester, Massachusetts, did not experience favorable selection related to perceived health status, functional limitations, or the number of chronic conditions. Brown (1988), Brown et al. (1993), and Brown, Bergeron, and Clement (1993) found evidence of favorable enrollment into and disenrollment from HMOs participating in the Medicare program.

To our knowledge, the only instance of unfavorable selection into Medicare HMOs reported in the literature occurred in Eggers and Prihoda's 1982 study. Enrollees in one of three HMOs had higher prior payments for outpatient and physician services, although no significant differences were detected in total prior payments.

Within the FFS sector, beneficiaries can also choose whether to buy a supplementary (or "medigap") policy. Only 11 percent of beneficiaries choose not to buy supplementary coverage (Chulis et al., 1993). These supplementary policies can simply fill in the gaps (i.e., coinsurance and deductibles) for services covered by the basic Medicare benefit, or they can add supplementary coverage for uncovered services such as outpatient prescription drugs. Garfinkel, Bonito, and McLeroy (1987) found that beneficiaries with chronic health problems were more likely than beneficiaries without chronic health problems to have a supplementary FFS policy. Thus, it appears from this study that supplementary insurers were not screening potential enrollees very aggressively. However, Rice and McCall (1985) found that the probability of having supplementary insurance for beneficiaries reporting

[2]For example, HMOs might induce providers in the FFS sector to adopt a more efficient style of medical practice (Welch, 1994).

[3]IPAs typically have broader provider networks than group-practice HMOs.

themselves to be in poor health was 11 percentage points lower than for beneficiaries reporting themselves to be in excellent health.

Dowd et al. (1994) found that the oldest, poorest, and to a lesser extent, the sickest Medicare beneficiaries in the Twin Cities in 1988 were in FFS Medicare without a supplementary policy. The youngest beneficiaries were enrolled in network HMOs. In many respects, selection into the FFS sector with a supplement resembled selection into the HMOs.

In summary, the literature suggests that group and network HMOs may enroll a relatively healthy population within the AAPCC rate cells. If the HMOs' selection advantage exceeds 5 percent of FFS costs, then payments to Medicare HMOs under the current AAPCC system will increase total Medicare costs.

CORRECTING BIASED SELECTION

Adding Variables to the AAPCC

The present AAPCC excludes many variables that have been shown to influence both Medicare HMO enrollment and FFS expenditures. Not surprisingly, therefore, a number of proposals have suggested adding such variables to the AAPCC. Included in the list of variables that might be added to the AAPCC are prior disability, utilization of inpatient or outpatient services in a prior time period, measures of chronic illness, and mortality (Brown et al., 1993; Brown, Bergeron, and Clement, 1993; Weiner et al., 1991; Ash et al., 1989; Beebe, Lubitz, and Eggers, 1985; Lubitz, Beebe, and Riley, 1985).

There are several problems with the "add more variables" strategy. First, the potential additional variables have thus far not explained a great deal of additional variance in expenditures. Second, some of the suggested additions to the AAPCC may be endogenous to (under the influence of) the health plan. The obvious examples are utilization of services in a prior time period (if the beneficiary was enrolled in his or her current health plan during that period) and health-status measures, including mortality. Inclusion of endogenous factors in the payment formula can create perverse behavioral incentives (i.e., increased payment for sicker enrollees could reduce the plan's incentive to keep enrollees healthy). Third, including more variables in the payment formula could create bias where none existed before. Variables currently omitted from the AAPCC formula might have offsetting effects on subsequent expenditures, some favoring HMOs and others favoring the FFS sector. Including a subset of these variables in the AAPCC could create bias if the remaining omitted variables favor one sector or the other.

Another conceptual problem with previous research on risk-adjusted payment to HMOs is that the usefulness of potential adjusters is measured by the amount of variance explained in expenditures for beneficiaries remaining in the FFS sector. A set of explanatory variables could explain 100 percent of the variance in expenditures for beneficiaries who choose to remain in the FFS sector but still yield a biased prediction of expenditures for people who choose the HMO sector. This is because the coefficients (effects) of the explanatory variables might be different for individuals choosing the HMO and FFS sectors. In other words, the coefficients for FFS enrollees might be biased estimates of the same coefficients for HMO enrollees.[4]

[4]The bias might be confined to the intercept term, or it could affect the coefficients of other included variables, if they were correlated with the omitted variables.

An Econometric Correction for Selectivity Bias

Rather than adding more variables to the AAPCC payment formula and measuring the change in the explained variance of FFS beneficiaries' expenditures, we attempt to measure the effect of all variables omitted from the AAPCC, including those that are not, and in some cases cannot, be observed. The approach is statistically complex, but the underlying idea is very simple and follows directly from the theory that explains how bias in the AAPCC might arise in the first place. Bias can arise only if there are unobserved variables that affect both the beneficiary's choice of the FFS sector and subsequent Medicare payments.[5] The basic approach is to construct an FFS expenditure equation that resembles the AAPCC payment formula and then to test for the presence of correlation between variables omitted from that equation and from another equation that determines whether beneficiaries choose the HMO or FFS sector. The presence of that correlation would produce sample selection bias or "selectivity" bias. This estimate of payment bias captures the effect of all unobserved variables that affect both health-plan choice and FFS expenditures.

The econometric correction for selectivity bias has three basic steps. The first step is to model the process by which beneficiaries choose the FFS versus HMO sector. This step produces an equation in which choice is a function of observed explanatory variables (Z) and an unobserved error term. The observed explanatory variables include the AAPCC rate-cell variables plus other variables that affect choice but not expenditures.

[5]The terms "payment" and "expenditure" are used synonymously throughout this article.

The second step is to model the process that generates expenditures for an FFS beneficiary as a function of observed AAPCC variables and an error term. The fact that many FFS beneficiaries have zero expenditures during a given period of observation creates special estimation problems that are discussed in the "Methods" section.

The third step is to estimate the choice and expenditure equations jointly, allowing the error terms in each equation to be correlated. A significant estimated correlation indicates the presence of variables, not included in the AAPCC formula, that are correlated with both health-plan choice and FFS expenditures. Selectivity bias thus is defined as a statistically significant correlation of these error terms.

One prior study has used this approach. Welch, Frank, and Diehr (1984) analyzed cost per enrollee under the Seattle Prepaid Health Care Project. Enrollees were given a choice between a prepaid group practice (PGP) and a traditional FFS health plan for the years 1971-75. The study population was the near-poor residents of a section of Seattle who were under 65 years of age. Welch, Frank, and Diehr first estimated differences in cost per enrollee between the PGP and FFS using ordinary least-squares (OLS) regression. The OLS cost comparisons, like the AAPCC payment formula, controlled for the enrollee's age and sex, in addition to race, education, family size, and health status. Based on the OLS results, the ratio of costs in the FFS plan to costs in the HMO was 1.47. The second estimation method included an econometric correction for selectivity bias. Using this method, the estimated ratio of FFS to PGP costs per enrollee was 3.66, a figure termed "implausibly high" by the authors.

Welch, Frank, and Diehr's results indicate that significant selectivity bias remained in the expenditure equation, even after including AAPCC variables and other personal characteristics. Data from a randomized trial of HMO versus FFS health-plan memberships in Seattle suggest that unobserved characteristics of health-plan enrollees may not be very important in comparisons of utilization and expenditure between FFS and prepaid plans (Manning et al., 1984), but the results may have been affected by attrition from the study. Twenty-nine percent of those initially contacted refused to participate in the study.

METHODS

Estimates of Biased Selection

Sample selection bias has a relatively long history in the econometrics literature, and recently there have been some important new developments. Often, the problem faced by researchers is to compare the experience of subjects in treatment and control groups in the absence of random assignment to those groups. Typically, the outcome variable is observed for both the treatment and control groups. A great deal of past research has employed selection models similar to ours to correct for nonrandom assignment. These "parametric" selection models, based on particular assumptions about the joint distribution of error terms in equations in the model, have been criticized on the grounds that results can be sensitive to the assumptions underlying the model (Little, 1985). Consequently, there has been considerable recent interest in the development of alternative approaches to correcting for selection bias. For example, McClellan, McNeil, and Newhouse (1994) provide an example of an instrumental variables estimator to the medical field.

Our problem is somewhat different from the standard problem found in the literature. In our application, the "treatment group" is the FFS sector and the "control group" is the HMO sector (or vice versa). However, we are not interested in comparing the effect of health-plan membership on expenditures. In fact, expenditures are observed only for subjects in the FFS sector. Instead, we seek to estimate the direction and magnitude of correlation between variables omitted from both the health-plan-choice equation and FFS-expenditure equation. Our statistical model, which is based on a particular assumption regarding the distribution of errors (omitted variables) in the choice and expenditure equations, provides a direct measure of selection bias.

The model for this analysis consists of a health-plan-choice equation and an expenditure equation for FFS enrollees. These equations are estimated simultaneously. In addition to selection bias, estimation of the FFS expenditure equation is complicated because the expenditure data contain a mass of observations at zero. We address that problem by estimating tobit and two-part expenditure equations, each corrected for selection bias. We conduct a number of tests to investigate the sensitivity of our results to distributional assumptions.

To reduce problems that arise from nonnormality and heteroskedasticity of the error term in the FFS expenditure equation,[6] we take the natural log of positive expenditures denoted $LCOST^F$ and write the following model:

$$LCOST_i^{F^*} = X_i \beta^F + \sigma^F u_i$$

where i indexes the individual, F indexes the FFS sector, and σ^F is the standard deviation of u_i. To apply the log transformation,

[6]The tobit estimator is inconsistent in the presence of non-normal or heteroskedastic errors. Our ability to apply the usual tobit specification tests is limited because the errors in our expenditure equation are additionally censored by the choice of FFS versus HMO sector. Nonetheless, a number of specification tests were performed and are discussed in the "Results" section.

we first add \$1.00 to every respondent's health expenditures, then compute the log of expenditures. Respondents with zero expenditures thus have zero expenditures on the log scale as well. The problem of a mass of observations at zero is addressed with a standard tobit model. $LCOST^{F*}$ represents potential cost. Observed cost ($LCOST^F$) is related to potential cost as follows:

Observed $LCOST^F = LCOST^{F*}$

if $LCOST^{F*} > 0$ (i.e., if $COST^{F*} >$ \$1.00)

$= 0$ otherwise,

thus:

$$\text{observed } LCOST^F = X\beta^F + \sigma^F u \text{ if } u > \frac{-X\beta^F}{\sigma^F}$$

$$= 0 \text{ if } u \le \frac{-X\beta^F}{\sigma^F}$$

The density function of $LCOST^F$ is:

$$\frac{1}{\sigma^F\sqrt{2\pi}} \exp\left[\frac{-1}{2}\left[\frac{(LCOST^F - X\beta^F)^2}{(\sigma^F)^2}\right]\right]$$

$$= \frac{1}{\sigma^F}\phi\left[\frac{LCOST^F - X\beta^F}{\sigma^F}\right] = \frac{1}{\sigma^F}\phi\,[u]$$

where ϕ is the standard normal density function. The error terms u and v^* (from the choice equation) are assumed to have a bivariate standard normal distribution, with correlation coefficient ρ^F. Let this bivariate density be denoted ϕ_B.

Three types of individuals are observed in the data: (1) those choosing the HMO sector; (2) those choosing the FFS sector and having no expenditures; and (3) those choosing the FFS sector and having positive expenditures. The probability of joining the FFS sector is estimated from a multinomial logit model with the probability of FFS choice equal to $F(-Z\gamma^F)$, where F is the normal cumulative distribution function. Expenditures are not observed for beneficiaries choosing the HMO sector, and thus the probability of observing such an individual is simply $1\text{-}F(-Z\gamma^F)$. The probability of observing the second type of individual is:

$$\int_{u=-\infty}^{-X\beta^F/\sigma^F}\int_{v^*=-Z\gamma^F}^{+\infty}\phi_B\,(v^*, u, \rho^F)\,dv^*\,du$$

The first integral represents zero consumption of health care services, and the second integral represents choice of the FFS sector. The third type of individual joins the FFS sector and has $COST^F$. The probability of observing this individual is:

$$\int_{v^*=-Z\gamma^F}^{+\infty}\frac{1}{\sigma^F}\,\phi_B\left[v^*, \frac{LCOST^F - X\beta^F}{\sigma^F}, \rho^F\right]dv^*$$

Because these three types of individuals comprise the entire data set, and because observations on individuals are assumed to be independent, the likelihood function for the data set is:

$$L = \prod_{i=1}^{N^F}\left[\int_{v^*=-Z_i\gamma^F}^{+\infty}\frac{1}{\sigma^F}\,\phi_B\left(v_i^*, \frac{LCOST_i^F - X_i\beta^F}{\sigma^F}, \rho\right)dv_i^*\right]^{D_i^F}$$

$$*\left[\int_{u=-\infty}^{-X_i\beta^F/\sigma^F}\int_{v^*=-\infty}^{-Z_i\gamma^F}\phi_B\,(v_i^*, u_i, \rho^F)\,dv_i^*\,du_i\right]^{(1-D_i^F)}$$

$$*\prod_{i=N_F+1}^{N_T}\left[\phi\,(-Z_i\gamma^F)\right]$$

where ϕ is the standard normal cumulative distribution function (CDF), N_F is the number of individuals choosing the FFS sector, N_T - N_F is the number of individuals choosing the HMO sector, and $D_i^F = 1$ if the individual consumes some health care services, and 0 otherwise. The first term in the likelihood function may be simplified to:

$$\frac{1}{\sigma^F}\,\phi\left[\frac{LCOST^F - X\beta^F)}{\sigma^F}\right]$$

$$\left[1 - \phi\left[\frac{-Z\gamma^F - \rho^F\dfrac{(LCOST^F - X\beta^F)}{\sigma^F}}{\sqrt{1-(\rho^F)^2}}\right]\right]$$

and so the log of the likelihood function may be written as:

$$\mathrm{LOG}\,L\,(\beta^F, \gamma, \rho^F, \sigma^F) = \sum_{i=1}^{N} - D^F C^F \ln \sigma^F$$

$$+ C^F D^F\left[\log \phi\left[\frac{LCOST^F - X\beta^F)}{\sigma^F}\right]\right]$$

$$+ C^F D^F\left[1 - \log \phi\left[\frac{-Z\gamma^F - \rho^F\dfrac{(LCOST^F - X\beta^F)}{\sigma^F}}{\sqrt{1-(\rho^F)^2}}\right]\right]$$

$$+ C^F (1 - D^F)\log\left[\phi(-Z\gamma^F) - \phi_\beta(Z\gamma^F, -\frac{X\beta^F}{\sigma^F}, -\rho^F)\right]$$

$$+ (1 - C^F)\log\phi(-Z\gamma^F)$$

where $C^F = 1$ if the FFS sector is chosen and 0 if the HMO sector is chosen. Φ_β is the bivariate standard normal CDF. Maximization[7] of this likelihood function yields consistent and asymptotically efficient estimates of:

- Parameters in the choice equation (γ^F),
- Parameters in the $LCOST^F$ equation (β^F),
- The standard error of the LCOST equation (σ^F), and most importantly,
- The correlation between errors in the COST and choice equations (ρ^F).

[7]The selectivity-corrected tobit model was estimated using the LIMDEP statistical program. The LIMDEP likelihood function was cross-validated by constructing the likelihood function and maximizing it using the GQOPT maximization program.

Equation Specification and Identification of the Selection Effect

Specification of the FFS-expenditure equation is determined by the AAPCC payment formula, because we wish to test for potential selectivity bias in the current AAPCC methodology. The explanatory variables in the FFS expenditure equation are beneficiary age, gender, and county of residence. The age/sex categories and county dummy variables in our analysis correspond to the AAPCC categories.

The purpose of the HMO/FFS choice equation is to provide selection correction for the FFS expenditure equation. The HMO/FFS choice equation is not meant to be a realistic description of the health-plan-choice process. Indeed, specifying a realistic health-plan-choice equation would make it impossible to address the objective of this study: to identify the correlation among variables that are omitted from both the health-plan-choice process and the FFS-expenditure equation. If we included measures of chronic illness in the health-plan-choice equation, for example, and chronic illness affected health expenditures, we would have removed a potentially important source of bias in the current AAPCC—a source of bias this study was designed to detect. Dowd et al. (1994) provides a detailed analysis of health-plan choice in the Twin Cities using these same data.

To provide selection correction for the FFS-expenditure equation, the choice equation must include the AAPCC variables plus other variables that affect choice but not expenditures. Two identifying variables are used in this analysis: whether the beneficiary purchases any insurance through a group policy and whether anyone outside the family contributes to the beneficiary's health insurance premium. Group insurance for the elderly is generally offered as a retirement benefit by a former employer. Furthermore, beneficiaries who purchase insurance through a group generally pay lower premiums, either because of group rates or because the premiums are subsidized by the former employer. Consequently, plans offered through a group and/or receiving a premium subsidy will be favored by beneficiaries. We assumed that group purchase and premium subsidies affect premiums but do not directly affect expenditures. That assumption proved troublesome, as we describe in the "Results" section.

Comparison to Mathematica Policy Research's Approach

Our analytic approach has much in common with that of Mathematica Policy Research, Inc. (MPR) (Hill et al., 1992; Brown et al., 1993), which estimated an expenditure equation using data on FFS beneficiaries. The explanatory variables consisted of AAPCC variables and other plausible predictors of expenditures. MPR used all the explanatory variables in the model to predict the cost of HMO enrollees, had they remained in the FFS sector. Those predictions of actual costs were compared with predicted AAPCC payments, which were obtained from the same regression equation, but using only the AAPCC variables as predictors. The prediction of over- or underpayment thus depended on the sign and magnitude of the effect of the error term, that is, the variables that were included in the model but that are excluded from the AAPCC payment formula. MPR recognized that other, unobserved variables might influence the FFS-expenditure equation and took steps to assess the importance of those unobserved variables. Those tests are discussed in the "Results" section.

We also use data on FFS beneficiaries to estimate an FFS-expenditure equation, but we are also concerned about the effects of unobserved variables. However, we use a different econometric model to assess the importance of unobserved variables, and we focus on the sign and magnitude of the selectivity correlation, rather than estimating the degree of over- or underpayment.

DATA

Twin Cities Medicare Market

The Twin Cities have a long history of developing innovative methods for financing and delivering health care. One of the unusual features of the Twin Cities market during the study period (1988-89) was the presence of five Medicare HMOs with TEFRA-risk contracts. These contracts place the HMO at financial risk for the full range of Part A and Part B Medicare services, as well as other services covered under supplementary benefit packages offered by the HMOs. Table 1 shows a diagram of the coverage and premiums of basic FFS Medicare and the five TEFRA-risk HMOs during 1988.

In-Person Survey Instrument

Random samples of Twin Cities Medicare beneficiaries were drawn by HCFA on three separate dates between September 15 and December 15, 1987. Two samples were drawn on each date. The first consisted of enrollees in the five TEFRA-risk HMOs. The second consisted of beneficiaries in the FFS Medicare sector. The FFS sector was oversampled slightly to increase the number of observations in the expenditure equation. The final number of eligible subjects was 1,233 HMO enrollees and 1,659 FFS beneficiaries. Subjects were interviewed in person, usually at the sub-

Table 1
Coverages Offered Under Selected Health Plans in the Twin Cities Medicare Market[1]: 1988

Organization, Plan, and Beneficiary Monthly Out-of-Pocket Premium	Inpatient Care (Part A)					
	Hospital	Skilled Nursing Facility	Home Health Care	Medical Care (Part B)	Additional Benefits Offered	Restrictions
Medicare	Days 1–60 deductible applies; days 61–90 coinsurance applies; 60 reserve days with coinsurance; mental health & chemical dependency 190 days coverage	Days 1–20 covered; days 21–100 coinsurance applies; 3 days prior hospitalization required for admission	Does not include custodial care	Deductibles and coinsurance apply[2]	NA	NA
Group Health Group Health Seniors $7.95	Covers deductible & coinsurance for Medicare-eligible services	Limited to Medicare-eligible coverage; 3 days prior hospitalization required for admission	Limited to Medicare-eligible coverage	Covers deductibles & coinsurance except coinsurance for emergency services & outpatient mental health & chemical dependency care	Prescription drugs (coinsurance); preventive dental (covered); additional dental care (coinsurance); hearing exams & aid (coinsurance); eyewear (coinsurance)	Enrollee care is provided through physicians or hospitals affiliated with Group Health and is only available by referral from health professionals
HMO Minnesota Medicare and More $15.50	Covers deductible & coinsurance for Medicare-eligible services as indicated on enrollee ID card or declaration page	Limited to Medicare-eligible coverage; policy does not indicate 3 days prior hospitalization is required for admission	Limited to Medicare-eligible coverage	Covers deductibles and coinsurance except coinsurance for outpatient mental health & chemical dependency care; other exceptions specified on ID card & declaration page	Hearing exam (covered)	Enrollee registers with Primary Care Office (PCO); indication of coinsurance or deductible for all services appears on enrollee ID card or declaration page; most services must be authorized in advance by PCO physician
Medcenters Medicare $16.50	Covers deductible & coinsurance for Medicare-eligible	Limited to Medicare-eligible coverage; policy does not indicate 3 days prior hospitalization is required for admission	Limited to Medicare-eligible coverage	Covers deductibles and coinsurance except coinsurance for emergency services & outpatient mental health & chemical dependency care	Prescription drugs (coinsurance); dental plan (available coverage); eyewear (coinsurance); hearing exam & aid (coinsurance)	Enrollee must use one specified clinic associated with one hospital; benefits and services must be provided and authorized by plan physician at chosen clinic

See footnotes at end of table.

Table 1—Continued

Coverages Offered Under Selected Health Plans in the Twin Cities Medicare Market[1]: 1988

Organization, Plan, and Beneficiary Monthly Out-of-Pocket Premium	Inpatient Care (Part A)					
	Hospital	Skilled Nursing Facility	Home Health Care	Medical Care (Part B)	Additional Benefits Offered	Restrictions
Physicians Health Plan Plus Select $32.50	Covers deductible & coinsurance for Medicare-eligible services	Policy does not indicate 3 days prior hospitalization is required for admission	Limited to Medicare-eligible coverage	Covers deductibles and coinsurance except coinsurance for emergency services & outpatient mental health & chemical dependency care	Eyewear (coinsurance); preventive dental care (covered); enrollee discounts on additional dental care	Coinsurance required on surgery unless a second opinion is obtained; enrollee chooses 1 hospital from a list of 29 from from which to receive services; many services require prior approval; services are limited to PHP providers
Physicians Health Plan Plus Choice Plan (Greater MN) $39.50	Covers deductible and coinsurance for Medicare-eligible services	Policy does not indicate 3 days prior hospitalization is required for admission	Limited to Medicare-eligible coverage	Covers deductibles and coinsurance except coinsurance for emergency services & outpatient mental health & chemical dependency care	None	Coinsurance required on surgery unless a second opinion is obtained; enrollee has choice of 37 hospitals from which to receive services; many services require prior approval; services are limited to PHP providers
Share Senior Care $9.95	Covers deductible and coinsurance for Medicare-eligible services	Waives 3 days prior hospitalization for admission	Limited to Medicare-eligible coverage	Covers deductibles and coinsurance except coinsurance for emergency services & outpatient mental health & chemical dependency care	Preventive dental (coinsurance); eyewear (coinsurance); prescription drugs (covered); hearing exam (covered)	Enrollee has choice of Share physician who refers to a Share hospital

[1]The metropolitan statistical area of Minneapolis-St. Paul, consisting of Hennepin, Ramsey, Dakota, Carver, Scott, Anoka, and Washington Counties.

[2]Covered services include: emergency care, home health services, physician services, pneumococcal vaccine, hepatitis B vaccine, outpatient mental health and chemical dependency services (limited to $250 per year), emergency room or outpatient clinic, laboratory tests, X-ray and other radiology, medical supplies, drugs (hospital care only), blood transfusions, limited chiropractic services, limited podiatrist services, limited dental services, surgery of the jaw and related structures, limited vision care services (optometrist), physical therapy or speech therapy, comprehensive outpatient rehabilitation facilities, certified independent laboratory fees, ambulance transportation (conditional), prosthetic devices (limited), durable medical equipment, portable diagnostic X-ray services, and hospice care (conditional). Hospital insurance pays a maximum of two 90-day periods and one 30-day period. No deductibles or copayments except for outpatient drugs ($5 or 5 percent) and inpatient respite care (5 percent of cost up to $520). Pays nursing and physician services.

NOTE: NA is not applicable.

SOURCE: Information provided by the various health plans named.

ject's place of residence. If the subject was unable to answer the questions, a proxy respondent was found and the instrument was administered to the proxy. Eight percent of all completed surveys were administered to proxies.

HCFA Payment Data

HCFA payment data were taken from the Medicare Automated Data Retrieval Service (MADRS) files for calendar years 1987, 1988, and 1989. A 1-year window of payment data was constructed for each successfully interviewed beneficiary starting at the date of the interview and ending 1 year later. Subjects who were not successfully interviewed were assigned pseudo-windows beginning in months that followed the same distribution as the successfully interviewed beneficiaries' starting months (in order to compare the payments for respondents and non-respondents). The surveys were conducted from November 1987 to April 1988, and thus the windows extended from November 1988 to April 1989. MADRS data were collected in September 1991, so the minimum time lag between the close of the window and compilation of the payment data (for subjects interviewed in April 1988) was 28 months. HCFA believes that claims data are 95 percent complete after a 9-month lag.

Some of the payment data had no date of service but had been assigned to a calendar year MADRS file.[8] Payment data without service dates were aggregated for each person, and a proportion of the payments was assigned to the beneficiary based on the proportion of that calendar year during which the beneficiary's window was open (e.g., if the window was open for only 1 month, only $^{1}/_{12}$ of the payment data without service dates would be assigned to that person).

[8]These data were omitted from an earlier analysis of payments (Wisner, Feldman, and Dowd, 1994).

Characteristics of the Sample

To be eligible for the study, beneficiaries had to be: (1) a resident of the Twin Cities metropolitan area (Hennepin, Ramsey, Dakota, Carver, Scott, Anoka, or Washington Counties); (2) over 65 years of age; (3) currently eligible for both Part A and Part B; and (4) not eligible for Medicaid (and thus not a Medicaid "buy-in" beneficiary). The best estimate of the distribution of Twin Cities Medicare beneficiaries who met the eligibility criteria, by health plan, comes from a sample of eligible beneficiaries drawn by HCFA for this study. The results from that sample are shown in Table 2.

More than 50 percent of beneficiaries who met the eligibility criteria were enrolled in HMOs. Share Health Plan had the largest percentage of HMO enrollees, followed by Physicians Health Plan (PHP). The FFS sector was oversampled slightly in our data, so that 57 percent of the eligible beneficiaries in the final sample were in the FFS sector.

The final classification of responses and calculated response rates for the interviews are shown in Table 3. Respondents and eligible non-respondents were compared on a variety of measures from the HCFA beneficiary data that were available for everyone in the sample. HMO enrollees are underrepresented among respondents. Fifty-seven percent of the eligible sample was in the FFS sector, but 63 percent of respondents were in the FFS sector.[9] There was no significant relation between response status and enrollment in a particular HMO, however. There was

[9]A possible explanation for the lower response rate among HMO enrollees is that there was considerable turmoil in the Twin Cities Medicare market during the survey period. Earlier in 1988, HMO Minnesota and MedCenter had announced plans to drop several rural Minnesota counties. During the survey period, PHP and Share announced similar plans. An outcry by enrollees, covered extensively in the local press, may have generated considerable resentment among HMO enrollees.

Table 2

Distribution of Beneficiaries Across Health Plans: November 1987

Health Plan	Number of Enrollees	Percent of HMO Enrollees	Percent of All Beneficiaries
Total Eligible Beneficiaries	182,005	—	100
HMO Minnesota	3,480	3.8	2.1
Physicians Health Plan	28,200	30.9	15.5
Medcenter	9,780	10.7	5.4
Group Health	12,060	13.2	6.6
Share	37,800	41.4	20.8
Total HMO Sector	91,320	100.0	50.4
Fee-for-Service Sector	90,325	—	49.6

NOTE: HMO is health maintenance organization.

SOURCE: Health Care Financing Administration: Data from the Office of Research and Demonstrations, 1987.

Table 3

Number of Persons Responding to In-Person Survey

Response	Total	Health Maintenance Organization	Fee-for-Service Sector
Total Eligible Respondents	2,891	1,233	1,658
No Interview[1]	514	356	158
Completed Interview	2,377	877	1,500

[1]Includes eligible individuals who could not be located, refused to participate, were still in process at the time the interviews ended, or for whom no proxy was available. These individuals constitute the non-respondents. Ineligible persons include those beneficiaries under age 65, receiving Supplementary Security Income, eligible for Medicaid, having health insurance through their or their spouse's place of employment, those who had moved out of the area at the time of the survey, and duplicate individuals who appeared in more than one of the samples drawn by the Health Care Financing Administration.

SOURCE: Dowd, B., Feldman, R., Moscovice, I., et al., University of Minnesota, 1995.

also no relationship between response category and county of residence. However, the proportion of subjects in the oldest and youngest age categories was significantly different for respondents and non-respondents, with younger enrollees disproportionately represented among respondents.

Table 4 shows the variable names and definitions, as well as means and standard deviations, for variables in the analysis. The mean expenditure for respondents in the FFS sector was $2,164, and the mean for non-respondents was $2,577. The difference was not statistically significant, however. Average FFS payments for respondents were lower than the average costs implied by Twin Cities' AAPCC payments. The 1988 weighted average AAPCC in the Twin Cities was $3,220.96. Langwell and Hadley (1990) report that MADRS (HCFA payment) data appear to underrepresent payments by 10-20 percent. The average underrepresentation in our data is much greater, almost 33 percent, but our data exclude disabled beneficiaries and those qualifying for Medicaid. Sixteen percent of FFS respondents had zero payments. Waldo and Lazenby (1984) found that 39 percent of Medicare beneficiaries had zero payments in 1982. That percent should be smaller in 1988 because FFS expenditures have risen faster than coinsurance and deductibles.

We performed several tests to determine whether response bias affects the estimated coefficients in the HMO/FFS choice equation or FFS expenditure equation. These tests utilized the beneficiary's age, sex, and county of residence, which were known from HCFA records for both respondents and non-respondents. The age and sex variables and the beneficiary's

Table 4
Descriptive Statistics and Variable Definitions[1]

Type of Variable and Variable Name	Mean	Standard Deviation	Definition
Personal Characteristics			
OTRPAY	0.18707	0.39005	1 if someone besides the beneficiary contributes to the premium, 0 otherwise
OTRMIS	1.52E-02	0.12234	1 if data on OTRPAY is missing, 0 otherwise
GRPPOL	0.38108	0.48576	1 if any health insurance is purchased through a group policy
GRPMIS	1.56E-02	0.12405	1 if data on GRPPOL is missing, 0 otherwise
ANOKA	4.34E-02	0.20381	1 if the beneficiary lives in Anoka County, 0 otherwise
CARVER	1.04E-02	0.10155	1 if the beneficiary lives in Carver County, 0 otherwise
DAKOTA	7.38E-02	0.26148	1 if the beneficiary lives in Dakota County, 0 otherwise
RAMSEY	0.29253	0.45503	1 if the beneficiary lives in Ramsey County, 0 otherwise
SCOTT	1.43E-02	0.11884	1 if the beneficiary lives in Scott County, 0 otherwise
WASH	4.64E-02	0.21048	1 if the beneficiary lives in Washington County, 0 otherwise
Chronic Illness[2]			
HIGHBP	0.38411	0.48649	High blood pressure
DIAB	8.98E-02	0.28602	Diabetes
ASTHMA	9.38E-02	0.29154	Asthma, emphysema or chronic bronchitis
ANEMIA	2.43E-02	0.15403	Anemia
HEART	0.23047	0.42122	Heart trouble or angina
CIRC	0.21137	0.40837	Circulation problems or hardening of the arteries
STROKE	4.90E-02	0.21601	Paralysis or effects of a stroke
NERVE	4.08E-02	0.19787	Nerve or muscle problems, such as Parkinson's Disease or epilepsy
ALZ	1.17E-02	0.10764	Alzheimer's disease
ARTHRIT	0.49002	0.50001	Arthritis or rheumatism
TUMOR	3.95E-02	0.19482	Tumor or a cancer other than a skin cancer
SKIN	8.29E-02	0.27579	Chronic skin problems
ULCER	0.11111	0.31434	Digestive problems, such as ulcers, gall bladder trouble, or colitis
LIVER	9.11E-02	0.095055	Liver problems, such as cirrhosis
KIDNEY	0.13976	0.34681	Kidney or bladder problems (men: including prostate)
SPEECH	3.56E-02	0.18531	Speech problems
HEAR	0.32639	0.46899	Hearing problems
MENTAL	2.60E-02	0.15929	Mental health problems
FFS-Sector Expenditure Equation[3]			
AM2	0.11972	0.32475	1 if beneficiary is male and (70 < age < 75)
AM3	0.06712	0.25033	1 if beneficiary is male and (75 < age < 80)
AM4	0.03944	0.19472	1 if beneficiary is male the (80 < age < 85)
AM5	0.04475	0.21331	1 if beneficiary is male and age > 85)
AF1	0.16055	0.36725	1 if beneficiary is female and (65 < age < 70)
AF2	0.1481	0.35532	1 if beneficiary is female (70 < age < 75)
AF3	0.1045	0.30601	1 if beneficiary is female (75 < age < 80)
AF4	0.08166	0.27394	1 if beneficiary is female (80 < age < 85)
AF5	0.09965	0.29964	1 if beneficiary is female age > 85
FFSSUP	0.80969	0.39268	1 if the beneficiary has supplementary insurance, 0 otherwise (coded only for FFS beneficiaries)
Annual Expenditures	$2,165.20	$5,671.50	HCFA payments paid on behalf of the beneficiary in the year following the in-person interview

[1] N = 2,304
[2] Coded 1 if the patient has the condition and 0 otherwise.
[3] FFS sample N = 1,445.

NOTE: FFS is fee-for-service. HCFA is Health Care Financing Administration.

SOURCE: Dowd, B., Feldman, R., Moscovice, I., et al., University of Minnesota, 1995.

county of residence were used in an estimated probit equation to predict choice of FFS versus HMO sector. Each demographic variable was also interacted with another variable that equaled one if the beneficiary responded to the survey, and zero otherwise. Coefficients of the interaction variables test whether the effect of the demographic variables on health-plan choice is significantly different for respondents and non-respondents. The tests showed that the oldest respondents of both sexes were less likely than non-respondents to join the FFS sector. Thus, the estimated effect of age on choice of the FFS sector (which is positive in the full model) may be conservatively biased (toward zero) in our data.

A similar test was performed on the expenditure equation. In this equation, none of the interactions with the age/sex or county variables was significant at the 0.05 level. An F-test showed that adding the respondent variable and the interactions did not significantly increase the explained variance in payments.

Four percent of beneficiaries in both the HMO and FFS sector died during the year. All the FFS-expenditure equations reported in this article were estimated with and without a dummy variable indicating whether the beneficiary died during the study year. The coefficient of the dummy variable was consistently positive and statistically significant but had no effect on the estimates of selectivity bias.

Before estimating the selection models, a test for heteroskedasticity was performed on the observations with positive expenditures. Using the Breusch-Pagan (1979) test statistic, the null hypothesis of homoskedasticity could not be rejected at the 5-percent level (test statistic = 16.31, with 15 degrees of freedom, critical value = 24.996).

RESULTS

Two-Sector Selection Model

For payment purposes, the crucial division of the Medicare market is between the FFS sector and the HMO sector. In calculating the AAPCC, HCFA does not distinguish between enrollees who have a medigap supplementary policy and those who do not. In paying HMOs, HCFA does not distinguish between IPAs and PGP HMOs.

The two-sector selection model jointly estimates the choice and FFS-expenditure equations, where "choice" is defined as 1.0 if the beneficiary selects the FFS sector (including FFS with a supplement) and 0.0 if the beneficiary selects any TEFRA-risk HMO. The results in Table 5 show that the selection identification vari-

Table 5

Two-Sector Selection Model: Choice Equation Coefficients

Variable	Coefficient	*t*-statistic	Prob $\|t\| > 0$
Constant	–0.18309	–2.017	0.04370
Selection Identification Variables			
OTRPAY	0.27888	2.826	0.00472
OTRMIS	–0.06361	–0.267	0.78957
GRPPOL	1.1226	14.787	0.00000
GRPMIS	0.47069	2.159	0.03086
AAPCC Variables			
AM2	–0.12942	–1.089	0.27622
AM3	–0.16751	–1.252	0.21051
AM4	0.00416	0.026	0.97894
AM5	0.42323	2.751	0.00595
AF1	–0.001539	–0.014	0.98879
AF2	0.072029	0.625	0.53168
AF3	0.032642	0.274	0.78443
AF4	0.17697	1.399	0.16189
AF5	0.28566	2.342	0.01919
ANOKA	–0.24371	–1.668	0.09533
CARVER	–0.31457	–1.152	0.24922
DAKOTA	0.15052	1.302	0.19285
RAMSEY	0.17696	2.640	0.00830
SCOTT	–0.36446	–1.397	0.16246
WASH	0.25044	1.610	0.10731

NOTE: Fee-for-service = 1, health maintenance organization = 0. AAPCC is adjusted average per capita cost.

SOURCE: Dowd, B., Feldman, R., Moscovice, I., et al., University of Minnesota, 1995.

ables, GRPPOL and OTRPAY (and their missing value counterparts),[10] are significant and positive predictors of choice of the FFS sector. The only other significant predictors of the FFS versus HMO sector are the oldest age categories for men (AM5) and women (AF5), which are positively associated with choice of the FFS sector. The latter finding makes the analysis of non-response bias (which showed that the coefficients on AM5 and AF5 may be underestimated) even more important. The proportionate reduction in prediction error afforded by the explanatory variables in the choice equation is 39 percent.[11]

The estimation results for the selectivity-corrected tobit expenditure equation are shown in Table 6. Several of the

Table 6

Two-Sector Selection Model: Selectivity-Corrected Tobit AAPCC Expenditure Equation Coefficients

Variable	Coefficient	t-statistic	Prob $\|t\| > 0$
Constant	4.2295	13.786	0.00000
AAPCC Variables			
AM2	0.53916	1.578	0.11463
AM3	0.76985	1.815	0.06951
AM4	1.4621	2.900	0.00373
AM5	1.4974	3.309	0.00094
AF1	0.40261	1.213	0.22499
AF2	1.0794	3.031	0.00243
AF3	1.6646	3.769	0.00016
AF4	1.7993	4.280	0.00002
AF5	1.3222	3.391	0.00070
ANOKA	0.02015	0.045	0.96379
CARVER	–0.49509	–0.486	0.62693
DAKOTA	–0.14078	–0.402	0.68778
RAMSEY	–0.13293	–0.617	0.53713
SCOTT	–0.39822	–0.360	0.71859
WASH	–0.87684	–2.076	0.03788
Sigma	3.465	37.227	0.00000
Rho	–0.18991	–1.966	0.04925
Log likelihood = –4775.987			

NOTES: Dependent variable = log of annual HCFA payments if payments > 0, and = 0 otherwise. HCFA is Health Care Financing Administration. AAPCC is adjusted average per capita cost.

SOURCE: Dowd, B., Feldman, R., Moscovice, I., et al., University of Minnesota, 1995.

age/sex categories are significantly and positively associated with expenditures (relative to the omitted "youngest male" category). The coefficients of the male categories increase with age, as expected, but interestingly, the largest coefficient for females is found in the 80-84 age range, rather than the 85-or-over range. Residents of Washington County have significantly lower expenditures than the omitted reference county, Hennepin County, which contains the city of Minneapolis.

The findings indicate that the FFS sector experiences unfavorable selection on the basis of observed variables. The oldest age categories for males and females are positively associated with both choice of the FFS sector and higher expenditures. Residency in Washington County is a source of very weak favorable selection into the FFS sector, because residents of Washington County prefer the FFS sector (= 0.107) and have lower expenditures.

Selection on the basis of observed variables that are included in the AAPCC does not result in over- or underpayments to HMOs, however, because the AAPCC payment formula corrects for that selection. Our interest lies in the effect of variables omitted from the choice and expenditure equations, as indicated by the correlation of the error terms in those two equations. That estimated correlation is negative and statistically significant at the 5-percent level. Negative correlation indicates that the omitted variables associated with choice of the FFS sector also contribute negatively to expenditures.[12]

[10]When data were missing, we set the missing variable equal to 0.0 and defined an indicator with the value of 1.0. Otherwise, the indicator took on the value of 0.0.

[11]We use the ∇ measure of prediction success, developed by Hildebrand, Laing, and Rosenthal (1977).

[12]In results not shown, we separated expenditures into Part A versus Part B expenditures and reran the model. For Part A expenditures, the estimated correlation was 0.033 with a t-statistic of 0.249. For Part B expenditures, the estimated correlation was -0.23572 (t-statistic = -2.381). Thus, the negative correlation seems to be entirely the result of the effect of favorable FFS selection on Part B expenditures.

Tests of Alternative Selection Models

Identification Problems

A finding of favorable selection into the FFS sector stands in stark contrast to previous studies that have found evidence of favorable selection into Medicare HMOs, and for that reason, this finding is suspect. Because the selection model is known to be sensitive to changes in both functional form and choice of variables, we estimated a variety of models to investigate the robustness of this result.

The first series of tests concerned the variables GRPPOL and OTRPAY, which are used to identify the expenditure equation. We estimated models that included only one or the other of these variables in the choice equation. Those tests revealed that the finding of a significant selection correlation depends entirely on inclusion of GRPPOL in the choice equation. When GRPPOL is omitted from the choice equation, the estimated (insignificant) correlation is 0.01467. The sensitivity of the results to inclusion of GRPPOL is because of its strong association with choice of the FFS sector (t-statistic = 14.787). If, for some reason, GRPPOL is also associated with FFS expenditures, then a significant selection correlation could be produced by the fact that GRPPOL is a not a legitimate identifying variable.

An important finding of our previous analysis of health-plan choice (Dowd et al., 1994) is that Medicare plans offered through former employers tend to be FFS supplements. We found that only 13 percent of HMO enrollees purchase any of their health insurance policies through a group, while 53 percent of FFS beneficiaries do so. Within the FFS sector, GRPPOL is associated with purchase of an FFS Medicare supplementary insurance policy (p = 0.412). Thus, GRPPOL is an important predictor of choosing the FFS sector largely because it is associated with the purchase of a Medicare supplement. Because owning a Medicare supplement may be associated with higher expenditures (by removing Medicare's coinsurance and deductibles), GRPPOL may not be a valid identification variable. However, unless GRPPOL is included in the choice equation, our model does not adequately distinguish beneficiaries joining the FFS sector from those joining HMOs. Thus, the challenge is to find a way to retain GRPPOL in the choice equation but to control for its correlation with ownership of a medigap policy in the expenditure equation.

A simple approach is to include a variable indicating ownership of an FFS Medicare supplement policy (FFSSUP) in the FFS expenditure equation. Adding FFSSUP to the expenditure equation purges the relationship between GRPPOL and FFSSUP from the estimated selectivity correlation, which shrinks to -0.15304 (t-statistic = -1.437), not statistically different from zero. The estimated coefficient on FFSSUP in the expenditure equation is 0.20101, also not significant.

This simple change in the model specification is not technically correct, however, because choice of an FFS supplement is endogenous. A better method would be to estimate the choice equation as a three-way choice among basic FFS Medicare, FFS with a supplement, and the HMO sector. This model could include separate expenditure equations for the basic FFS sector and FFS with a supplement. Unfortunately, there are two problems with this approach. First, only 275 beneficiaries chose basic FFS in our data; this is too few to estimate a separate expenditure equation for basic FFS. Second, allowing the coefficients of the AAPCC variables to be different for beneficiaries who do and do not purchase supplementary policies is equivalent to assuming that the current HMO payment formula includes such an adjustment. In fact, the AAPCC makes no such adjustment.

Because of these problems, we estimated a model in which the AAPCC coefficients in the two FFS-sector expenditure equations were constrained to be the same; FFSSUP was added to the expenditure equation to allow a shift in the intercept if the beneficiary had purchased a supplementary policy. Of course, the AAPCC does not allow an intercept shift for "ownership of a supplement," but limiting the effect of a supplement to an intercept shift is the most conservative specification that retains the desirable uniform coefficients of the AAPCC variables in the two FFS sectors. It also allows FFSSUP to remain in the expenditure equation, thus purging the FFSSUP effect from the selectivity correlation.[13] The results from estimating this three-sector model implied weak, and not statistically significant, selection into both FFS sectors.

A second three-sector model was estimated in which the selectivity correlations were allowed to differ for basic FFS and FFS with a supplement. The estimated correlations indicated favorable selection into the FFS-with-a-supplement sector, relative to basic FFS and HMOs, and unfavorable selection into basic FFS Medicare, relative to the other two sectors. However, neither correlation was significant at the 10-percent level.

Another criticism of the identifying variables GRPPOL and OTRPAY is that when insurance is available through a group or when premiums are subsidized, the health-plan-choice environment is dramatically altered. There are two interpretations of this choice environment. The first is that the availability of group coverage or a premium subsidy dramatically alters the probability that the group policy or subsidized policy will be chosen. Because the "group" most often offering insurance to Medicare beneficiaries and subsidizing the premium is the former employer, and because employers are more likely to offer FFS supplements than HMOs, both GRPPOL and OTRPAY should be positively associated with choice of the FFS sector. That is exactly what our data show. GRPPOL and OTRPAY allow intercept shifts of the probability that the FFS sector will be chosen.

A second interpretation of the problem is that beneficiaries with access to retiree group policies or employer subsidies do not consider any other choices. In that case it would be incorrect to include those beneficiaries in the choice equation. To address this concern, we first reestimated the model, dropping respondents who received any premium subsidy. GRPPOL remained a highly significant predictor of health-plan choice, and the estimated selectivity correlation rose to -0.3968 (t-statistic = -3.236). Second, we dropped all respondents who had access to subsidized, retiree group coverage but retained those with other types of group coverage or subsidies from other sources. Again, GRPPOL was highly significant in the health-plan-choice equation, and the estimated selectivity correlation was -0.3209 (t-statistic = -2.740).[14] Thus, the criticism that group coverage and subsidized premiums alter the choice environment beyond the simple intercept shifts in our original model appears to have some validity. When the sample is restricted to beneficiaries whose choices across health-plan products are not influenced by group policies and premium subsidies, the estimated degree of favorable selection into the FFS sector increases.

[13]Construction of the selectivity-correct tobit likelihood function with more than two sectors is explained in Dowd et al. (1991).

[14]Adding FFSSUP to these two equations reduced the estimated correlations, but both remained highly significant. In the equation dropping anyone with a premium subsidy, the estimated correlation was -0.327 (t-statistic = -2.588). In the equation dropping subjects with employment-based retirement plans and subsidies, the estimated correlation was -0.26704 (t-statistic = -2.122).

Tobit Specification

Another type of specification error arises from our use of the tobit expenditure model. Tobit may be viewed as a restricted form of a general two-part model (Manning et al., 1981). In the two-part model, one equation describes the probability that the FFS beneficiary will have positive expenditures. A second equation describes the expected value of expenditures, conditional on expenditures being positive. The coefficients of the AAPCC variables in each part could be different; also, each part could have a separate error term, which would generate two estimates of the selectivity correlation. The tobit model imposes two important constraints on the general two-part model: First, the coefficients in the two parts are constrained to be equal; second, there is only one error term, and thus only one selectivity correlation to be estimated.[15]

We relaxed these constraints by estimating a selectivity-corrected probit equation for some versus no expenditure, and a selectivity-corrected OLS equation for FFS beneficiaries with positive expenditures. The expenditure variable in the second equation was defined as before (natural log of positive values). Both the estimated coefficients and selectivity correlations were considerably different in the two parts of the model. The estimate of selectivity correlation was -0.331 (t-statistic = -2.00) in the selectivity-corrected probit model, as opposed to -0.0724 (t-statistic = -0.230) in the positive expenditure equation. No significant selectivity was detected when FFSSUP was added to the equation.[16]

[15]In fact, the hypothesis that the coefficients in the two parts of the model are equal is the basis of Cragg's (1971) specification test.

Comparison to MPR's Results

As part of their analysis, MPR estimated selectivity-corrected models (Hill et al., 1992). However, MPR modeled FFS expenditures as an OLS equation with dollars, rather than the log of dollars, as the dependent variable. There was no correction for the mass of observations at zero expenditures.[17] The estimated selection correlation indicated favorable HMO selection but was statistically insignificant. We estimated a similar model with our data and also found a small and statistically insignificant correlation (0.079 by the two-step estimation method; 0.085 using a maximum-likelihood estimator) indicating favorable HMO selection. Including FFSSUP in the expenditure equation, however, reduced the correlation virtually to zero. The two-step selection correction utilized by MPR assumes that a linear-regression relationship exists between the error term in the choice equation and expenditure equation. That assumption is jeopardized by the mass of observations at zero in health expenditure data.

The tobit model addresses the mass of observations at zero, and in our data, estimation of a tobit model on untransformed health expenditures reversed the sign of the selectivity correlation (to indicate favorable FFS selection) but remained small (-0.06) and statistically insignificant. Adding FFSSUP to the tobit expenditure equation increased the esti-

[16]In theory, an improved specification would consist of three equations: (1) choice of sector; (2) some versus no expenditures; and (3) level of positive expenditures. The positive-expenditure equation in that model would be subject to two selection processes, described by the first two equations. The analysis would posit a trivariate distribution of the three errors and estimate the correlations among all errors. Estimation of the three-equation model is unwieldy, because it is difficult to find variables that affect only the probability of some expenditures without also affecting the level of positive expenditures. In the absence of such variables, the performance of selection-correction models is likely to be poor (Manning, Duan, and Rogers, 1987).

[17]MPR subsequently investigated a two-part expenditure model but without a correction for selectivity bias.

mate (in absolute value) to -0.107 (t-statistic=-1.096).

The tobit model for untransformed expenditures is misspecified, however. The selectivity-corrected tobit requires maximum-likelihood estimation, which imposes the stronger assumption that the error terms in the two equations have a bivariate normal distribution. There is little hope of satisfying that assumption in untransformed health expenditure data. It was after taking the log of positive expenditures to satisfy the bivariate normality assumption that the selectivity correlation became statistically significant, as reported in Tables 5 and 6.

Analysis of Chronic Conditions

A number of analysts have suggested adding measures of chronic illness to the AAPCC payment formula to correct a hypothesized payment bias. To investigate the effect of including chronic illness in the payment formula, we added variables indicating the presence of 18 chronic conditions to the 2-sector choice equation and the expenditure equation. The results, shown in Tables 7 and 8, suggest that adding chronic conditions to the AAPCC would cause a minor reduction in the estimated selectivity correlation, from -0.18991 (using the specification in Tables 5 and 6) to -0.15371 (t-statistic = -1.584, = 0.113). When FFSSUP is added to the equation, the estimated correlation falls to -0.10552 (t-statistic = -0.993, = 0.32).

Examination of the coefficients of the chronic conditions explains the weak effect of the chronic conditions on the estimated selectivity correlation. Conditions that are significantly associated with choice of sector tend not to be significant predictors of expenditures.

Adding chronic conditions to the AAPCC formula could create a bias if the current omission of chronic conditions from the AAPCC payment formula were offset by the effects of other omitted variables. However, our results indicate that adding chronic conditions to the AAPCC payment formula in our site and time period would not create biased HMO payments.

Table 7

Chronic Conditions Added to the Two-Sector Model: Choice Equation Coefficients

Variable	Coefficient	t-statistic	Prob $\|t\| > 0$
Constant	–0.14293	–1.528	0.12660
Selection Identification Variables			
OTRPAY	0.28805	2.893	0.00382
GRPPOL	1.1314	14.669	0.00000
OTRMIS	–0.063077	–0.260	0.79508
GRPMIS	0.50132	2.250	0.02444
AAPCC Variables			
AGEBEN2M	–0.11502	–0.957	0.33872
AGEBEN3M	–0.13454	–0.996	0.31944
AGEBEN4M	0.012675	0.079	0.93738
AGEBEN5M	0.40941	2.517	0.01184
AGEBEN1F	0.0081841	0.074	0.94087
AGEBEN2F	0.089984	0.778	0.43641
AGEBEN3F	0.055277	0.460	0.64525
AGEBEN4F	0.19958	1.541	0.12339
AGEBEN5F	0.29571	2.349	0.01883
ANOKA	–0.22782	–1.570	0.11641
CARVER	–0.32418	–1.164	0.24448
DAKOTA	0.14143	1.215	0.22449
RAMSEY	0.17226	2.528	0.01146
SCOTT	–0.37186	–1.337	0.18120
WASHTON	0.26320	1.633	0.10240
Chronic Illness Measures			
HIGHBP	–0.080497	–1.579	0.11438
DIAB	–0.060893	–0.996	0.31910
ASTHMA	0.020429	0.296	0.76694
ANEMIA	–0.0064679	–0.082	0.93498
HEART	–0.030224	–0.534	0.59356
CIRC	–0.035528	–1.113	0.26580
STROKE	–0.042688	–0.787	0.43155
NERVE	0.048501	0.895	0.37058
ALZ	–0.020857	–0.445	0.65627
ARTHRIT	–0.037038	–0.935	0.34993
TUMOR	–0.058516	–0.403	0.68712
SKIN	0.068300	1.136	0.25595
ULCER	0.053206	1.136	0.25601
LIVER	0.025737	0.388	0.69820
KIDNEY	0.044475	0.878	0.37972
SPEECH	0.30855	1.980	0.04772
HEARING	–0.077193	–1.452	0.14652
MENTAL	–0.042709	–0.562	0.57427

NOTES: Fee-for-service = 1, health maintenance organization = 0. AAPCC is adjusted average per capita cost.

SOURCE: Dowd, B., Feldman, R., Moscovice, I., et al., University of Minnesota, 1995.

[18] Our chronic-illness questions were worded carefully to elicit information about the presence of chronic conditions, not whether respondents were bothered by the condition, which might reflect the degree to which the HMO managed the chronic condition successfully.

Table 8

Chronic Conditions Added to the Two-Sector Model: Selectivity-Corrected Tobit AAPCC Expenditure Equation Coefficients

Variable	Coefficient	*t*-statistic	Prob |*t*| > 0
Constant	3.9420	12.804	0.00000
AAPCC Variables			
AGEBEN2M	0.57654	1.687	0.09159
AGEBEN3M	0.69985	1.682	0.09258
AGEBEN4M	1.1864	2.284	0.02236
AGEBEN5M	1.5125	3.326	0.00088
AGEBEN1F	0.44514	1.348	0.17759
AGEBEN2F	1.1602	3.324	0.00089
AGEBEN3F	1.6398	3.791	0.00015
AGEBEN4F	1.6634	3.910	0.00009
AGEBEN5F	1.3054	3.305	0.00095
ANOKA	0.015827	0.034	0.97290
CARVER	–0.68593	–0.657	0.51141
DAKOTA	–0.091752	–0.264	0.79175
RAMSEY	–0.15526	–0.722	0.47056
SCOTT	–0.25043	–0.218	0.82740
WASHTON	–0.82907	–2.000	0.04546
Chronic Illness Measures			
HIGHBP	0.10383	1.062	0.28827
DIAB	0.12801	1.117	0.26409
ASTHMA	–0.10852	–0.539	0.59003
ANEMIA	0.21817	0.931	0.35167
HEART	0.91915	6.180	0.00000
CIRC	0.017801	0.211	0.83278
STROKE	–0.24193	–1.581	0.11396
NERVE	–0.038712	–0.097	0.92307
ALZ	–0.15851	–1.218	0.22326
ARTHRIT	0.059547	0.685	0.49361
TUMOR	–0.18320	–0.616	0.53762
SKIN	0.070876	0.237	0.81229
ULCER	–0.40491	–1.457	0.14513
LIVER	–0.26978	–2.338	0.01939
KIDNEY	0.28200	1.372	0.17012
SPEECH	0.17854	0.342	0.73254
HEARING	–0.11212	–0.537	0.59158
MENTAL	–0.087079	–0.400	0.68922
Sigma	3.3828	37.748	0.00000
Rho	–0.15371	–1.584	0.11309
Log likelihood = –4736.219			

NOTES: Dependent variable = log of annual HCFA payments if payments > 0, and = 0 otherwise. HCFA is Health Care Financing Administration. AAPCC is adjusted average per capita cost.

SOURCE: Dowd, B., Feldman, R., Moscovice, I., et al., University of Minnesota, 1995.

However, other questions still remain about the inclusion of chronic illnesses, for example, HCFA's ability to measure them accurately, and whether they are entirely beyond the HMO's control.[18]

DISCUSSION AND CONCLUSIONS

Our most striking finding from the different specifications of the model is that there is no evidence of favorable HMO selection within the AAPCC payment cells in the Twin Cities in 1988. In fact, some of our estimates of the two-sector selection model indicate favorable selection into the FFS sector. This estimate of biased selection varies with model specification and subsample of respondents included in the analysis and may be affected somewhat by non-response bias as well.[19] The strongest findings of favorable FFS selection occur in the simple two-sector choice-model specification for individuals who do not have access to employment-based retiree group insurance or subsidized premiums. In additional tests, incorporating endogenous selection of FFS supplements, we found no statistically significant evidence of favorable selection into either the FFS or HMO sector. A finding of no favorable HMO selection in the Twin Cities during the study period has an important implication for Medicare payment policy. In the absence of correlation between variables omitted from the health-plan-choice equation and FFS-expenditure equation during the study period, HMO payments based on 95 percent of costs may actually have yielded a 5-percent savings to HCFA.

An interesting empirical epilogue to the study makes the possibility of unfavorable HMO selection more plausible. Since 1988, there have been significant changes in the Medicare health-plan market in the Twin Cities. Instead of five large TEFRA-risk plans, there now are three risk plans, but only two have significant enrollment. There are four health care prepayment plans (HCPPs), however, all with significant enrollment. In recent interviews, Twin Cities health plans cited low AAPCC rates and the abil-

[19]The preference for the FFS sector is underestimated among our oldest respondents, as opposed to non-respondents, and older beneficiaries have higher expenditures.

ity of HCPPs and FFS Medicare supplement plans to screen potential enrollees as factors contributing to their decision not to renew risk contracts.

The analysis has several important limitations. Our data pertain to the Twin Cities Medicare market in 1988. This is an important site and time period, because five TEFRA-risk HMOs operated in the market during that period. Our results therefore represent a mature Medicare HMO market with longstanding HMOs, resulting in some consumers with a high degree of "brand loyalty" and high HMO market penetration, but these results may not be generalizable to other areas with fewer or smaller HMOs, or even to the Twin Cities market today.

The second limitation concerns a general restriction imposed by selectivity models. These models assume that the relation between the error terms in the choice and expenditure equations is linear. Non-linear relationships (a U-shaped curve, for example) could be substantively important, but they might produce an estimated correlation of zero.

Third, our study, like that of MPR, estimates the degree of selection relative to an estimated payment equation, rather than the actual AAPCC payment formula. Our expenditure equation also differs from the actual payment formula in that the cell-specific payment rates (the estimated coefficients on the age/sex and county variables) are corrected for selection bias. The payment rates in the actual AAPCC formula are not corrected. Put another way, our results indicate that a payment system in which HMOs were paid the average cost of FFS beneficiaries in the AAPCC-defined age, sex, and county cells would not overpay HMOs in the Twin Cities, because it does not appear that there is a strong relationship between variables omitted from the health-plan-choice equation and FFS-expenditure equation. Actual payments to HMOs in that period may have been too high or too low.[20]

What should be the next steps in this area of research? It is possible that interest in competitive rather than regulatory pricing in the Medicare program may make adjustments to the AAPCC-based payment a moot point. Indeed, that would be our preference (Dowd et al., 1992; Dowd, Feldman, and Christianson, 1996). However, as long as interest in the AAPCC continues, one important point should be kept in mind: Analyses of expenditures among FFS beneficiaries may not provide accurate information about bias in payments to HMOs, because the expenditure equation for FFS beneficiaries may not be a reliable predictor of expenditures for HMO enrollees. Our results suggest that the applicability of the FFS equation to HMO enrollees could vary dramatically for different groups of beneficiaries. We found, for example, that favorable FFS selection may be more likely among subjects who do not have access to group coverage or subsidized premiums. As employers begin to offer more HMOs to their retirees and offer these plans on a more equal footing with FFS supplements, the overall results from studies like ours may change dramatically. Efforts to assess bias should not rely on any single approach, but more attention to the effects of unobserved variables appears to be warranted.

[20]Nelson and Brown (1989) found that "average reimbursements computed from HCFA claims data are considerably lower than the values implied by the county AAPCC values." These authors note that the discrepancy is too large to be attributable to hospital cost pass-throughs or the periodic reconciliations that are included in full Medicare costs. Thus, HMO participation in the Twin Cities market may have cost HCFA money even if there was no favorable selection into HMOs.

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