Forthcoming, Health Economics

How Profitable is Risk Selection?

A Comparison of Four Risk Adjustment Models

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April 27, 2001

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Summary

To mitigate selection triggered by capitation payments, risk-adjustment models bring capitation payments closer on average to individuals' expected expenditure. We examine the maximum potential profit that plans could hypothetically gain by using their own private information to select low-cost enrollees when payments are made using four commonly-used risk adjustment models. Simulations using a privately-insured sample suggest that risk selection profits remain substantial. The magnitude of potential profit varies according to the risk adjustment model and the private information plans can employ to identify profitable enrollees.

Keywords: Risk Adjustment; Selection; Asymmetric Information;

Introduction

While capitation payments to health plans encourage efficiency and cost containment, such payments also create strong incentives for plans to attract low cost enrollees. Risk adjustment, whereby capitated payments are adjusted to reflect the expected cost of individual enrollees, is a frequently recommended mechanism for mitigating the inequity and inefficiency of this biased selection of enrollment in health plans. It is believed that the potential financial gains from selection can be reduced and therefore the incentives of selection can be lessened as long as capitation payment systems are adjusted with refined adjustors to improve their accuracy of predicting medical expenditures. Yet it remains to be seen how well existing risk-adjustment models, which only imperfectly predict future use, successfully eliminate the profitability of risk selection and lessens financial incentives for health plans to practice favorite selection. This paper empirically tests the magnitude of the incentive for health plans to select low cost enrollees under four commonly used risk-adjustment models.

Selection only arises markets with asymmetric information. If health plans have better information about the expected costs of their enrollees than the payer (also called the sponsor) that is paying capitated premiums, then health plans may try to attract profitable enrollees. Even if health plans do not have any better information than the payer, risk selection of profitable enrollees may still be a problem if consumers are better informed about their health care needs than health plans, and health plans distort their benefit features or services offered so as to attract healthy people. This type of adverse selection (creaming) is not the focus here (See Glazer and McGuire (2000) for discussion of this different problem). The asymmetric information in our paper stems from health plans, as we assume that health plans have more information. This paper does not attempt to model how effectively health plans are able to selectively attract profitable enrollees. Instead we focus on the issue of what the maximum possible profit could be achieved under different assumptions about the information available to the payer for risk adjustment and to the health plan for enrollee selection. Even if plans are only able to imperfectly select profitable enrollees, it is useful to quantify the extent to which feasible risk adjustment mitigates this problem of risk selection.

There is a considerable literature that demonstrates that risk selection exists and can be a profitable activity. One approach has been to document the magnitudes of actual risk selection. This evidence has been the most convincing in the US Medicare market. For example, Straumwasser et al. (1989); and especially Hill and Brown (1990, 1992) present convincing evidence that Medicare HMO (Health Maintenance Organization) enrollees have substantially lower health costs then Medicare beneficiaries who stay in the traditional fee-for-service sector. Further evidence is provided by Riley et al. (1989, 1991) who demonstrate that mortality rates of these HMO enrollees is lower than in the FFS sector and by Lichtenstein et al. (1991) and Kravitz et al. (1992), who show that they are also healthier based on self-reported health status and medical conditions. By their nature, these studies examine the degree of risk selection under the existing highly imperfect risk adjustment payment models, and cannot assess how selection would change with more powerful risk adjustment.

A different approach has been to examine the potential for profitable risk selection under different risk adjustment mechanisms while assuming a specific distribution of expected health costs. Feldman and Dowd (1982) simulate the potential profit from risk selection under the Medicare HMO system. Ellis and McGuire (1987) build upon this approach and similarly predict that substantial profits can be earned if HMOs are able to do modestly select. In the most highly developed framework, Newhouse et al. (1989) examine the profit that could potentially be obtained by HMOs practicing selection under the Medicare program's Average Adjusted Per Capita Cost (AAPCC) system. The simulations in each of these papers suggest that HMOs can obtain substantial profits if they are able to identify profitable enrollees and costlessly dump unprofitable them.

An important weakness of this simulation literature is that it looks at hypothetical risk selection without specifying the information sets that are available to the different agents (health plans and sponsors). HMOs may be able to do much better or much worse than the simulated amounts depending upon the information available selecting enrollees. The contribution of this paper is that we examine how large the incentives are for empirically feasible risk selection, and explore whether available risk adjustment models change these magnitudes.

We examine the profitability of risk selection while assuming that risk adjustment is made using one of four prominent risk adjustment models. We compare these models to each other, as well as with a baseline model that assumes "no risk adjustment", i.e., in which plans are paid a fixed dollar amount for each enrollee regardless of his/her individual characteristics. The first risk adjustment model is simple adjustment for age and sex, which is widely used in the U.S. and elsewhere. The second approach is the Ambulatory Cost Group (ACG) model developed by Weiner et al. (1996). The third approach uses the Diagnostic Cost Group (DCG) framework described in Ash et al. (2000). And the final model uses prior year expenditures to predict subsequent year expenditures (e.g. Anderson et al., 1986, 1989). For a given risk adjustment model, we simulate the profit opportunities for a health plan when health plan itself uses additional information to predict individuals' future cost and use that to select profitable enrollees.

In the following section, we set out the assumptions about a health plan's selection behavior under capitation payment systems. In the next section we describe the data and estimation methods. The empirical results are presented in the subsequent section. Finally we conclude in the last section.

Risk Adjustment and Selection

In this study, we assume that each competing health plan is capitated, which is to say that they receive a fixed payment per period from a payer (Medicare, Medicaid, employers or coalitions) for each individual they enroll. These capitated payments are risk-adjusted, using information available to the payer that is also always known by the plan. There is no direct premium contribution from individual consumers to the health plan. Plans selection behavior under a given risk-adjusted capitation payment rests on 3 key assumptions.

First, a health plan can obtain additional information regarding individuals' health expenditure rather than risk adjustors without incurring any cost. Under the asymmetric information structure, the plan employs the additional information to obtain its own expectation about enrollees' expenditure. For example, if the payer uses age and sex as risk adjustors to set up premiums, the plan can employ prior utilization in addition to age and sex to form their own expenditure prediction. The asymmetric information may arise from several possibilities: compared to the payer, the plan has more access to enrollees' information; even when the payer has the same information, some information may not be appropriate to be included in the capitation formula. Van de Ven and van Vliet (1992) summarize the requirements that information be qualified as risk adjustors.

Our remaining assumptions follow Newhouse et al. (1989). Our second assumption is that each plan is only interested in short-term profits. In our simulations we focus on static, one-year profit maximization without addressing the reality that selection could differ if multiple years are considered, or there is a reputation effect of a plan engaging in selection. In addition, it is often impossible for a health plan to cancel coverage for a given individual, and few individuals change health plans in a given year. All of these real world issues would be important to model in a more realistic dynamic model.

Our final key assumption is that plans can costlessly exclude an individual or select those to enroll. We realize that in the United States this type of selection is often either illegal (as in the Medicare program), unethical, or contractually prohibited (as with most private employers). Nonetheless we believe that this assumption is useful in helping to understand the implications of perfect selection, even if in reality there are constraints on achieving this perfect selection.

Taken together, our three key assumptions imply that for any given risk-adjusted capitation payment, each health plan can use private information to costlessly identify individuals with non-negative expected profits in the following year and costlessly enroll only those individuals for only that one year. We do not model here the cost implications of this selection on the individuals that are dumped outside of the plan, which we have done elsewhere (Shen and Ellis, 2001). Nor do we address here the issue of optimally setting premiums in the presence of this selection behavior (Shen and Ellis, 2001). The focus here is on the profit implications if conventional risk adjustment is used to set capitated payments, and plans are able to perfectly select against this using private information.

Data and Estimation Methods

The data for this study comes from the Mercer privately-insured dataset for the years of 1992 and 1993. The data contains information on diagnoses, individuals' demographics characteristics, and the total covered charge, which is the sum of insured and out-of-pocket payments (excluding prescription drugs). There are various levels of cost-sharing in this dataset. How risk adjustment differs by various cost sharing schemes is beyond our study scope. Hence we assume away cost-sharing difference. We use prospective adjustors, which means that information from Year 1 (1992) is used to determine the premiums for Year 2 (1993). All prospective models share the same feature that plans have difficulty to obtain health care history of new enrollees. This is true for prior use, ACG, DCG models considered in this study. There are several possibilities for plan to obtain new enrollees' health care history and incorporate it into selection. In many cases, insurance plans offer various product lines. New enrollees for one product line may switch from others, which plans should have no problem to obtain their health care use history. In other cases, plans may get the information from provider networks. In the last resort, when there is no information available for new enrollees. Plans can potentially allow open enrollment and selection can be conducted after enrollees stay in the plan for a while.

We restrict our analysis to people eligible for the entire twenty-four months in order to avoid the complication of having to worry about partial year enrollees. There are 827,536 non-elderly people, all under the age of 65. The average cost per individual in 1993 is $1,556.

We examine four alternative risk-adjustment models that use different information as adjustors: age and sex, prior year spending, and two diagnosis-based models, ACGs, and DCGs. Table 1 summarizes the information used by each of the four risk-adjustment models. The risk-adjusted premiums are determined by minimizing the prediction error of health care expenditure. Three function forms are commonly used to predict health care expenditure. The simplest is a linear model estimated by ordinary least squares (OLS). Other functional forms address the issue of skewness in health care expenditure: two-part models of health spending developed by Duan et al. (1983) and nonlinear transformations of dependent variable, such as the logarithm of health cost examined by Manning et al. (1987). However, both nonlinear approaches lead to biased estimation under heteroskedasticity (Mullahy (1998) and Manning (1998)). Mullahy (1998) and Ellis and Azzone (1998) argue that as sample sizes become large, the simple linear model may perform as well as the other two. Given the large sample size in our study and given that linear models are close to the cell-based approach used in practice (i.e. the calculation of the average expenditure per risk group), we focus on linear models and use OLS regression for all our estimations.

In this study, we run OLS regressions with covered cost in 1993 as the dependent variable and individuals' information (risk adjustors) in 1992 as independent variables. We also model the health plan’s expectation of health care cost by OLS regression. The only difference is that the plan employs additional information than risk adjustors as independent variables in its forecasting. Alternative information sets used by the plan are examined in the simulations below. When there is no risk adjustment, i.e. the plan receives the same premium for every enrollee, the premium simply equals the average cost (grand mean) as the result of the assumption of linear model.

As has been done in other empirical studies on risk-adjustment models (Ellis, Pope et al., 1996), we divide the sample randomly into two halves to avoid overfitting the data. Our estimation sample has 413,866 observations while our validation sample has 413,670 observations. The estimation sample is used to estimate risk-adjustment models used by payers and expenditure forecasting models employed by plans, respectively. The estimated coefficients from the estimation sample are then applied to the validation sample to calculate the risk-adjusted capitation payments and the plan's predicted expenditures.

Plan selection is assumed to work as follows. Profitable individuals whose expected expenditures are equal or less than adjusted payments are identified. These are the individuals that the plan prefers to enroll. All unprofitable enrollees are assumed to be excluded. Profit levels and rates are then calculated for enrollees only. The total revenue that the plan can earn is the sum of premiums over profitable enrollees. The total cost is the sum of the actual covered charges in 1993 over the profitable enrollees. The profit is calculated by subtracting the total cost from the total revenue. The profit rate is the profit divided by the revenue.

Estimation Results

First, we report the following statistics for all risk-adjustment models in Table 2: R-Squares, standard errors, and mean absolute errors (MAE). These statistics are widely used by researchers to compare the predictive power of different models. With R-Square of 0 under grand mean regression, any risk adjustment such as simple age-sex model can improve the predictive power significantly compared to no risk adjustment. The results based on our non-elderly sample also demonstrate, as have other studies, that diagnostic information can improve significantly predictive power compared to the simple age-sex model. R-Squares in validation sample are 0.079 and 0.106 for ACG and DCG models respectively compared to 0.019 for age-sex model. With the R-Square of 0.096, a simple prior use model does nearly as well as the diagnostic models in terms of predictive power.

For each risk-adjustment model, the amounts of gross profits that a plan can achieve by using various information sets to identify profitable individuals are presented in Table 3. Table 4 presents corresponding gross profit rates. Overall, the gross profits that the plan can gain by selection vary over different risk adjustment models and the information the plan employs for forecasting individuals' expenditure. It ranges from \$68 to \$262 million. The gross profit rates range from 60% to 16%. When the payer and the plan have the same information about individuals’ health care cost (payer’s information set is identical to the plan’s information set), the plan cannot identify profitable enrollees and select them, hence the total profit is 0 and all individuals will be accepted in the plan.

When there is no risk adjustment and the payer pays the plan the average cost (grand mean) for every enrollee, the plan can gain \$167 millions by simply using age and sex to identify profitable enrollees. The plan can gain more by employing prior year spending, ACG or DCG information in addition to age and sex to predict expenditure, with the maximum of \$262 millions achieved when the plan uses all available information to identify profitable enrollees. However, the profit rate under the age-sex scheme is 53%, higher than the cases when the plan uses prior-year spending (43%) or DCG (52%) to select enrollees. The profit rate is the gross profit divided by the revenue (sum of profit and cost). Therefore, the results indicate that the total cost for the age-sex case is also smaller than the cost for the prior-year spending or DCGs and the difference is larger than the difference in the gross profit.

Even though age-sex risk adjustment model can decrease the plan's potential profit of selection significantly compared to no risk adjustment, the plan can still gain substantial profit by employing any one of prior year spending, ACGs or DCGs to predict individuals' cost. The maximum profit of $208 million under age-sex risk adjustment is achieved when the plan combines prior year spending, ACGs and DCGs (with age-sex) to predict expenditure and select individuals.

If prior year spending and age-sex are used for risk adjustment, the maximum profit that the plan can gain drops to $120 millions. This amount of profit is achieved when the plan uses both ACG and DCG in addition to the risk adjustors to identify and select profitable individuals.

Diagnosis-based risk-adjustment models are more successful at reducing the profitability of selection by the plan. The ACG model is the most efficient risk adjustment model for restraining selection behavior as we model it here. If the payer uses ACGs to adjust payments, the health plan can gain at most $92 million by using both prior-year spending and DCG for selection.

For all four of the risk-adjustment models, the plan can always obtain maximum profit using all three types information available for selection. Hence, as long as there is no cost incurred in collecting information for selection, the plan will always prefer to use as much information as possible to identify profitable individuals. In our simulations, the gain from this additional information is generally quite large.

The percentage of individuals selected into the capitation payment system also varies (Table 5). When the plan has the same information as the payer, there is no selection and enrollment rate is 100%. Given that the plan prefers to use all information for selection under all the risk adjustment models examined in this study, we can expect that enrollment rate be 70% when age and sex are used for risk adjustment, and only 57% when ACG model is used for risk adjustment.

Discussion

So far, our simulations of gross profit rely on the assumption that the plan only enrolls individuals with non-negative expected profit. van Barneveld et al. (2000) argue that plans may ignore small predictable profits and losses and still enroll these individuals because of the costs of selection and the statistical uncertainties about the net benefits of selection. Their study suggests that the incentive of selection measured by WMAPR (weighted mean absolute predicted results) is overestimated if the small predicable profits or losses are not ignored.

In order to see if this is a problem in our setting, we explore this issue by extending our simulation of gross profit and HMO rates when the plan employs a less perfect selection, by enrolling individuals with small expected profits or losses. The selection criterion takes the following values: individuals are enrolled as long as the expected profits is no less than –100, -50, 0, 50, 100, 150, 200, 300, 400 or 500. The first two thresholds permit plans to enroll people with small losses, the third one is our base model in the previous sections, and the rest of the values correspond to cases where plans only enroll people with at least small positive expected profits. As expected, as the threshold of expected profit increases, fewer individuals are selected into the plan. Tables 6-9 present the results when the payer uses age-sex, prior-year spending, ACG, and DCG to adjust payments for the plan. Overall, profits gained by the plan are still substantial even if the plan enrolls individuals with small expected profits or losses.

When the payer uses age-sex to adjust premiums (Table 6), the selection criterion leading to maximum gross profit varies across information sets used by the plan to selection enrollees. For example, using DCGs to select enrollees, the plan can achieve maximum gross profit by enrolling individuals whose expected profit is equal or more than \$50. When ACG is used for selection, the plan can achieve maximum gross profit by enrolling individuals with non-negative expected profit. Finally, if prior-year spending or all information is employed for selection, the maximum gross profit is reached with the selection threshold of \$100.

The results based on the other three risk adjustment models reveal a similar pattern: because of the statistical uncertainties about the net benefits of selection, the maximum gross profit does not always occur when the plan selects enrollees with non-negative expected profit. Furthermore, the plan can never achieve maximum gross profit by selecting enrollees with small losses. Among all the values considered here, \$200 is the highest threshold value that leads to the maximum gross profit. It happens when the payer uses the prior-year spending for risk adjustment and the plan uses all information for selection (Table 7). There is one exception. When the payer uses ACG to adjust premiums, the plan can always achieve the maximum gross profit by enrolling individuals with non-negative expected profit (Table 8).

Conclusions

It has been well known that selection is a serious concern. To mitigate selection triggered by the capitation payment system, several risk-adjustment models have been developed in order to make the capitation payment close to individuals' expected expenditure. Traditionally, comparisons of these models are based on R-Squares or other statistics that measure the prediction power. By comparing the potential profit that plans can gain under different risk adjustment models, this study provides another tool to examine how well commonly used risk adjustment models can reduce selection incentive.

This study demonstrates that plans can gain significant profit as long as they are able to costlessly obtain additional information than the refined risk-adjustors to identify and costlessly able to select individuals with non-negative expected profit. The potential profit that the plan can gain is still considerable even if it enrolls individuals with small expected profits or losses. In many cases, the maximum gross profit is only achieved when the plan selects enrollees with some small expected profits, which results in lower enrollment compared to the case when the non-negative expected profit is used as selection criterion. Therefore, if the plan tries to maximize its profit by taking into consideration of statistical uncertainties about the net benefits of selection, the degree of selection can be relative large (i.e. plans will have small enrollments). Of course, what we present here is an extreme case where the plan is assumed to be able to perfectly dump unfavorable enrollees each year. No plan would ever be able to actually achieve the degree of selection assumed here. But the potentially large gross profit of selection that our experiment presents still suggests that current existing refined risk adjustment may not be able to reduce selection to a negligible level.

Given imperfections of risk adjustment payment systems, many studies suggest a mix of capitation payment and cost-based reimbursement payment systems to reduce selection incentives. Newhouse et al. (1997) for example assert: “We believe that a portion of reimbursement of a health plan should be based on actual use.” This strategy is also referred as risk sharing. Van de Ven and Ellis (2000) provide extensive summary on various forms of risk sharing that have been proposed. Other researchers believe risk adjustment should not focus only on empirical research of the statistical determinants of health expenditure (Glazer and McGuire (2000) refer this as “conventional risk adjustment”). Instead, “Optimal risk adjustment”, which views the weights on risk adjustors as the optimal solution to a regulatory problem controlling for selection or other market failures, should be pursued (Encinosa (1998), Glazer and McGuire (2000), Selden (1998), Shen and Ellis (2001)).

Although we have answered here one set of questions related to risk adjustment, our work raises many new questions as well. Will more refined risk adjustors reduce potential profitability of selection? How well does risk sharing and optimal risk adjustment reduce selection profitability? How effectively is selection done in practice? With all the unanswered questions, there is definitely growing need for further research on risk adjustment.

Table 1: Risk-Adjustment Models

MODELS	ADJUSTORS
Age-Sex	16 age-sex cells
Prior-Year Spending	Total covered charge in 1992, Age-Sex
ACG	82 ACGs, Age-Sex
DCG	23 DCGs, Age-Sex

Table 2: The Comparison of Predictive Power

	Estimation Sample			*Validation Sample*		
	R^2	Std. Err.	MAE	R^2	Std. Err.	MAE
Grand Mean (No Adjustment)	0.000	6,941	2,182	0.000	7,196	2,201
Age-Sex	0.020	6,872	2,075	0.019	7,127	2,095
Prior-Year Spending	0.103	6,575	1,898	0.096	6,840	1,918
ACG	0.081	6,655	1,849	0.079	6,904	1,865
DCG	0.109	6,552	1,883	0.106	6,803	1,902
Sample Size		413,866			413,670	

Table 3: Gross Profit for All Specifications (in Millions)

	Plan Information Set				
Payer Information Set	Age-Sex	Prior-Year Spending	ACG	DCG	All
Grand Mean (No Adjustment)	167	226	254	260	262
Age-Sex	0	185	194	180	208
Prior-Year Spending	N/A	0	108	101	120
ACG	N/A	78	0	68	92
DCG	N/A	101	89	0	110

Table 4: Gross Profit Rates for All Specifications

	Plan Information Set				
Payer Information Set	Age-Sex	Prior-Year Spending	ACG	DCG	All
Grand Mean (No Adjustment)	53%	43%	60%	52%	59%
Age-Sex	0%	36%	47%	36%	46%
Prior-Year Spending	N/A	0%	32%	22%	30%
ACG	N/A	17%	0%	16%	22%
DCG	N/A	21%	24%	0%	29%

Table 5: Plan's Enrollment Rate for All Specifications

	Plan Information Set				
Payer Information Set	Age-Sex	Prior-Year Spending	ACG	DCG	All
Grand Mean (No Adjustment)	49%	83%	66%	68%	69%
Age-Sex	100%	82%	64%	83%	70%
Prior-Year Spending	N/A	100%	60%	83%	67%
ACG	N/A	68%	100%	52%	57%
DCG	N/A	78%	59%	100%	61%

Notes for Tables 3-5:

1. Payer Information Set: The risk-adjustment models that the payer uses to determine the subsequent year's payment
2. Plan Information Set: In addition to risk adjustors, the plan uses one of these variables to predict the subsequent year's expenditure.
3. All: Prior year spending + ACG + DCG.

Table 6. Risk Adjust Model: Age – Sex (Gross Profit in millions)

	Plan Information Set							
	Prior-Year Spending		**ACG**		**DCG**		**ALL**	
Selection Criterion	Gross Profit	Enrollment Rate	Gross Profit	Enrollment Rate	Gross Profit	Enrollment Rate	Gross Profit	Enrollment Rate
$-100	174	85.5%	193	69.0%	179	83.1%	206	73.4%
$-50	180	84.1%	194	67.2%	179	83.1%	207	71.7%
$0	185	82.4%	**194**	**64.0%**	180	82.8%	208	70.0%
$50	191	80.0%	194	63.5%	**181**	**81.6%**	208	68.2%
$100	**196**	**76.0%**	194	62.3%	178	76.0%	**208**	**66.5%**
$150	192	65.5%	194	60.9%	175	67.6%	208	64.8%
$200	175	51.5%	193	59.9%	168	57.1%	208	63.3%
$300	169	41.6%	193	56.8%	155	44.6%	206	60.8%
$400	153	32.6%	185	50.2%	155	44.6%	193	50.2%
$500	145	26.5%	163	36.7%	141	36.5%	180	42.5%

Table 7. Risk Adjust Model: Prior-Year Spending (Gross Profit in millions)

	Plan Information Set					
	ACG		**DCG**		**ALL**	
Selection Criterion	Gross Profit	Enrollment Rate	Gross Profit	Enrollment Rate	Gross Profit	Enrollment Rate
-$100	105	65.0%	99	84.5%	118	71.4%
-$50	107	62.7%	100	84.0%	119	68.9%
$0	108	60.4%	**101**	**83.3%**	120	66.7%
$50	109	58.0%	92	67.0%	121	64.3%
$100	110	56.7%	85	52.1%	122	62.1%
$150	**110**	**54.9%**	88	48.4%	122	60.1%
$200	110	52.9%	81	40.8%	**122**	**58.4%**
$300	97	37.7%	62	28.0%	112	43.2%
$400	85	26.8%	53	19.5%	99	30.9%
$500	72	19.7%	39	12.5%	89	24.4%

Table 8. Risk Adjust Model: ACG (Gross Profit in millions)

	Plan Information Set					
	Prior-Year Spending		**DCG**		**ALL**	
Selection Criterion	Gross Profit	Enrollment Rate	Gross Profit	Enrollment Rate	Gross Profit	Enrollment Rate
-$100	70	89.3%	65	89.5%	90	83.7%
-$50	74	87.3%	66	88.7%	92	81.5%
$0	**79**	**68.3%**	**68**	**52.4%**	**92**	**57.9%**
$50	76	39.6%	67	31.9%	90	39.1%
$100	71	29.4%	66	27.3%	86	30.6%
$150	62	22.7%	65	22.3%	85	27.8%
$200	60	19.2%	63	19.8%	83	25.5%
$300	49	12.9%	61	17.6%	79	21.3%
$400	42	9.3%	50	12.0%	69	16.3%
$500	38	7.2%	48	9.7%	64	14.0%

Table 9. Risk Adjust Model: DCG (Gross Profit in millions)

	Plan Information Set					
	Prior-Year Spending		**ACG**		**ALL**	
Selection Criterion	Gross Profit	Enrollment Rate	Gross Profit	Enrollment Rate	Gross Profit	Enrollment Rate
-100	81	86.6%	86	63.8%	108	67.3%
-50	90	83.6%	88	62.0%	109	64.4%
0	101	78.1%	89	58.9%	110	61.8%
50	**102**	**58.5%**	90	56.8%	111	59.6%
100	78	30.2%	91	55.7%	**111**	**58.2%**
150	45	15.5%	**91**	**54.9%**	111	56.8%
200	46	13.9%	91	54.0%	111	55.4%
300	40	10.0%	73	34.5%	96	38.9%
400	38	7.7%	56	19.6%	75	21.6%
500	36	6.1%	43	14.2%	60	16.1%

Notes for Tables 6-9:
1. Plan Information Set: In addition to risk adjustors, the plan uses one of these variables to predict the subsequent year's expenditure.
2. All: Prior year spending + ACG + DCG.
3. Selection Criterion: the plan enrolls individuals with expected profit >= selection criterion

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