Selection in Medicare HMOs: Absence of Evidence from Aged versus Disabled Payment Rates[†]

Randall P. Ellis[‡]

Professor

Department of Economics

Boston University

and

Manuel García-Goñi

Assistant Professor

Departamento de Economía Aplicada II

Universidad Complutense de Madrid

and SESAM (Seminario de Estudios Sociales de la Salud y los Medicamentos, Universidad Carlos III de Madrid)

[†] Research support for Ellis was 100% provided by grant number R01 HS10620-01A1 from the Agency for HealthCare Research and Quality (AHRQ). Research support for García-Goñi was 100% provided by grant number 30-P-91713/1-01 from the Centers for Medicare and Medicaid Services (CMS). We thank Tom McGuire, Kevin Lang, and participants at seminars at Boston University, Universidad Carlos III de Madrid, the Conference of the Spanish Health Economics Association and EEA-ESEM for their helpful comments. The remaining errors are the authors' responsibility.

[‡] Contact address: Professor Randall P. Ellis. Department of Economics. Boston University. 270 Bay State Road. Boston, MA 022l5. Email: ellisrp@bu.edu

Selection in Medicare HMOs: Absence of Evidence from Aged versus Disabled Payment Rates

Abstract

This paper explores whether US Medicare health maintenance organizations are able to influence selection by selectively attracting or repelling aged and disabled Medicare enrollees in response to payment rate differences at the county level. We use the fact that in each county there are two different Medicare HMO payment rates: one for aged and another for disabled enrollees. We use a model in which HMOs choose either the recruiting effort for aged and disabled enrollees independently, with selection, or the same recruiting effort for both populations, without selection. We find no evidence of selection of this type.

1. Introduction

Managed Care is the dominant form of insurance coverage in the U.S., where about 90% of workers participating in a health plan are in some form of managed care (2001 Health Confidence Survey). For managed care plans to have appropriate incentives to contain costs, it is often recommended that plans receive a capitated payment so that they can benefit from any cost savings achieved. As Keenan et al. (2001) discuss, payments to managed care plans are overwhelmingly capitated in public programs, while capitation is relatively rare among the privately insured. Although capitation can create desirable efficiency incentives - managed care plans (HMOs) want to manage care effectively - it also creates strong selection incentives: avoiding unprofitable enrollees may be easier than managing care (Newhouse 1996).

Prior to the Balanced Budget Act (BBA) of 1997, capitated payments to Medicare HMOs were based on a five-year average of each county's cost experience in Medicare fee for service plans. These county averages, called the Adjusted Average Per Capita Cost (AAPCC) reflected actual county utilization, and were updated every year up until 1997. From 1998 onward, all the Medicare+Choice county rates use 1997 AAPCC payment rates, extrapolated forward using complex update formulas. Since 2000, diagnosis based risk adjustment formulas are also being used, starting from the same original 1997 county payment factors. Details of these extrapolation formulas and risk adjustment are not important to this paper, however the key point is that since 1997 changes in county payment rates were large, and exogenous of actual spending and HMO enrollment in each county. These large changes in payment rates provide a useful natural experiment for evaluating health plan responses to exogenous payment changes.

While the risk adjustment models currently in use by Medicare are an improvement over simply using demographic information (age, gender, whether in a nursing home and Medicaid eligibility) to predict costs, they remain deficient in that health plans still have incentives to use their own private information to better predict the cost of each insured. Chapman (1997) and Shen and Ellis (2002a), among others, have demonstrated that with the existing risk adjustment formulae, health plans still have a considerable incentive to select profitable enrollees (good risks) if they are able to. Numerous studies have shown evidence of risk selection in the Medicare population (Brown et al. 1993; Riley et al. 1991, 1996). Ellis and Gurol (2004) among others have also shown that plans make decisions about which counties to enter and exit that are elastic to Medicare payment rates.

Even if health plans have incentives to select good risks, it is unclear how they may be able to do so. Since the Medicare program requires open enrollment, plans cannot directly turn down unprofitable enrollees (bad risks). Instead, health plans must affect selection indirectly. We can divide the possible indirect selection strategies into two sets, focusing in the individual and service level respectively. A first set of these is composed by "dumping" strategies following Ellis (1998), and includes referring patients with serious chronic conditions to providers in a different health plan, or not offering the services at all that are required by bad risk individuals (Shen and Ellis 2002b).

The second set of indirect strategies is "skimping" strategies. Example of the strategies in this set is to structure coverage in such a way that is unattractive for bad risks. It can be done by not contracting with physicians who have the best reputation of treating patients or, by underproviding quality or quantity of specific services which tend to attract bad risks. The "skimping" strategies all imply service distortion and have been analyzed in Glazer and McGuire (2000) and Frank, Glazer and McGuire (2000). In both papers, health plans use quality of services as the tool for selection, and have incentives to overprovide quality in some services and underprovide the quality in others. Glazer and McGuire (2002a) chooses the weights in the risk adjusters that impose the restrictions assuring the efficiency in offered quality of services and then minimize the access problem (selection) as much as possible. Cao and McGuire (2003) and Cao (2003) find evidence of service distortion in Medicare where HMOs ration services differently, providing more health care in primary care services while less in mental health care services.

This paper tests the first set of indirect strategies - "dumping" strategies - and explores whether there is any evidence about how Medicare+Choice health plans influence selection by looking at enrollment responsiveness to Medicare payment rates at the county level for aged versus disabled enrollees. We take advantage of a rarely emphasized feature of the M+C program, which is that in each county there are two Medicare payment rates, one for aged (age 65 and over) enrollees and another for disabled enrollees (under age 65). Although health plans must offer the aged and disabled enrollees the same benefits and charge both types the same enrollee premium (which is often zero) plans receive payments from the CMS that use different county averages for aged and disabled enrollees. We examine whether there is evidence that HMOs differentially attract or repel aged or disabled enrollees as the relative payment for these two groups vary across counties.

After this introduction, section 2 presents a model in which the HMO maximizes profits by choosing the level of effort to use in selecting enrollees. Section 3 introduces the data used in the analysis. Section 4 shows the estimation methods we use. In section 5, we present the results of the estimation, and finally, we conclude in section 6.

2. Model

Let us assume that enrollees are of two types in the Medicare population: aged (a) and disabled (d). The health plan (HMO) is a profit maximizing agent reimbursed through a payment system including two different premiums, one for each type of enrollees. The HMO knows the existence of each type of patient and can increase enrollment by expending costly recruiting effort. This effort can be of three types: that oriented toward attracting only aged enrollees Ea, that attracting only disabled enrollees, Ed, and that attracting both aged and disabled enrollees equally, Eu. We call the former two types of recruiting effort targeted recruitment, and the last type untargeted recruitment effort. We measure these efforts in units of their cost per enrollee recruited, and hence Ea, Ed, and Eu also measure the cost to the health plan of each type of enrollee recruitment effort.[1]

Therefore, the health plans choose the combination of recruiting effort that maximizes the profit function.

$$\max_{E_a, E_d, E_u} \Pi = N_a(E_a, E_u)\left[P_a - C_a - E_a - E_u\right] + N_d(E_d, E_u)\left[P_d - C_d - E_d - E_u\right] \quad (1)$$

where Na is the number of total aged enrolled in the HMO, which is a function of the recruiting effort specific for aged Ea and the non-specific recruitment effort Eu. Nd is the number of total disabled enrolled, depending on Ed and Eu. Pa and Pd are the premiums received by the health plans for the enrollment of aged and disabled patients respectively. Finally, Ca and Cd are the costs of the health services provided to aged and disabled enrollees respectively.

2.1. Scenario 1: Ea and Ed chosen independently

Imagine first that the health plans can differentiate perfectly the types of consumers and the effort targeted for the two types is chosen independently so that there exists a selective behavior. In this case, the health plan does not use the untargeted recruiting effort Eu. Under these assumptions, $N_a(E_a, 0) = N_a(E_a)$ and $N_d(E_d, 0) = N_d(E_d)$. The profit maximization problem becomes:

$$\max_{E_a, E_d} \Pi = N_a(E_a)[P_a - C_a - E_a] + N_d(E_d)[P_d - C_d - E_d] \qquad (2)$$

The first order conditions of the health plan profit maximization problem are given by:

$$\begin{aligned} \frac{\partial \Pi}{\partial E_a} &= (P_a - C_a - E_a)\frac{\partial N_a}{\partial E_a} - N_a = 0 \\ \frac{\partial \Pi}{\partial E_d} &= (P_d - C_d - E_d)\frac{\partial N_d}{\partial E_d} - N_d = 0 \end{aligned} \qquad (3)$$

Let $\varepsilon_{aa} = \frac{\partial N_a}{\partial E_a}\frac{E_a}{N_a}$ be the elasticity of Na with respect to the recruiting effort specifically targeted to the enrollment of aged patients Ea. Similarly, let $\varepsilon_{dd} = \frac{\partial N_d}{\partial E_d}\frac{E_d}{N_d}$ be the elasticity of Nd with respect to Ed. Now, the two first order conditions become:

$$\begin{aligned} \frac{\partial \Pi}{\partial E_a} &= (P_a - C_a - E_a)\frac{\varepsilon_{aa}}{E_a} - 1 = 0 \\ \frac{\partial \Pi}{\partial E_d} &= (P_d - C_d - E_d)\frac{\varepsilon_{dd}}{E_d} - 1 = 0 \end{aligned} \qquad (4)$$

Thus, we obtain the optimal choice of targeted effort Ea^* and Ed^* as:

$$E_a^* = (P_a - C_a)\frac{\varepsilon_{aa}}{1+\varepsilon_{aa}}$$
$$E_d^* = (P_d - C_d)\frac{\varepsilon_{dd}}{1+\varepsilon_{dd}}$$

As a result, the recruiting effort is increasing in the premium obtained by the health plan for the targeted population, and decreasing in the cost of the health services provided to the enrollees and in the cost of the recruiting effort. The number of aged enrollees Na (Nd) is a function of the targeted recruiting effort Ea (Ed), which depends on the premium Pa (Pd) received by the health plan for those enrollees. As a consequence, Na and Nd depend individually on Pa and Pd, and a change in the relative premiums will change the relative number of enrollees of the two different types of patients.

2.2. Scenario 2: Ea and Ed cannot be chosen independently

We assume now that the health plans cannot target the recruiting effort for the different types of patients, and the only recruiting effort that it can assume is the untargeted effort Eu. Thus, $Ea = Ed = 0$, and the number of aged and disabled enrollees depends only on the untargeted effort: $N_a(0,E_u) = N_a(E_u)$ and $N_d(0,E_u) = N_d(E_u)$. The profit maximization problem is given by:

$$\max_{E_u} \Pi = N_a(E_u)\left[P_a - C_a - E_u\right] + N_d(E_u)\left[P_d - C_d - E_u\right]$$

with the first order condition:

$$\frac{\partial \Pi}{\partial E_u} = (P_a - C_a - E_u)\frac{\partial N_a}{\partial E_u} + (P_d - C_d - E_u)\frac{\partial N_d}{\partial E_u} - (N_a + N_d) = 0$$

Let $\varepsilon_{au} = \frac{\partial N_a}{\partial E_u}\frac{E_u}{N_a}$ be the elasticity of the enrollment of aged in the HMO with respect to the untargeted effort Eu and $\varepsilon_{du} = \frac{\partial N_d}{\partial E_u}\frac{E_u}{N_d}$ be the elasticity of Nd with respect to Eu. Now, the first order condition becomes:

$$\frac{\partial \Pi}{\partial E_u} = (P_a - C_a - E_u)\frac{\varepsilon_{au} N_a}{E_u} + (P_d - C_d - E_u)\frac{\varepsilon_{du} N_d}{E_u} - (N_a + N_d) = 0$$

and we find the optimal untargeted effort Eu^*:

$$E_u^* = \frac{\left[\frac{(P_a - C_a)N_a}{N_a + N_d}\varepsilon_{au} + \frac{(P_d - C_d)N_d}{N_a + N_d}\varepsilon_{du}\right]}{1 + \frac{\varepsilon_{au} N_a}{N_a + N_d} + \frac{\varepsilon_{du} N_d}{N_a + N_d}}$$

Let us assume that the percentage change in the number of aged and disabled enrollees in the health plan is the same for a percentage change in the untargeted recruiting effort. Thus, both elasticities are the same and $\varepsilon_{au} = \varepsilon_{du} = \varepsilon_u$. Now, the optimal untargeted recruiting effort is given by:

$$E_u^* = \frac{\varepsilon_u}{1 + \varepsilon_u}\left[\frac{(P_a - C_a)N_a}{N_a + N_d} + \frac{(P_d - C_d)N_d}{N_a + N_d}\right]$$

and rewritten as

$$E_u^* = \frac{\varepsilon_u}{1+\varepsilon_u}\{[\lambda_i P_a + (1-\lambda_i)P_d] - [\lambda_i C_a - (1-\lambda_i)C_d]\}$$

where $\lambda_i = \frac{N_a}{N_a + N_d}$ is the HMOs own proportion of enrollees that are aged among total HMO enrollees.

Notice here that the optimal untargeted recruiting effort Eu^*, depends only on the average premium received for the two combined types of enrollees (Pa and Pd), and hence, increasing one premium relative to another has no effect on Eu^*. Because, as in the previous scenario, the number of aged and disabled enrollees is a function of the recruiting effort assumed by the HMO, Na and Nd increase in the average payment, but not with changes in one premium relative to another.

3. Data

We utilize county level data that is available on the Centers for Medicare and Medicaid Services - CMS - (former HCFA) web site.[2] This data base contains information on the rates paid by the CMS to HMOs for each enrollee aged, disabled, or with end stage renal disease (ESRD), and the Medicare enrollment in HMOs and FFS plans of each type of enrollee (aged, disabled, or ESRD), besides other information as the wage indexes for each year and the demographic factor in every county. So as to focus on the period where county payment changes are all exogenous to any HMO entry or exit, we have used county level data from year 1997 to 2003 and only for aged and disabled enrollees. Thus, the ESRD population is out of our sample in this analysis.

From all the counties in the U.S. we exclude of the sample the counties in Alaska, Virgin Islands, Hawaii, and Puerto Rico so that we only consider the counties belonging to the 48 continental states and D.C. We also had to exclude the counties of Manassas

Park City, Virginia; Loving, Texas; Cibola, New Mexico; and La Paz, Arizona because either there were no data on enrollment for years 1997 and 1998, or there was no disabled enrolled in any health plan for at least one year of the sample, and therefore our analysis does not apply. As a consequence, we have a panel data sample of 3,107 counties during years from 1997 to 2003, which is 21,749 observations for each variable.

In order to do the analysis we deflated the county payment rates paid to plans for aged and disabled enrollees using the national Consumer Price Index for Medical Care, and then also deflated these national CPI-adjusted payment rates using county-level wages rates (which were normalized to one).[3] The resulting measures for each county, called Pa and Pd, respectively for aged and disabled, are adjusted for both national trends and county level cost of living adjustments. The number of enrollees of each type (aged and disabled) in a county for both types of health plans (HMO and FFS) allows us to calculate the market share for HMOs in each county and for both aged and disabled, Sa and Sd, and the national average market shares for each year, $\overline{S_a}$ and $\overline{S_d}$. We also use the geographical area factor as a control variable for the different counties.[4] Table 1 presents descriptive statistics of the variables used.

4. Estimation Methods

In order to determine whether there is or not evidence of selection in the health care market we look for a significant response in the number of aged and disabled enrollees to changes in the relative premiums or in the average payment for both types of enrollees. Therefore, the specification of our model of Medicare enrollment is as follows:

$$N_a = f'(\frac{P_a}{P_d}, \lambda P_a + (1-\lambda)P_d, X, Z, \eta_a)$$

$$N_d = g'(\frac{P_a}{P_d}, \lambda P_a + (1-\lambda)P_d, X, Z, \eta_d)$$

Where Pa and Pd are the deflated county specific prices of aged and disabled people respectively, λ is the national average proportion of all enrollees enrolled in HMOs who are aged, X is a vector of characteristics of the county, Z is a vector of characteristics of the plans serving the county, and ε_a and ε_d are error terms, and time and county subscripts are being omitted for simplicity.

Notice that the coefficient on the first term answers our key hypothesis about whether the plan is able to react to changes in the relative prices of aged versus disabled enrollees, while the coefficient on the second term, tells us whether there is an average income effect.

Because it is natural to assume that the terms η_a and η_d will be heteroskedastic according to the size of the county in which the HMO operates, we deflate the dependent variables Na and Nd by Ma and Md, the total number of Medicare enrollees who are aged and disabled in the county, respectively. Hence our new dependent variable becomes the aged and disabled market shares of the HMO in a county, Sa and Sd, rather than Na and Nd, and the coefficient on $\frac{P_a}{P_d}$ is an elasticity of the market share with regard to these relative prices. In order to capture time trends in HMO enrollment and make the coefficients on the $\frac{P_a}{P_d}$ terms in each equation be as close as possible to elasticities at the overall national mean, we deflate each of the county level market shares, S_a and S_d, by the national average market shares, $\overline{S_a}$ and $\overline{S_d}$ for each year.

Because we do not observe all of the variables that may potentially affect the dependent variables but only the county- and year- specific geographical area factors, we instead include year (γ_t) and county (δ_c) fixed effects in each equation. Using linear approximations, our final specification is

$$\frac{S_a}{\overline{S_a}} = \alpha_a\left(\frac{P_a}{P_d}\right) + \beta_a[\lambda P_a + (1-\lambda)P_d] + \phi GAF_{at} + \gamma_{at} + \delta_{ac} + \eta_a$$
$$\frac{S_d}{\overline{S_d}} = \alpha_d\left(\frac{P_a}{P_d}\right) + \beta_d[\lambda P_a + (1-\lambda)P_d] + \phi GAF_{dt} + \gamma_{dt} + \delta_{dc} + \eta_d$$

Since we do not have a priori reasons to believe that a linear rather than a log linear specification is preferred, we estimate the above model as shown, and also in semi-logarithmic form.[5]

As one further specification test, we also re-estimate this model using λ_C instead of λ, where λ_C reflects the county specific proportions of aged population in the county (not the HMO enrollment weights but the eligible aged over the aged and disabled population). This alternative specification is possibly relevant if the income effects from Medicare price changes vary by county because of differences in proportion of aged and disabled Medicare eligible in a county.

5. Estimation Results

Table 2 presents our results from the estimation of the two equation linear model in which the dependent variables are the market share in the counties for aged and disabled respectively deflated by its national average ($\frac{S_a}{\overline{S_a}}$ and $\frac{S_d}{\overline{S_d}}$). After controlling for fixed effects for counties and years, we observe that the coefficients for the relative premium rates received by the health plans are both significant but with the same sign. In order to provide evidence of selection in our model, we should observe that relative premiums matter, but the signs on the price terms in the two equations should be different (positive in one equation and negative in the other). Concerning the second coefficient of key interest, we find that the average price is significant and also positive in both equations.

Evidence of selection by HMOs in our model is associated with different signs on the coefficient for the relative rates because when the relative price of aged on the disabled enrollees increases (decreases), an HMO that selects maximizes profits by attracting more aged (disabled) enrollees. In order to get that result, the HMO should increase the effort targeted for the aged (disabled) population. Thus, it is expected that evidence of selection would require that HMOs react to changes in relative prices by increasing the recruiting effort targeted for one group of patients and decreasing the recruiting effort targeted for the other, which is translated in a different sign of both coefficients. Stated differently, significant positive coefficients for the average premium is consistent with the behavior of an HMO health plan without selection. The higher is the average premium received by the plan, the more enrollees of both types the plan is willing to attract through a higher untargeted recruiting effort. One reason explaining our result with the same sign on the coefficients for the relative rates ($\frac{P_a}{P_d}$) for the two equations, where the dependent variables are the deflated market share in the counties for aged and disabled, is the existence of omitted variables in our analysis. As Glazer and McGuire (2002b) discuss, health plans obtain revenue from multiple payers and not only from Medicare, and therefore they face a mix of incentives that affect their choice of targeted or untargeted recruiting effort.

A semi-logarithmic equation (an approximation to the log linear form) provides a second specification for testing our model. The results of the estimation in table 3 5 use the same the dependent variables as in the previous two tables, the deflated market shares of aged and disabled in HMOs in each county respectively. The coefficients for the log of relative prices (premium) received by the HMO for aged and disabled enrollees are significant and again positive in both equations. The log of average payment is also significant and positive. Thus, with the semi-logarithmic specification, we obtain the same result of the absence of evidence in selection through the different premiums obtained by the health plans with the enrollment of aged and disabled patients.

Because income effects from Medicare price changes might vary by county due to population composition differences, we reestimated all four equations using county specific rather than national average proportions of aged and disabled populations weights when calculating the average price. The results confirm those already reported: there is no evidence of a selective behavior through differential response to the payment rates received for aged and disabled.

6. Conclusions

Managed Care plans have incentives to select enrollees with expected lower costs. The health economics literature has shown evidence of adverse selection, and also that those incentives to select exist even with the risk adjustment formulae applied for the Medicare population (Brown et al. 1993; Riley et al. 1991 and 1996). However, the existing literature has not convincingly shown how health plans select enrollees. This paper has explored the evidence on how Medicare+Choice HMOs influence selection by looking at premiums and enrollment responsiveness rates at the county level for aged versus disabled enrollees. Our approach is the first to take into account the fact that in each county there are two different Medicare payment rates, one for aged, and the other for disabled.

We developed a conceptual model that helps explain conditions under which HMOs will and will not respond selectively to aged versus disabled payment rates. If targeted recruiting effort is feasible, so that aged and disabled populations can be attracted separately, then we would expect to see a response of enrollments to payment rate changes. If HMOs cannot selectively recruit, and only untargeted recruiting effort is feasible, then we do not expect to see enrollment share changes between aged and disabled enrollments. The two different behaviors (with or without selection) are associated to different responses of the enrollment on the relative premium and on the average premium received by health plans for the enrollment of each type of Medicare beneficiary.

We find no evidence that HMOs differentially attract or repel aged or disabled enrollees as the relative premium received by the health plan varies. Since whether an enrollee is aged or disabled is easily observed, and payment rate differences easily noted, this suggests that creaming and dumping of individuals is not the mechanism used. We cannot rule out with our methodology the possibility that health plans cream or dump enrollees for other reasons, however our results, together with previous results that clearly find Medicare health plans as attracting relatively health enrollees, are more consistent with a service selection story in which health plans disproportionately discourage high cost and encourage low cost enrollees based on the specific services tat are offered.

Our results suggest that plans are not able to cream or dump enrollees of any type although they would like so. However, this lack of response by health plans to relative payment rates make does not directly reject the assumption of service level distortion in a model using "skimping" strategies.

[1] This distinction between targeted and untargeted recruitment effort parallels the distinction in Glazer and McGuire (2002a) between qualities offered by health plans for different services with or without service distortion, which is private versus public goods. In our model, we do not calculate welfare gains or losses, but only use the model to distinguish predictions. We could redefine our effort variables Ea, Ed, and Eu to be quality or advertising or any activity that affects demand and costs.

[2] Data is available at the CMS web page:

http://www.cms.gov/healthplans/rates/default.asp

[3] CMS does not provide comparable relative wage county data for 1997. Therefore we used 1998 wage factors for deflating payment for that year.

[4] The geographical area factors (GAF) are those factors used to adjust the national average rate in calculating the blended rates and are almost invariant in time. Because they are only available from 1999 onward, we assume that the GAF for years 1997 and 1998 were are the same as for 1999.

[5] The specification for the semi-logarithmic form is as follows:

$$\frac{S_a}{\bar{S}_a} = \alpha_a \ \mathrm{Ln}(\frac{P_a}{P_d}) + \beta_a \ \mathrm{Ln}[\lambda P_a + (1-\lambda)P_d] + \phi Ln(GAF_{dt}) + \gamma_{at} + \delta_{ac} + \eta_a$$
$$\frac{S_d}{\bar{S}_d} = \alpha_d \ \mathrm{Ln}(\frac{P_a}{P_d}) + \beta_d \ \mathrm{Ln}[\lambda P_a + (1-\lambda)P_d] + \phi Ln(GAF_{dt}) + \gamma_{dt} + \delta_{dc} + \eta_d$$

We also considered running models with ln $(\frac{S_a}{\bar{S}_a})$ and ln $(\frac{S_d}{\bar{S}_d})$ as the dependent variables; however the problem with this specification is that in some counties market shares are zero so that logs are not defined. Note that $\frac{S_a}{\bar{S}_a}$ will in many cases be close to one, and hence, the first order approximation, Ln $(\frac{S_a}{\bar{S}_a}) \approx \frac{S_a}{\bar{S}_a} - 1$, should be a reasonably close one. Hence our linear in shares specification will yield results that approximate those using a log of shares specification.

References

Brown, R.S., J.W. Bergeron, D.G. Clement, J.W. Hill, and S. Retchin (1993): Does Managed Care Work for Medicare? An Evaluation of the Medicare Risk Program for HMOs. Report under HCFA Contract Number 500-88-0006. Princeton, NJ. Mathematica Policy Research, Inc.

Cao, Z. and T.G. McGuire (2003): Service Level Selection by HMOs in Medicare. Journal of Health Economics 22: 915-931.

Cao, Z. (2003): HMO selection at the service level: evidence from Medicare plan choice behavior. Chapter 3 of Service-level Risk Selection by HMOs in Medicare, Ph.D. Dissertation, Boston University.

Ellis, R.P., and I. Gurol (2004): Health Plan Entry and Exit in the Medicare Managed Care Market. Unpublished BU Working paper.

Glazer, J., and T.G. McGuire (2002a): Setting Health Plan Premiums to ensure Efficient Quality in Health Care: Minimum Variance Optimal Risk Adjustment. Journal of Public Economics 84: 153-173.

Glazer, J., and T.G. McGuire (2002b): Multiple payers, commonality and free-riding in health care: Medicare and private payers. Journal of Health Economics 21: 1044-1069.

Health Confidence Survey (2001). Sponsored by the Employee Benefit Research Institute (EBRI) and Mathew Greenwald & Associates (MGA).

Newhouse, J.P. (1996): Reimbursing Health Plans and Health Providers: Efficiency in Production versus Selection. Journal of Economic Literature 34: 1236-1263.

Riley, G., J. Lubitz, and E. Rabey (1991): Enrollee Health Status under Medicare Risk Contracts: An Analysis of Mortality Rates. HSR: Health Services Research 26(2): 137-163.

Riley, G., C. Tudor, Y. Chiang, and M. Ingber (1996): Health Status of Medicare Enrollees in HMOs and Fee-for-Service in 1994. Health Care Financing Review 17(4): 65-76.

Shen, Y. and R.P. Ellis (2002a): Cost-Minimizing Risk Adjustment. Journal of Health Economics 21: 515-530.

Shen, Y. and Ellis, R.P. (2002b): How Profitable is Risk Selection? A Comparison of Four Risk Adjustment Methods. Health Economics 11(2): 165-174.

Table 1: Statistics for the premium rates and enrollment of aged and disabled patients in Medicare HMOs. Number of observations: 21,749

Variable	Mean	Std. Deviation
payment rate for aged	463.58	75.75
payment rate for disabled	430.45	84.28
FFS disabled enrollees	1626	4048
HMO disabled enrollees	69	391
FFS aged enrollees	10549	29762
HMO aged enrollees	1635	9833
Ratio of aged to disabled prices, $\frac{P_a}{P_d}$	1.09	0.15
income effect variable	408.77	67.92

Table 2: Linear models for aged enrollees using county fixed effects

Independent variables	Aged HMO market share over its national average	Disabled HMO market share over its national average
Ratio of prices	0.302** (0.104)	1.624** (0.205)
Average price (/1000)	1.335** (0.137)	1.247** (0.272)
Geographical area factor	1.237 (1.377)	36.576** (2.721)
Year 1998	0.191** (0.028)	0.192** (0.055)
Year 1999	0.064* (0.028)	-0.191** (0.055)
Year 2000	-0.846** (0.027)	-1.251** (0.054)
Year 2001	-1.108** (0.032)	-0.616** (0.064)
Year 2002	-1.134 (0.033)	-1.521** (0.065)
Year 2003	-1.048** (0.033)	-1.412** (0.065)
Constant	2.731* (1.386)	-34.000** (2.740)
R-squared	0.941	0.813
Adj. R-squared	0.931	0.781
Number of observations	21,749	21,749

[a]Standard errors in parenthesis. Significant at 5% (*) and 1% (**) levels.

Table 3: Semi-logarithmic models for aged enrollees using county fixed effects

Independent variables	Aged HMO market share over its national average	Disabled HMO market share over its national average
Log Ratio of prices	0.428** (0.125)	2.151** (0.249)
Log Average price	2.471** (0.121)	2.083** (0.241)
Log Geographical area factor	1.253 (1.470)	39.143** (2.925)
Year 1998	0.193** (0.027)	0.202** (0.055)
Year 1999	-0.012 (0.028)	-0.245** (0.055)
Year 2000	-0.941** (0.028)	-1.331** (0.055)
Year 2001	-1.270** (0.034)	-0.728** (0.067)
Year 2002	-1.282** (0.034)	-1.614** (0.068)
Year 2003	-1.173** (0.034)	-1.486** (0.068)
Constant	-9.969** (0.725)	-7.693** (1.442)
R-squared	0.942	0.813
Adj. R-squared	0.933	0.782
Number of observations	21,749	21,749

[a]Standard errors in parenthesis. Significant at 5% (*) and 1% (**) levels.