Final Report on Case Mix Adjustment 2000 CAHPS® Medicare Disenrollment Reasons Survey

November 2002

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CMS Contract No. 500-95-0061

This project was funded by the Centers for Medicare and Medicaid Services under contract no. 500-95-0061/Task 5. The statements contained in this report are solely those of the authors and do not necessarily reflect the views or policies of the Centers for Medicare and Medicaid Services. The contractor assumes responsibility for the accuracy and completeness of the information contained in this report.

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Executive Summary

One of the analytic tasks for the Medicare CAHPS® Disenrollment Survey was to develop recommendations regarding case mix adjustment as a strategy for reporting the reasons beneficiaries disenrolled from plans. To our knowledge, case mix adjustment has not previously been applied to adjust the reasons given by enrollees for voluntarily leaving managed care plans. However, other CAHPS® measures reported to the public on the Medicare.gov web site are case-mix adjusted to facilitate comparisons between beneficiaries' ratings and reports of care provided by Medicare+Choice organizations and care provided under Original Medicare.

Case mix adjustment is a tool that adjusts for sociodemographic differences in the populations, in this case, those served by various plans. It is used in reporting information about plan performance to accommodate the fact that some plans have beneficiary members that are more difficult or complex for plans to provide with care or services, and they may be penalized by that fact. Overrepresentation of various beneficiary characteristics such as advanced age or perceived poor health status, may negatively impact on a plan when compared to other plans. Thus, the general research question for this task was to determine whether case-mix adjustment of disenrollee reasons might be able to provide information that would fairly treat all plans, thus providing better support for decision-making by beneficiaries and potentially assisting plans in targeting plan quality improvement or plan design actions.

Disenrollment reasons reported to the public are based on the most important reason for leaving a plan. Reasons are grouped into two main composites: CARE & SERVICES and COSTS & BENEFITS. Since a respondent could only cite one most important reason, the dependent variable for the analysis was the probability that a beneficiary would cite a reason within the CARE & SERVICES grouping (or the COSTS & BENEFITS grouping).

Prior CAHPS® and disenrollment research assisted us in determining the independent variables or potential case mix variables. The variables we included in our analysis were Age, Perceived health status, Race, Education, Gender, Proxy[1] and Ansproxy[2]; we also included CMS Region; and cross-product terms between all other individual level variables and CMS Region. The cross-product terms (in this case) help us to account for differences that occur in the reporting of the most important reasons given the impact of their geographic location. For example, if a particular region has a population that is more predominantly Asian than the population in the other regions, the coefficient from the cross-product would account for those regional differences.

[1] The Proxy variable indicates whether someone assisted the beneficiary in completing the survey.
[2] The Ansproxy variable indicates that someone else answered the questions for the beneficiary.

The analysis file consisted of completed responses to the 2000 Medicare CAHPS® Disenrollment Reasons Survey. When any of the case mix potential adjusters were missing we attempted to acquire the information through the Medicare enrollment file. However in some cases, when the information was not available in either file, these cases were then treated as missing. Because we were interested in modeling the probability that a beneficiary would cite a reason within the CARE & SERVICES grouping as a function of the independent variables (age, race, gender, perceived health status, proxy, ansproxy, region, region interactions, and health plan), we selected the logit function as the statistical tool for the analysis. We used a series of nested models and the likelihood ratio test to compare models and select our final model.

The final case mix model included dummy variables for Age, Race, Perceived Health Status, Education, Gender, CMS Region and cross-products with CMS Region. This model was a significant improvement over one that adjusted only for Age and Perceived Health Status.

While the model was significant and its capacity for prediction was beyond that of pure chance, it was not particularly robust. Other variables that might be explored as potential case mix factors include marital status, income, perceived mental health status, dual-eligibility and functional status of the individual. While there is evidence of plan variables that influence other plan outcomes, there is no evidence relating them directly to reasons for disenrollment, and they may be inappropriate for case mix analysis.

Preliminary results of this analysis were shared with the Disenrollment Survey Technical Expert Panel (TEP). TEP members had some initial concerns about "washing away the differences" between plans with a case mix adjustment, when the goal was to present differences in plans. In addition, they expressed concern about the use of perceived health status as exogenous to the plan. They thought health status might reflect plan efforts, rather than serving as a characteristic of the individual, in the models. However, the literature on "perceived health status" generally supports its inclusion as a characteristic of the individual. At least one TEP member felt that it is only appropriate to consider case mix adjustment of disenrollment reasons if the disenrollment rates are also adjusted for case mix. The Disenrollment team will investigate this option as part of its case mix analysis tasks for the coming year.

In addition, while the results of the modeling were not robust, there was some evidence that case-mix adjustment would lead to some changes in the relative standings of plans with respect to beneficiaries' reasons for leaving if reasons were reported as a percentage of *disenrollees*. However, since reasons for disenrollment are currently publicly reported as a percentage of *enrollees* (with a far larger denominator), the potential case mix effect is significantly diminished. Consequently, only a very few plans would experience a change in relative standing as a result of case mix adjustment using the final model. This finding supports CMS' current decision not to use case mix adjustment when reporting disenrollment reasons to the public. However, further analysis and review may suggest that it would be appropriate to case mix adjust the reasons for public reporting. This decision will be reevaluated over time after additional data are collected and further analyses are conducted.

Final Report on Case Mix Adjustment Of the 2000 Disenrollment Survey

Introduction

The Consumer Assessment of Health Plans (CAHPS®) Medicare Disenrollment Reasons Survey, is part of the CAHPS® series of surveys; this survey collects information from recent disenrollees of Medicare Managed Care (MMC) on the reasons they left the plan. The Balanced Budget Act (BBA) of 1997 required comparative information on health plans to be made available by the Centers for Medicare and Medicaid Services (CMS) to assist Medicare beneficiaries in selecting a health plan. The Disenrollment survey was designed specifically to provide information on the "reasons" beneficiaries have voluntarily disenrolled from a health plan. This information (on the reasons for disenrollment) was to be included on the CMS consumer website "Medicare Health Plan Compare."

The Disenrollment Survey Analysis Team[3] was tasked by CMS to develop recommendations for a case mix adjustment strategy for reporting the plan comparative data on the most important reason that triggered disenrollment. However, uncertainty about the appropriateness of case-mix adjusting reasons information precluded presentation of case mix adjusted reports on the CMS website for the first year of the Medicare CAHPS® Disenrollment Reasons Survey.

In this report, we first suggest a potential rationale for the investigation of case mix adjusting the Reasons survey information. We then review the extant literature to identify variables used in previous studies related to plan ratings and other plan outcomes that might be potential variables for the case mix. Following the discussion on potential adjusters, we review the Harvard Model used to case-mix adjust ratings of health plans in the Medicare Managed Care (MMC) CAHPS® surveys. This model might serve as a potential model for adjusting the reasons for disenrollment. We then present a potential model developed by the University of Wisconsin for case mix adjusting the reasons for disenrollment. Following the discussion on the development of the model, we provide the statistical results of the model. Evidence from practical application of the model is then provided, and we discuss the potential impact of this evidence on the public reporting of disenrollment reasons. Finally, input from the Disenrollment Survey Technical Expert Panel (TEP) input is discussed in relation to next steps for the case-mix adjustment project.

Rationale for Case Mix Adjustment of Disenrollment Reasons

Case mix adjustment has not previously been applied (to our knowledge) to adjust the reasons given for voluntarily leaving managed care plans. Thus, our justification for developing and testing a strategy of case mix adjusting reasons for disenrollment is based

[3] The Center for Health Systems Research and Analysis at the University of Wisconsin-Madison and RTI International.

on research on other case mix adjusted health plan outcomes. We first looked to other CMS surveys such as the MMC CAHPS® Survey. In MMC CAHPS® surveys, plans differ in their rates of beneficiary satisfaction with medical care and health plan performance, and some of this variation was thought to be the result of differences in the characteristics of the enrollees served by the plan or the environment in which the plan operates rather than specific actions taken by the plan. Prior to reporting the results on the CMS consumer website, case-mix adjustment was implemented to provide more "fairness" in the ratings of plans, given that some plans enroll beneficiaries that require more intensive care or additional services and the belief that they should not be penalized for this extra burden.

Before we adopted the same rationale, we further explored the evidence for linkages between plan ratings, plan satisfaction, disenrollment, and the reasons for disenrollment. What factors do these outcome measures have in common?

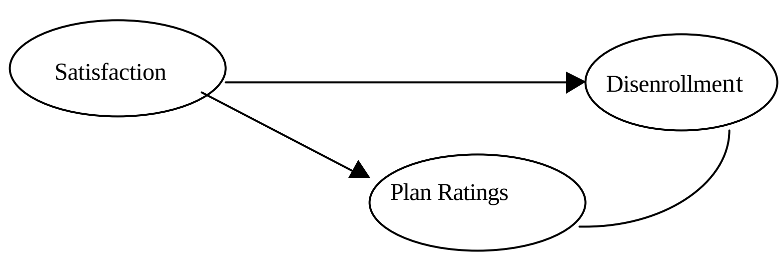
First, all are "consumer-reported or driven" outcomes of participation in a managed care plan. Consumer measures differ from those reported by the plans, by the providers within the plan, or from other survey data related to plan outcomes (HEDIS).

Second, the consumer reported outcomes (plan dissatisfaction, plan ratings and plan disenrollment) have been shown to be associated. There is evidence of a relationship between dissatisfaction with a plan and disenrollment, and dissatisfaction with a plan and plan ratings. Dissatisfied enrollees are more likely than satisfied enrollees to disenroll from the plan (Klinkman, 1991; Grazier, Richardson, Martin, and Diehr, 1986; Juba, Lave, and Shaddy, 1980; Allen, Darling, McNeil and Basten, 1994; Patrick, Martin, Madden et al., 1997).

Major causes of dissatisfaction include problems with access to care (especially access to the enrollees usual provider of care) and costs of care, resulting in lower plan ratings, plan switching, or disenrollment with a return to Fee For Service (FFS) (Schlesinger, Druss, and Thomas, 1999; Grazier et al., 1986). Newcomer, Preston, and Harrington, 1996, also reported that enrollee satisfaction with their physician, holding other factors constant, reduced the risk of disenrollment by 16%.

Figure 1 reflects our conceptual model of the relationship between plan satisfaction, ratings, and disenrollment. As suggested above, we believe that satisfaction influences plan ratings and disenrollment. Disenrollment and plan ratings are viewed as associated but not necessarily influencing each other.

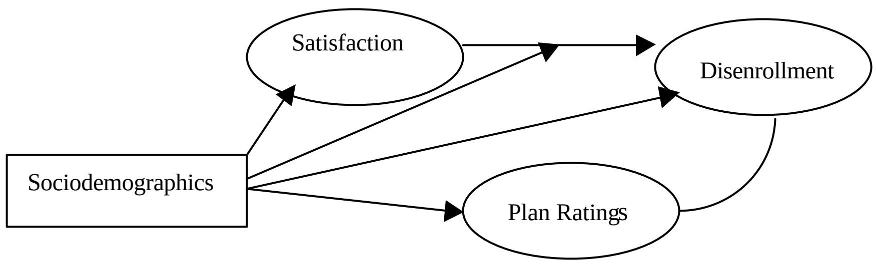
Figure 1



Third, the same sociodemographic factors influence enrollee satisfaction, plan ratings (quality indicators), and disenrollment. In Figure 2 we add the sociodemographic factors. Schlesinger et al., 1999, in a study of a commercial population, found that dissatisfaction, plan ratings and disenrollment were all affected by the demographics of the enrollees. Zavlavsky, Hochheimer, Schneider, Cleary et al., 2000, in their analysis of the impact of sociodemographic case mix on HEDIS plan ratings (in a commercial population), found that the ratings of plan quality indicators by individuals were linked to their sociodemographic status.

Using employee data, Schlesinger et.al.,1999, found that sicker enrollees report more plan dissatisfaction, and health status also affects the relationship between dissatisfaction and disenrollment. The path to disenrollment is altered when the dissatisfied enrollee reports poor health status—while sicker enrollees report more dissatisfaction than healthier employees, they have a lower rate of disenrollment than healthier enrollees. Thus, perceived health status mediates the impact of dissatisfaction on disenrollment, and as a result not everyone who is dissatisfied disenrolls. The arrow in Figure 2 that intersects the path between Satisfaction and Disenrollment reflects this mediating effect. It is also true that some who disenroll are not dissatisfied (Schlesinger et al., 1999; Patrick et al., 1997; Newcomer et al., 1996).

Figure 2



Similar results were found when a functional measure of health status was included in the analysis; the likelihood of disenrollment was lowered by more than 25% when the individual was "impaired" compared to those without impairment (Newcomer et al., 1996.) Some have suggested that individuals who are in the midst of receiving care or who are in poor health are less likely to move to another plan; their potential lack of understanding of how the new plan works, and the potential interruption of care delivery make switching difficult (Grazier et al., 1989).

Other factors influencing satisfaction with a plan, plan ratings, and disenrollment, are related to plan characteristics, such as: type of plan, choice of plans for beneficiaries, overall managed care penetration, operational maturity, etc. For example, Schlesinger et al., 1999, found that the type of managed care plan with the lowest satisfaction scores did not have higher rates of disenrollment, even when controlling for other enrollee characteristics. However, when they split the enrollees into two samples (impaired and not impaired), they found that plan type did have an effect—the motivation to disenroll almost doubled for HMOs over FFS. Among the dissatisfied group of enrollees with impairment, those in HMOs had the strongest association between dissatisfaction and intention to disenroll—almost four times higher than in Fee For Service. In this study, they were not developing a case mix adjustment but rather looking at the relationship between satisfaction, intention to disenroll and plan type. Other plan factors influencing ratings, satisfaction, and disenrollment are discussed in the section titled "Other Variables Influencing Plan Outcomes."

In summary, the evidence of relationships between satisfaction, plan ratings, and subsequent disenrollment have been shown in a number of studies. In addition, other studies have shown that sociodemographics of enrollees affect satisfaction, ratings (quality indicators) and disenrollment. We suggest that the "reasons" for disenrollment are similar to these other outcomes, especially disenrollment, and that similar sociodemographics will affect the disenrollees reasons for disenrollment.

One final consideration in determining whether case mix adjustment is appropriate or necessary is the strength of the effect of case mix adjustment on alternative outcomes. The impact (on plans) of case mix adjustment may be limited to only a few plans, such as was found by Zaslavsky, Hochheimer et al., 2000, when they examined health plan quality. In their study, only 3 out of 20 plans would have changed their ranking when case mix adjustment was applied. Other studies have also found that case mix adjustment had a relatively small impact on the overall plan performance ratings, yet for some small number of plans the change in performance rating was substantial (Elliott et al., 2001; Cioffi et al., 2001). If the impact is substantial even for just a small number of plans, this may still be enough to justify including case mix adjustment when the data is made publicly available and is certainly enough to justify exploration of a strategy for case mix adjustment of the Reasons survey.

Review of Literature to Identify Potential Variables

In developing a strategy for case mix adjusting the reasons for disenrollment, a number of preparatory steps were taken. Because this is the first attempt to case mix adjust reasons for voluntarily leaving managed care plans, the literature review would of necessity focus on similar methodological research related to case mix adjustments of other plan outcomes. These plan outcomes included: plan ratings, satisfaction ratings, use of inpatient hospitalization pre-and post-enrollment, the quality of care to vulnerable populations and disenrollment. We were interested in determining the significant individual variables (the characteristics of the individual) and other variables reported in these other studies.

While the Reasons for Disenrollment Survey focused on only Medicare Managed Care, we expanded the review to include literature on case mix adjustment of enrollee and disenrolle experiences with plans for the Medicare FFS environment and for commercially-insured plans, as appropriate.

Characteristics of the Individual Relevant to Case Mix Adjustment

The individual characteristics that were included as independent variables in the reviewed studies from managed care plans were generally some mix of the following: age, perception of health status, race or ethnicity, education, income, gender, and mental health perception. In the FFS studies of Medicare beneficiaries, dual eligibility status was also included.

Other measures also associated with the individual enrollee included proxy status for the survey respondent--indicating that someone other than the enrollee was responding to questions regarding plan satisfaction, utilization, and reasons for disenrollment, etc.

Geographic variables included in the reviewed studies included a variety of measures reflecting either the residence of the beneficiary, or the plan's coverage area. Measures used included: urban/rural status, Metropolitan Statistical Areas, states, and HCFA (now CMS) regions.

In the commercially insured populations, the "individual" characteristics sometimes also included: family income, family type, employment and source of income.

We first cite the relevant findings for each of the characteristic variables of the individual, followed in the next section by other significant variables. We do not discuss the "family" characteristics from the commercial plans, given our interest in the Medicare population.

<u>Age</u>

In the reviewed articles, "Age" was found to have a significant impact on: comparative plan ratings (Zaslavsky et al., 2000; Riley, Ingber, and Tudor, 1997; Elliott et al, 2001;

Cioffi et al., 2000); enrollee satisfaction (Patrick et al., 1997; Newcomer et al., 1996), utilization (Schneider, Zaslavsky, and Epstein, 2002), quality of care measures (Zaslavksy et al., 2000); and, post-disenrollment admission to inpatient rates (Morgan, Virnig, DeVito and Persily, 1997). Thus, it was clear that a measure of “Age” should be included in the initial analysis for the case mix adjustment.

Gender

“Gender” had a significant impact on rates of plan disenrollment and subsequent admission rates to inpatient care (Morgan et al., 1997). Other related studies found an effect of “gender” on reported levels of plan satisfaction (Schlesinger et al., 1999) and on quality of care measures (Zaslavsky et al., 2000). Gender also had a significant impact on “self-reported health status,” with women being 4 times more likely to report poor health status if their educational achievement was below the upper secondary education level (Leinsalu 2002).

Education

“Education” had a significant effect, on plan ratings (Elliott et al., 2001); the performance ratings were positively associated with higher education levels (Elliott et al., 2001; Cioffi et al, 2000; Zaslavsky et al., 2000).

Education also impacted quality of care measures (Cioffi et al., 2000; Zaslavsky et al., 2000); and whether enrollees in Medicare managed care plans received clinical preventive services for breast cancer screening, eye exams for patients with diabetes, beta blocker medication after myocardial infarction and follow-up after hospitalization for mental illness (Schneider et al., 2002). Those with less education were less likely to receive all 4 clinical preventive services (Schneider et al, 2002). Thus, education had an effect on care delivery and consequently plan ratings. Education was also related to self-reported health status in a number of studies (Leinsalu 2002; Bobak, Pickhart, Hertzman, Rose and Marmot, 1998; Malmstrom, Sundquist and Johansson, 1999). These relationships suggest including education in the case mix adjustment strategy.

Race

Schneider et al., 2002, found that “Race” had a significant effect on access to needed clinical services in Medicare managed care plans. Interestingly, the differences found for access to needed clinical services were within-plan differences and not across plans or geographic location. An earlier study reported that African-Americans are less likely to receive all 4 clinical preventive services (Schneider, Zaslavsky, and Epstein, 2000). [The 4 clinical preventive services are listed in the “Education” variable.] The same study examined use of hospital services, and found African-Americans were slightly more likely than other groups to have higher admission rates, generally associated with either a lack of access to ambulatory care, or poor quality ambulatory care. Riley et al., 1997, found disenrollment varied by race categories; African-Americans and others had higher rates of disenrollment than did Caucasians. However, not all effects of minority status on plan outcomes are negative—ratings of plan performance were positively associated with the percent of Asians in the plan (Zaslavsky et al., 2000).

Given the variation of ratings of plans by different races, and the findings that some minority populations experienced disparities in access to needed services within plans and differential rates of disenrollment, it is not a leap to hypothesize that minority groups or vulnerable others who leave plans at differential rates might also have different reasons for leaving. Including "Race" as a case mix variable is important, though the effects may only be significant for some racial groups.

Income

Morgan et al., 1997, in a study examining differences in the use of inpatient medical services in FFS, HMO enrollees and HMO disenrollees and demographics, found that unadjusted inpatient admission rates in the three groups were a function of HMO enrollment status, age, sex, and household-income level. Across all three groups, admissions were more frequent among the low-income group, older beneficiaries, and men. This finding held with the disenrollees as well.

Schlesinger et al., 1999, also found that family income was predictive of reported levels of satisfaction in a commercial population.

Other studies found perceived control over one's life was associated with self-reported health (Bobak et al., 1998; Leinsalu 2002), and, it can be assumed that, having lower income is also associated with less sense of control over one's life.

These studies suggest that the reasons for disenrollment might also be affected by beneficiary income. However, we did not have this information available for the analysis.

Dual-Eligibility Status

In the Medicare FFS CAHPS® test of case mix adjustment; dual eligible status was included, given that approximately 11.2% of the 2000 MFFS sample had a dual-eligible status. [For more details see Elliott, Hambasoomian, Edwards, and Soloman, Final Task 9 Report: Analysis of Case-Mix Strategies and Recommendations for Medicare Fee-For-Services CAHPS®, 2000.] In the MMC case mix adjustment; it was not included, since the number of individuals in the sample with dual eligible status was significantly smaller.

We also did not include dual eligible status as a potential adjuster, for the same reason that Harvard chose not to include it—a potentially small subset of the population in managed care plans. For this analysis, the population was reduced further since we were using only a subset of the enrolled population, those who disenrolled with the dual-eligible status.

General Health Perception/Perceived Health Status

A better rating on "General Health Perception" is associated with higher plan ratings, satisfaction and reports of care (Zaslavsky et al., 2000; Elliott et al., 2001; Cioffi et al., 2000; Newcomer et al, 1996). However, the fact that poor perceived health status is a strong predictor of mortality (in a prospective study) even when controlling for a physician's evaluation of health status (Pijls, Feskens, and Kromhaut, 1993) suggests that it differs in some manner from a "medical measure" of health status.

Some case mix studies do not include health status as a case mix variable, given the conviction that health status is under the plan's control. Other evidence counters this assumption; some studies indicate that perceptions of health status are affected by a variety of psychosocial and socioeconomic variables as well as by actual physical health status (Leinsalu 2002; Bobak et al., 1998; Meurer, Layde and Guse, 2001). This would suggest that "perceived health status" is not under the control of the plan.

If the plan were to have control of the individual's perceived health status, one would expect that modifications to plans, such as increased cost sharing, would impact on the individual's perceived health status. Cost sharing is expected to reduce the use of care, and therefore, it might negatively impact on health status. A study by Wong, Andersen, Sherbourne, Hays and Shapiro, 2001, of data from the Medical Outcomes Study, suggests there is not such a relationship, they reported that while cost sharing reduced the use of care for both minor and serious symptoms in a population of chronically ill adults, it did not alter self-reported health status.

Given this evidence, we will include perceived health status as an individual characteristic in the case mix for the reasons survey; perceived health status does not appear to be under the control of the health plan, and it impacts on the other plan outcomes.

Perceived Mental Health Status

An individual's perceived mental health status has also been shown to impact on plan ratings as well as on disenrollment.

Depressive symptoms were found to be associated with lower perceived health status (Meurer et al., 2001) and conversely improvement in perceived mental health status resulted in significant improvements in health status (Ibrahim et al., 2002). Mental health status was also unaffected by cost sharing that led to reduced use of care for serious symptoms (Wong et al., 2001). Again, similar dynamics may be operating for "perceived mental health status" as appear for perceived health status. In the earlier test of Medicare FFS CAHPS®, mental health was found to add significant explanatory power to their model (Elliott et al., 2001). However, in this case, we did not include perceived mental health status in our modeling of year 2000 data—we were awaiting results[4] from the

[4] In a memo dated May 7, 2002, the results of the analysis of Year 5 Managed Care and FFS CAHPS, were reported. The Managed Care CAHPS team found that mental health status is a significant predictor of satisfaction with health

Managed Care CAHPS® team's efforts to investigate the mental health measures for their case mix adjustment strategy.

Proxy

Some individuals are unable to complete the survey without assistance, and a "proxy" either assists the individual or actually answers the survey on the beneficiary's behalf. Two proxy measures representing those two levels of reporting are included in the reasons survey.

While proxy did not have a large influence on the case mix adjustment for the Medicare Managed Care CAHPS® study, they included it in their recommended model, given perceived issues of credibility with the plans. They suggested that plans might be concerned about the numbers of individuals that disenrolled and had a proxy complete the questionnaire (Cioffi et al., 2001). In the Medicare FFS CAHPS® test of case mix adjustment models, proxy was significant—no proxy assistance resulted in more favorable ratings (Elliott, Hambarsoomian, Edwards, and Solomon, 2001).

Given these findings, we have decided to test two measures of proxy in our analysis for the development of the case mix model.

Geography

In 1973, Wennberg and Gittleson, described patterns of hospitalization that varied between neighboring communities. Since that "groundbreaking" study, measures of geography have been included in most health care research, including other CAHPS® studies of plan outcomes (Cioffi et al., 2000). Geography (MSA and CMS Region) showed statistically significant variation on rates of disenrollment (Riley et al., 1997), on effects of general health perception on global ratings (Elliott et al., 2001), and on plan performance ratings (Cioffi et al., 2000). Residing in an urban area was positively associated with health plan quality as measured by HEDIS (Zaslavsky et al., 2000). Thus, a geographic measure should be tested in the case mix modeling for this survey.

Whether a geographic measure is considered as a characteristic of the individual or as a contextual variable or as a plan variable, the geographic measure picks up unmeasured elements of the health care utilization "culture" and the socioeconomic environment affecting the individual beneficiary's behaviors, thus adding more contextual information to the model. We proposed to include a geographic variable to add contextual information.

care, the health plan, the physician and specialists. The results held with the FFS respondents. Worse mental health resulted in lower CAHPS scores.

Other Variables Influencing Plan Outcomes

Geography

Given the evidence we discussed above, we elected to add the CMS Region as our contextual variable. Because we did not have beneficiary zip code, we used the plan region to express the effects. Given that some plans provide care across regions, the plans were assigned to a specific region by determining which region was the primary service area (assigning the plan to the region in which it had the most enrollees).

Plan Measures

There are a number of plan measures that have been included in other studies, and even though we will not be including them in this analysis they provide some insight. We first provide a brief description of the plan measures, and then a discussion follows.

Some studies have included plan choice as an independent variable, i.e., whether the disenrollee had choice in the plans available to them. Another similar measure is overall penetration of managed care plans in the area; higher levels of penetration suggest that the plans in the area may be in greater competition for enrollees. This differs from the choice measure because choice involves a plan that is actually open for enrollment, whereas, penetration of plans includes all plans whether or not all plans are open for enrollment. Theoretically, greater penetration in the market drives competition that, in turn, could drive improvements in benefits or services—resulting in reduced disenrollment rates and potentially different reasons for disenrollment (than would occur in areas of low penetration).

Others have examined duration of enrollment in the plan, given findings that individuals who are newer plan enrollees have a higher tendency to disenroll (Schlesinger et al., 1999). This may be due to confusion about how a plan works. Still others include plan service area, market share, or organization maturity; these measures reflect on the "age" of the plan—generally "older" plans have greater market share and more experience in providing managed care services and in describing them to potential enrollees, thus reducing confusion and dissatisfaction, and disenrollment (Newcomer et al., 1996).

Differences in the structure of managed care are associated with reported problems with plans (Schlauffer, McMenaim, Cubanski, and Hanley, 2001). They examined whether managed care organizations differing in structure, such as: Independent Practice Associations (IPAs)/Networks of providers, health maintenance organizations (HMOs) or Preferred Provider Organizations (PPOs), varied in terms of the reasons enrollees reported as problems. Adults in IPA/Network or staff/group HMOs reported more problems getting a referral to a specialist and difficulty in selecting a doctor or hospital than PPOs. Alternatively, misunderstanding of benefits or coverage and problems with claims were higher for PPOs and IPA/Networks than for group HMOs. HMO's had the lowest rate of reported problems. This study examined many of the same reasons as

found in the preprinted reasons for disenrollment in the Medicare CAHPS®
Disenrollment Survey.

Schlesinger et al., 1999, examined the impact of managed care structure on rates of dissatisfaction and intention to disenroll. Dissatisfaction with a plan was associated with greater intention to disenroll from an HMO compared to FFS.

While each of the plan variables just discussed are significant for other plan outcomes, we chose to parallel the Harvard model for this first analysis. Any further attempts to conduct a case mix adjustment could explore other variables as long as they reflect characteristics of the individual or other contextual effects.

Summary of Literature on Potential Variables

In the reviewed literature, we examined the individual impact of characteristics of the beneficiary, on disenrollment rates, measures of satisfaction, utilization and quality of care measures, along with other plan ratings. We also looked at other variables including contextual variables. While some studies we reviewed did not focus on case mix adjustment, they did examine the effect (on other plan outcomes) of specific individual characteristics and other variables such as the region in which the enrollee resided. The reviewed studies included some mix of the following individual variables: age, perception of health status, race or ethnicity, education, gender, mental health perception, dual eligibility and geographic measures. Geographic variables included in the reviewed studies were urban/rural status of the plan's beneficiaries, and plan market areas, Metropolitan Statistical Areas, states, and HCFA (now CMS) regions.

Some authors concluded (the above mentioned) sociodemographic impacts were related to plan performance measures and there was significant variation in the sociodemographic case mix of plans and variation across plans within states.

In the introduction, we made the link between satisfaction with care and disenrollment and consequently suggested that these are linked to the reasons for disenrollment. Given the significant impact of sociodemographic characteristics and geographic location on satisfaction with a plan and other plan outcomes, it was apparent that we should test age, gender, race, education, perceived health status, and CMS region in our case mix adjustment analysis. We will assess whether the impact of these variables on the most important reason for disenrollment is similar to those for other outcomes of interest (plan performance ratings, satisfaction with care, quality of care, and utilization). We will also determine whether the case mix adjustment has similarly weak effects overall but significant effects for a small number of plans as was found in other case mix adjustment studies.

Data and Measures

The data used for this study were from the Medicare CAHPS® Disenrollment Survey 2000[5]. The survey questions were administered to samples of disrenrollees selected on a quarterly basis for the study period of January 2000 to December 2000. In the Disenrollment Survey, beneficiaries were asked a series of questions about specific reasons for voluntary disenrollment, referred to in this report as "pre-printed reasons.[6]" In addition, an open-ended question was asked regarding "what was the one most important reason" (MIR) for voluntary disenrollment. The Disenrollment Survey Team coded responses to this open-ended question using a coding schema that contains the "pre-printed reasons" and some additional codes for responses that could not be matched to the pre-printed reasons.

Disenrollees were excluded from the survey data at any point in the processing when it was determined that the disenrollment was involuntary, either due to personal factors such as moving from the plan area, or due to plan-related factors, such as the plan leaving the market.

The analysis file used for the case mix adjustment contained the unweighted[7] results of the pre-printed reasons, the most important reason and demographics from completed surveys of disenrollees. When demographic information was missing from the disenrollment survey file, we added it from the Medicare administrative data, where possible.

A summary of the preprinted reasons questions and a crosswalk with the consumer and plan groupings of the most important reason codes is included in Appendix 1. Appendix 2 contains the frequencies for the demographic information contained on the file.

Composites of Survey Items

In selecting the dependent variables for our analysis, we relied on the earlier work by CMS and the Agency for Healthcare Quality and Research (AHRQ); they had sponsored research that explored how the information collected about disenrollment reasons could be shared with Medicare beneficiaries. The research results suggested it would be difficult for beneficiaries to interpret and make plan selection decisions based on the results of many different "reasons." Through testing with potential consumers of the information, two categories of reasons appeared to be meaningful, these two general composites were:

Members left because of Care and Services (CARE & SERVICES)
Members left because of Costs and Benefits (COSTS & BENEFITS)

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[5] The disenrollment survey was originally developed and tested by the "original CAHPS team" of researchers from Harvard Medical School, RAND, and Research Triangle Institute (RTI).
[6] Three "reasons" were dropped from the case mix analysis; the "dropped" reasons were due in part to characteristics of the beneficiary situation rather than fully under the control of the plan. The questions that were dropped are asterisked on the Preprinted Reasons Questions in Appendix 1.
[7] Because response propensity weights were developed using some of the proposed case mix variables, unweighted data were used for the analysis.

Yet, there was also concern about how to share information (as required) about the reasons for disenrollment with the participating health plans. It was thought that some consumers and most plans would desire more details on the reasons (than beneficiaries) in order to assist others in selecting a plan, to improve plan services, and reduce the rate of disenrollment from the plan, yet they too might find it overwhelming to examine results for many separate "reasons." Findings from a factor analysis of these reasons at the plan level revealed eight separate factors or groupings, these were used for reporting plan level results. Using the individual level data in the analysis resulted in five groupings of reasons for consumers, these were available for those consumers who desired information beyond the two general categories of reasons. See Appendix 1 for the crosswalk between the preprinted reasons and the factors for consumers and health plans. [For more detail see the report submitted to CMS, dated August 23, 2001, and titled "Grouping Disenrollment Reasons for Reporting Results from the Medicare CAHPS® Disenrollment Reasons Survey."]

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The two composites CARE & SERVICES and COSTS & BENEFITS (that are used for the high-level reporting of the results to consumers) were the primary target for the initial case mix adjustment activities for the Most Important Reason (MIR) for voluntary disenrollment.

Methodology

In this first section of the methods used for the case mix adjustment, we briefly summarize the characteristics of the Harvard approach for their case mix adjustment of the MMC CAHPS® plan performance data. As was mentioned earlier, there was a desire to maintain some consistency between the approaches to case mix adjustment given the public reporting of the results. Following the background information on the Harvard approach [See the Harvard Task 9 Report produced by Cioffi, Cleary, Ding, Shaul, Zaborski, and Zaslavsky, 2000], there is a more detailed discussion of the methods used by the University of Wisconsin for the "reasons" case mix adjustment.

Harvard Model

Researchers at Harvard developed the case mix adjustment methodology for the Medicare MMC-CAHPS®. There are now five years of MMC-CAHPS® data available for refining the case mix adjustment model; in their September 12, 2000 report, they examine models on three years of data, 1997, 1998, and 1999. In the MMC-CAHPS®, respondents were asked to rate and report on their experiences with different aspects of their medical care and their health plan. The ratings they assigned to medical care and health plan performance were constructed as numeric scales requiring respondents to rate their medical care or their health plan on a 0 to 10 scale. The resulting scores (0 to 10) from the worst possible to the best possible were then used as dependent variables in the analysis.

In addition to the rating scores on medical care and overall health plan performance, Harvard also examined other dependent variables, these were the five CAHPS® composites of ratings the enrollees gave in response to questions about plan services, design, provider and plan communication, and marketing. The five composites were: Getting care you need; Getting the care quickly; Doctor/nurse communicates well; Doctor/clinic staff are courteous and helpful; and Health plan paperwork and information. The five composites were composed of two to four items, rated on either a 3-point or 4-point scale.

Given their literature review and earlier analysis work, Harvard researchers presumed that "age" and "perceived health status" should be included as control variables in the case mix model before other potential individual level adjusters were added. They removed the plan effects from their model, in order to assess only the effects of the individual adjusters. Using linear regression analysis in a series of models, and controlling for age and health status, they examined respondent education, race, medical conditions, IADLs, independence status, the assistance of a proxy in answering the question (proxy) or actually answering the question for the respondent (ansproxy) and an area level measure based on the zip code of the beneficiary residence, determining whether there was significant variation and influence on ratings or the CAHPS® composites.

Because the survey could not include all possible effects of geographic location, the zip code of the beneficiary's residence was added, to provide more "context" to the model. The underlying culture and characteristics of the area would thus be included in the tested model. For example, zip code would add the impacts from the healthcare culture and other sociodemographic characteristics, such as racial composition of the area. Utilization of healthcare services is a cultural phenomenon and has been shown to vary across geography, other sociodemographic factors not included in the models, such as average or median income, are also then expressed through the zip code variable.

After controlling for age and health status, the other four variables that had the greatest explanatory power were: education, proxy, ansproxy, and gender (male). Proxy and ansproxy did not have a substantial effect on plan variation. However, Harvard chose to include them in the suggested core model, for additional credibility with the health plans.

The Harvard team then tested the impact of moving to dummy variables for "age," "perceived health status," and "education." The impact was measured by how much variance was accounted for by each independent variable and by the impact on the ratings and the composites, and improved R-square. The dummy variables were found to provide more information and improved statistical results.

They also tested for interactions between the CMS region and the other adjusters in the models, as the interaction between a linear effect on the scales of the original responses, except for proxy and region (zip code of the respondent). Strong regional effects were found for the interactions of region and health status, education, and Hispanic zip code. Because of inconsistencies across years of data, their final recommendation was to only include interactions between CMS region and health and education.

They recommended that the core case mix model include: self-reported age, treated as dummies; self-reported health status, treated as dummies; self-reported educational achievements with dummies for each level; proxy and ansproxy (binary) variables; and region interactions for the linear effects of health status and education. They were continuing to explore other potential adjusters (such as mental health status) at the point in time when this analysis began.

In the case mix base model for the "Rating of the Health Plan," the total model R^2 values for years 1997, 1998, and 1999 were 0.074, 0.076, and 0.082 respectively. These were the highest R^2 values for any of the dependent variables. This suggests that while the models were statistically significant, the amount of variance explained by the models was not large. When the case mix adjustments were applied to the rankings of plans, plan rankings were not greatly changed. However, for a few plans the case mix adjustment determined the plan's rank and not the actual plan performance.

University of Wisconsin Model

Introduction

Researchers at the University of Wisconsin conducted the Disenrollment Reasons Survey case mix analysis.

As in any research study, the selection of a statistical method is dependent upon a number of factors, such as the available data, the purpose of the study, and the population under study. In this case, the purpose of this analysis was to develop a case mix adjustment model that addressed the variation across plans in the characteristics of the individual disenrollees and the impact of variation associated with geographic location. The case mix results might then be used to adjust the "percent of disenrollees (within the plan) indicating a specific composite," allowing for comparison of these results across plans in the public reports.

As previously described, the "reasons" data included in the case mix analysis were the responses to the question, "What is the one most important reason you left [health plan name]?" This question followed a series of preprinted potential reasons (in the form "Did you leave [health plan name] because…") to which respondents answered with a "yes" or "no". The population under study consisted of voluntary disenrollees with completed surveys, from Medicare Managed Care Plans in Year 2000.

The purpose of the study as described above, was to examine whether there were certain individual characteristics or contextual factors that were influencing the reason for disenrollment of beneficiaries in specific plans. If so, we needed to be able to estimate the impact for each variable, and take into account the impact of all other variables at the same time. This would create a predicted value that could be compared to the actual observed number of beneficiaries citing a reason within either the CARE & SERVICES composite.

To adjust data for differences in case-mix, there are essentially two choices. You can stratify the sample into different sub-samples, a simple example would be to divide the sample into two categories of either high or low risk for disenrollment and then conduct the rest of the analysis separately for the high risk and the low risk beneficiaries for a particular outcome. Alternatively, you can specify the differences in disenrollees or plan geography within one model.

Creating a risk stratification system with all of the cells resulting from the cross-classification required for this research question would be at best unwieldy and in the worst case statistically inappropriate. It would likely result in empty cells or cells with very few cases. In addition, we do not necessarily know which variables to stratify upon. It could also increase the level of complexity for displaying information to consumers, requiring the individual to determine which strata they are interested in prior to examining the results.

Therefore, we assessed the three factors (study purpose, population, and available data) and determined that using regression would be the statistical method of choice. Regression would allow us to assess the independent impact of a variable given the presence of the other independent variables in one regression model, and it would allow us to create predicted values based on the sum of the effects for each plan.

Logistic Regression

In the "reasons" analysis, the dependent variable was the endorsement of a most important reason in either the CARE & SERVICES composite or the COSTS & BENEFITS composite. This dichotomous qualitative variable was transformed into two dummy variables; if an individual cited a reason within a composite their reason was included in the dependent variables as a "1." If they did not cite a reason within that composite, they were coded as a "0" for that composite. This differed from the dependent variables based on plan ratings that were treated as continuous variables in the Harvard models.

Because we were interested in modeling the probability that a beneficiary would cite a reason within the CARE & SERVICES composite (or the COSTS & BENEFITS composite) as a function of the independent variables (age, race, gender, perceived health status, proxy, ansproxy, region interactions), we selected logit function as the statistical tool for the analysis. With a logit function, the relationship between the dependent and independent variables is not directly estimated but rather is indirectly estimated using the natural logarithm of odds of y=1. The model assumes a linear function between the log of odds and the independent variables in the model x_1, x_2, x_k…. This model can be written in the following form:

$$\text{Let } p=\Pr(Y=1)\text{, then } \ln (p/(1-p)) = a_1(\text{intercept}) + b_1{*}x_1 + b_2{*}x_2 + \ldots + b_k{*}x_k$$

Maximum Likelihood Estimation (MLE) is used to obtain our model's estimated parameters. After the intercept is computed—the predicted probabilities can be obtained through the following formula that is derived from the above equation.

$$p=\exp (a_1 + b_1{*}x_1 + b_2{*}x_2 + \ldots + b_k{*}x_{k)} / [1 + \exp(a_1 + b_1{*}x_1 + b_2{*}x_2 + \ldots + b_k{*}x_{k)}]$$

The computation for the logistic regression was run in SAS version 8.1.

Variable Selection for the Logistic Models

The criteria for selection of case-mix variables include a number of considerations that should be addressed. First, if a variable is to be a measure of a disenrollee's characteristics, these characteristics must be beyond the control of the plan, and they should be significantly related to the reason for disenrollment. They should also be measures that are reliable and valid, and they should make a difference in the final interpretation of the reasons for disenrollment.

The location of the individual within a region contributes additional information about contextual factors of the region in which both the individual and the plan are located. These regional factors influence individual functioning and these influences are beyond the plan's control and beyond the individual's control. Thus, regional influences in this case are included as interactions between the characteristics of the individual and the region.

The independent variables we would include in our analysis at the individual level are Age, Perceived health status, Race, Education, Gender, Proxy[8] and Ansproxy[9]; at the contextual level they include CMS Region; also included are cross-product terms between individual level variables and CMS Region. The cross-product terms (in this case) help us to account for differences between the individual's characteristics and those that are related to the region. For example, if a particular region has a population that is on average significantly older than the population in the other regions, but not all individuals are the "average age" within the region, the coefficient from the cross-product term would account for those differences.

<u>Hypothesis and Modeling Strategy</u>

Our hypothesis was that case-mix adjustment would improve upon the reporting of problems beneficiaries cited relating to CARE & SERVICES or COSTS & BENEFITS[10], by fairly treating those plans with beneficiary members that are more difficult or complex for plans to provide with care or services. The reason for the need for additional or more complex care may be the result of various beneficiary characteristics such as advanced age or perceived poor health status, or other factors such as the unique characteristics associated with a specific region. Disenrollee reasons information that was case-mix adjusted could provide better support for decision-making by beneficiaries and could assist plans in targeting plan quality improvement or plan design actions.

<u>Single Factor Models</u>

The first step in our modeling strategy was to begin by exploring the effects that each individual variable had on the composite. We would include in the exploratory analysis the following variables: Age, Gender, Race, Perceived Health Status, Education, CMS Region, Proxy, and Ansproxy. In these models the variables Gender, Proxy and Ansproxy were treated as binary variables, while Age, Perceived Health Status, Education, and CMS Region were treated as ordinal (recognizing that this may be more appropriate for the first three of these four variables than for CMS Region). As mentioned, logistic regression creates maximum likelihood estimates which are indirectly estimated using the natural logarithm of odds of y=1. In this case, the odds of y=CARE

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[8] The Proxy variable indicates whether somone assisted the beneficiary in completing the survey.
[9] The Ansproxy variable indicates that someone else answered the questions for the beneficiary.
[10] It is important to note that any most important reason cited by a beneficiary was characterized within either the CARE & SERVICES composite or the COSTS & BENEFITS composite, i.e., these two composites were constructed to be mutually exclusive.

& SERVICES. The model assumes a linear function between the log of odds and the independent variables in the model such as age, gender, etc.

Models with Dummies

We then created models with dummies for the categories in Age, Gender, Education, Race, Perceived Health Status, Proxy, Ansproxy, and CMS Region. A dummy variable is a dichotomous variable constructed from a categorical independent variable. It is scored, “1” if the characteristic is present, and “0” if it is not present, thus creating mutually exclusive categories. This essentially allows us to capture the information present in a categorization schema, such as the five perceived health statuses (excellent, very good, good, fair, poor), and to identify differences between the levels of the independent variable and the dependent variable. In logistic regression with dummy variables, a “reference” variable is needed within each variable. The reference variable allows comparisons within the model to the referenced category. For example, we could determine whether the odds of citing a reason within the composite may be two or three times more likely for those rating their health as poor in comparison to those in the reference category who rate their health as excellent.

We would determine through review of the maximum likelihood coefficients and the odds ratios whether to include dummy variables in the multivariate analysis.

Nested Logistic Multivariate Regression Models

In the first multivariate logistic regression model, we followed Harvard in assuming that Age and Perceived Health Status should serve as controls for the composites. We found that this model (B1) could serve as the base model in a nested modeling approach. We could use the base model (B1) for testing the additional improvement in fit given the addition of any other variables, by comparing changes to the likelihood ratio test statistic (also called model chi square test) from the base model. The base model (B1) included the following:

(B1) = Intercept + Age Group + Perceived Health Status

The next model (B2) included all other variables except health plan ID (contract number). The model (B2) included the following:

(B2) = Intercept + Age Group+ Perceived Health Status +Gender + Race + Education + Proxy + Ansproxy + CMS Region + Region Interactions

We would then run a backward selection of Model (B2) to determine which variable groups would stay in the model. We then constrained the model to include all main effects for which interactions were important. The constraint was done because backward stepping could potentially include the interaction without the corresponding main effects, a nonsensical result. Also, even if one or more dummy categories within a variable were not significant we still included them in our final model. The variables left in the model would then constitute the Model (B3):

(B3) = Intercept + Age Group + Perceived Health Status + Gender + Race + Education + CMS Region + Region Interactions
A separate part of the analysis was related to estimating the differences in odds ratios of the plans for the specific composite (or the unique plan contribution to the fit of the model); we added the Health Plan ID (contract number) to model (B3). By adding Health Plan ID we could measure effects of the plan in relation to the other independent variables. This model included the following:

(B4) = Intercept + Age Group + Perceived Health Status + Gender + Race + Education + CMS Region + Region Interactions + Health Plan ID

The coefficients of the Health Plan ID could provide us with a method for determining the relative odds for the plan of having disenrollees with a reason that was in the CARE & SERVICES composite. However, it was not in consideration for the recommended case mix model, given the inclusion of the Health Plan ID.

Statistical Tests

The closest equivalent to the F test for linear regression (a test of significance) in logistic regression is the likelihood ratio test. This is a test of the null hypothesis that the independent variables have no impact on the outcome, against the study hypothesis that the independent variables have some influence on the outcome.

Significance for the Single Factor Models was determined by examining the likelihood ratio chi-squared test for the contribution of the explanatory variables, and the maximum likelihood estimates, the odds ratios and the p values for each.

We used a series of nested models[11] for the comparisons of multivariate model fit. Nested models allowed us to test whether adding variables to our base model would improve the goodness-of-fit of the model. With a nested model, the Likelihood Ratio for a model (A) that is nested in Model (B) will always be less than or equal to the Likelihood Ratio for Model (B). We can subtract the Likelihood Ratio for Model (A) from Model (B), to produce a chi square statistic, with degrees of freedom equal to the difference in the number of estimated coefficients, to determine whether adding the term(s) improved the overall fit of the model (Agresti, 1990). If the overall fit of the model does not improve, we may choose to not include the variable(s) in the final model.

Unlike linear regression, there is no R-square equivalent for logistic regression models. There are other tests for model fit that we used to assess the models, including: the AIC

[11] If you have two models (A & B), Model A is nested within Model B when Model A has all of the variables present in Model B, but Model B has some additional variables.

[12](Browne and Cudeck, 1989; Cudeck and Browne, 1983), the Adjusted R^2, the Hosmer-Lemeshow Fit Index[13], and the C-statistic[14]. These tests are explained in the footnotes or with the results of the analysis.

<u>Criteria for Multivariate Model Evaluation</u>

There are at least seven criteria by which we can evaluate the models to determine the best fitting model. First, we examine the probability coefficient of the individual variables of interest, and determine whether they contribute to our understanding of the effects.

Next, we can look at the absolute fit of the model using the Maximized R-squared; the C-statistic or the Hosmer-Lemeshow chi squared; or, we can look at the relative fit of the model using the likelihood ratio to compare to a base model or the AIC.

While it is important for an individual model to fit well, we must also take into account the concept of model parsimony, that is, whether a simple or more complex model should be used. Parsimony in model selection suggests that even though a variable might account for some small proportion of the variance, a simple model is preferred (if it has essentially similar results) over a more complex model.

But we must also consider whether the model has face validity with those who would be "affected" by the model, in this case health plans and consumers. This may result in a more complex model if the stakeholders believe in specific variables as explanatory factors for the outcome.

We then examine the sensitivity and specificity of the model—that is, we cast the results in to a classification table to assess how well it can correctly classify the outcomes of interest (composites). Model "sensitivity" is the ability of the model to correctly capture the "event" (citing CARE & SERVICES) among those in the sample for whom the "event" occurred. Model "specificity" is essentially the ability of the model to rule out the event among those for whom it did not occur. The classification table also provides a picture of the percent of false positives and false negatives.

Finally, we must look at whether there is a practical impact, in this case, a model may be significant yet it may not alter the results reported to the public, e.g., on the CMS website. If this is the case, it may not be as important to include case-mix adjusted data in the CMS consumer report. Yet, from the plans' perspective, even if only a small number of plans are significantly affected (show a higher rate of endorsing the CARE & SERVICES composite), they may appreciate knowing that they are providing care and

[12] The AIC is justified in this case, since we are using maximum likelihood estimation. Note that a lower AIC suggests a better fitting model.
[13] The null hypothesis for the Hosmer-Lemeshow Goodness-of-Fit Test is that the best predictor of the dependent variable is the constant term. Non-significant values are thus desired for the study hypothesis.
[14] The C-statistic reflects the proportion of pairs of cases with different observed outcomes in which the model results in a higher probability for the cases with the event than for the cases without the event or outcome. Values will lie between 0.5 and 1.0.

services to a population whose characteristics increase the odds that they will cite a reason for disenrollment in the CARE & SERVICES composite.

We can observe the differences between plans by examining the observed percent of those endorsing the composite versus Model (B3)'s predicted percent of those endorsing the composite, adjusted for the percentage of disenrollees shown on the website. Alternatively, we can examine the results from Model (B4)—"plan coefficient" or odds ratio estimate and its antilog to determine where the plan stands in relation to the reference plan. That is, we can look and see if the plan odds are greater (odds > 1.0) or lesser than average (odds <1.0) taking into account the differences in characteristics of the individual disenrollees and the impact of region in comparison to the reference plan.

Results

Impact of Single Factor Models

As was mentioned above, we began by testing a series of single factor models to determine the effect each individual variable had on the two composites. We included in the analysis the following variables: Age, Gender, Race, Perceived Health Status, Education, CMS Region, Proxy, and Ansproxy. We can examine the impact or probability coefficient for each of the individual variables in the model to determine whether the model that includes the variable tells us more about the outcome than a model without the variable. This was accomplished by examining the maximum likelihood estimate, its standard error, and the p-value. The results of the single factor models, e.g., the logistic regression of the CARE & SERVICES composite with the independent variables, are shown through the use of asterisks in the first Column of Table 1. We see that Age, Education, Gender, Ansproxy, and CMS Region were significant in these models.

Table 1: Single Factor Logistic Regression Results—CARE & SERVICES Composite

Single Factor Results	**Results for the Dummy Variables**		
(Results are asterisks *)	Item Category	Logistic Regression Coefficient	Antilog (B)
Self-Perceived Health[15]			
	Poor (vs reference)	0.00707	1.007
	Fair (vs reference)	0.0445	1.046
	Good (vs reference)	0.00332	1.003
	Very good (vs reference)	0.0472	1.048
	Excellent (reference variable)		
Age ***			
	64 or younger (vs reference)	-0.3670***	0.693
	65 to 69 (reference variable)		
	70 to 74 (vs reference)	0.0266	1.027
	75 to 79 (vs reference)	0.1511***	1.163
	80 or older (vs reference)	0.2634***	1.300
Race[16]			
	White (reference variable)		
	Black (vs reference)	-0.0105	0.990

[15] Note: Self-perceived health is not significant, unless it is within an interaction with region, then it is significant at the <.0001. The region interactions are not shown here.
[16] Note: Race is not significant, except for Asian when categories of race are treated as dummies. When placed within an interaction with region it is significant for all dummies.

Single Factor Results	Results for the Dummy Variables		
(Results are asterisks *)	Item Category	Logistic Regression Coefficient	Antilog (B)
	Other (vs reference)	-0.2401	0.787
	Asian (vs reference)	-0.2324*	0.793
	Hispanic (vs reference)	0.0676	1.070
	Native American (vs reference)	-0.0256	0.975
Education ***			
	8th grade or less (vs reference)	-0.00121***	0.999
	Some high school (vs reference)	-0.1035*	0.902
	High school grad or GED (reference variable)		
	Some college or 2 yr degree (vs reference)	-0.2547***	0.775
	4 year college grad (vs reference)	0.3855***	1.470
	More than 4 yr college (vs reference)	0.3972***	1.488
Gender* **			
	Male (reference variable)		
	Female (vs reference)	0.1437***	1.154
Proxy			
Used a proxy to assist with survey		-0.0560	0.946
Ansproxy*			
Someone else answered the questions		-0.1418*	0.868
CMS Regions ***			
	Region 1 (vs reference)	0.0802	1.084
	Region 2 (vs reference)	-0.3382***	0.713
	Region 3 (vs reference)	-0.7680***	0.464
	Region 4 (vs reference)	0.0270***	1.027
	Region 5 (vs reference)	-0.3464***	0.707
	Region 6 (vs reference)	0.6937***	2.001
	Region 7 (vs reference)	-0.0960***	0.908
	Region 8 (vs reference)	-0.1881***	0.828
	Region 9 (vs reference)	0.1908**	1.210
	Region 10 (reference variable)		

Note: *Coefficient significant at the .05 alpha level; **coefficient significant at the .01 alpha level; ***coefficient significant at the .0001 alpha level.

Because it was possible for the effects of a number of the individual categorical variables to be weakened by examining the aggregated effect rather than the various categories within the variable, we disaggregated the effect through use of dummy variables. This was also consistent with Harvard's approach. Using only the aggregated effects would have masked the impact of certain races, certain age categories, or certain self-perceived health status (e.g., Did perceived poor health status have the same effect on the composite as an excellent rating?).

The regression coefficient for the dummy variable (Age) in a logit model represents the Age-dependent increment to the log-odds of citing a reason in the CARE & SERVICES composite. If the predicted or P values in the model are significant we decided to include the variable in the multivariate logistic regression models. However, this does not mean that the predicted values are necessarily a true representation of the observed values. The antilog represents the odds of selecting a reason in the CARE & SERVICES composite.

The logistic regression results (coefficients and odds ratio) for models of the dummy variables for the CARE & SERVICES composite are shown in the remaining three columns in Table 1. The dummy variables were found to provide more information and improved statistical results.

In the analyses of dummy variables, significant results were found for the following age dummy variables: Age 64 or younger, 75 to 79, and 80 or older in comparison to the reference age of 65-69. All levels of Education were significant when compared to the reference category, High School Grad or GED attained. Gender and Ansproxy were also significant. All CMS Region dummies, except Region 1, were significant when compared to the reference region. We also modeled interactions and found that those between Perceived Health Status and CMS Region, and Interactions between Race and CMS Region were significant. The interaction results are not shown in Table 1.

Nested Logistic Multivariate Models

As indicated in the strategy section, we fit a series of nested models. The first multivariate logistic regression is considered the base model (B1), and it consisted of the dependent variable CARE & SERVICES[17] and two independent variables used as control variables, Age with dummies and Perceived Health Status with dummies. This model was significant at the $p<0\ .0001$. The maximized $R^2=0.0098$ (the closer the values of R^2 to 1, the better the fit of the model, a maximized R^2 can achieve the value of one). The Hosmer-Lemeshow Chi squared Test was not significant at 0.896 with 7df; non-significant p values (p>Chisq) for the test indicate that the model fits the data. However, the C-statistic (C=0.546) suggests this model is only slightly better than chance. Since it was our base model, we expected other models to have improved fit statistics.

The next model (B2) added dummy variables for Gender, Race, Education, Proxy, Ansproxy, Region and Region interactions to the base model variables. We could compare the improvement in fit from the base model (B1) by subtracting the model likelihood ratio of (B1) from (B2) and subtracting the degrees of freedom similarly. The

[17] We discuss the Care Composite only given that the COST and BENEFITS composite was the inverse of the CARE & SERVICES composite.

resulting difference in likelihood ratio was 676.2793 with 43 degrees of freedom, this was a significant improvement in fit with a p=<0.0001. The maximized R^2 = 0.0591 was improved over Model (B1), the Hosmer-Lemeshow chi square was 18.7241 with 8 degrees of freedom, and a p=< 0.0864 which signified somewhat worse fit than model (B1), while C=0.621 suggested a better fit than Model (B1).

The next model, (B3) was created with backwards selection of Model (B2), to determine which variables (if any) would be dropped from the model. We could compare Model (B3) to the base Model (B1). This also resulted in a significant model with a difference in likelihood ratio =666.7927 and 39 degrees of freedom, p=<0.0001. It was only slightly less improvement than that for the comparison of the base model (B1) and model (B2). The other fit statistics for Model (B3) were comparable to Model (B2). In the backward selection the variables Proxy and Ansproxy were dropped. Because of the close comparability in fit, and the reduction in variables resulting in a simpler model—suggesting greater parsimony—we selected this model over (B2) as our recommended model for the case mix adjustment. The Model (B3) maximum likelihood estimates and their corresponding confidence intervals are located in Appendix 3. The model fit statistics are located in Appendix 4.

The last model, Model (B4), added the Health plan ID (contract number) to the remaining variables in Model (B3). However, this addition to the model was only for the purpose of examining differences in plan coefficients and odds ratios and not for assessing the significance of a case mix model. As one would expect, there was a significant improvement in fit over the statistics for the Model (B3) comparisons with (B1). The difference in likelihood ratio was = 2422.9851 with 177 degrees of freedom which was significant at the p=<0.0001, suggesting there was a significant amount of unique plan variation. The other statistics for this model also reflected a fairly consistent improvement in the goodness-of-fit. The maximized R^2 =0.2219, the Hosmer-Lemeshow chi square statistic was better than it was for the comparison results for Model (B3), as was the C-statistic, which was now showing that the model was able to predict the outcome of interest 74% of the time —a 24% improvement over chance. The Model (B4) maximum likelihood estimates and their corresponding confidence intervals are located in Appendix 3. The model fit statistics are located in Appendix 4.

To examine the health plan coefficients and the odds ratios for those coefficients in Model (B4), see Appendix 5. The odds ratios tell us what the probability of a response in the CARE & SERVICES is for a specific plan with the other factors in the model, this also helps us in comparing plans. Again it should be noted that the odds ratios are describing differences as related to the reference variable (plan).

We further examined the predictive capacity of our recommended model (B3) for the CARE & SERVICES composite, and we included the same information for Model (B4) to show the effects of adding the health plan ID. The model sensitivity and specificity results are located in Appendix 4. When we used a .49 probability level, Model (B3) was able to correctly predict (based on the variables in the model) 59% of the reasons in the CARE & SERVICES composite, the addition of the plan, Model (B4), improved the model's capacity to correctly predict 65.9% of the outcomes that that were in the data. The sensitivity of Model (B3) was 67.3% with 49.2% specificity, while the sensitivity of Model (B4) was 68.5% and the specificity was 63.2%. As expected, by adding the unique variance of the plan, greater prediction occurred. Model (B3) incorrectly identified about 41.7% of the endorsements as falling into the CARE & SERVICES composite incorrectly (False positives) and 41.2% of the true endorsements as not being in the CARE & SERVICES composite (False negatives).

The results of our analysis suggest that while we do have an adequate case-mix model other "missing variables" would improve the fit of the model. At this point the two additions (under study by others) would likely be perceived mental health perception and dual-eligibility. To add these variables to the model would require a merge of at least one additional year of data to achieve adequate cell sizes. The cell sizes could still be too small for the analysis, given that logistic regression models require about 80 cases in a cell (Glantz and Slinker, 1990).

Results from the Practical Application of the Case Mix Model

An important factor we needed to consider in assessing the value of this model was whether the model, when used to adjust the percentages of enrollees in the plan endorsing the composite, would alter the plan's "ranking" within their state. Further, we needed to take into account the manner in which this information is portrayed to the public. In this section we examine the practical results from applying the case mix adjustment. In the next section, we further describe the impact of decisions related to public reporting that reduce the effect of the case mix adjustment. Appendix 6 contains the results of our practical application.

First, we examined the difference in Model (B3) between the observed percent of disenrollees endorsing the CARE & SERVICES composite (Appendix 6: Col. 1) and the model predicted percent (Appendix 6: Col. 2); the difference between the observed and predicted percentages appears in Appendix 6: Col 3.

For public reporting of disenrollment reasons, the percent of disenrollees endorsing a particular composite are applied to the plan's adjusted disenrollment rate[18] (Appendix 6: Col. 4). For example, if 40% of disenrollees leave for reasons in the CARE & SERVICES composite and the plan's adjusted disenrollment rate is 20%, the number that is reported to the public for the percent of *enrollees* leaving due to CARE & SERVICES is 8% (40% of 20%). The actual impact of applying a case-mix adjustment when reporting to the public is determined by looking at both the impact of the model on the percent of disenrollees leaving for a particular reason *and* the plan's adjusted disenrollment rate.

[18] The unadjusted disenrollment rate is the number of individuals disenrolling from the plan, as a percentage of the cumulative annual enrollment. Some people leave a plan when their employer or former employer drops the plan from their benefits, this is not necessarily a voluntary decision—so disenrollment rates reported to the public do not include non-voluntary disenrollments.

The case mix model's impact (difference between observed and predicted) as shown in Col. 3, reflects the difference between the observed and predicted percent of disenrollees citing CARE & SERVICES. This difference ranged from –30% to + 35%, before taking into account the plan disenrollment rate.

The impact of applying the observed and predicted results to the percent of enrollees reduced the range of differences between observed and predictedto -12% to +16%. In other words, for a plan with a difference of –12%, the case mix adjustment made them look (given their case mix) as if an additional 12% of enrollees left due to reasons within the CARE & SERVICES composite. Conversely, it makes the COST & BENEFITS composite look like the percent of enrollees went down by 12%. At the other end of the spectrum, for a plan with a difference of 16%, the effect of the case mix adjustment was to make the plan look (given their case mix) as if the percent of enrollees endorsing a reason in the CARE & SERVICES composite went down by 16%.

Conclusions

Application of the Case Mix Model

While a case-mix model may be statistically significant, it still may not be appropriate to use if there are not substantial practical effects from its use. In this analysis, we examined the plan standings using both adjusted and unadjusted measures. See Appendix 6, titled, "Potential Impact of Case Mix Adjustment on 2000 Disenrollment Reason Information Reported to Consumers."

We found there were some health plans for which case mix adjustment results in a significant difference between the observed percent of disenrollees citing a reason within the CARE & SERVICE composite and the predicted percent of disenrollees with a most important reason in the CARE & SERVICES composite. However, reasons for disenrollment are not reported to the public based on percentages of disenrollees leaving for particular reasons but rather based on percentages of *enrollees*. This is because disenrollment reasons are reported to explain disenrollment rates – the denominator is the number of enrollees. Consequently, when the observed and predicted percents of disenrollees citing a reason within the CARE & SERVICES composite are the disenrollment rates, these differences are significantly reduced).
For example, if a plan had a 12% disenrollment rate, this publicly reported rate would be apportioned between the CARE & SERVICES composite and the COSTS & BENEFITS composite based on the applicable percentages.

When we examined the potential changes in ranking of plans within states (since this is how disenrollment rates and reasons are reported to the public) that would have occurred under case mix adjustment, , some small differences were still evident. However, the change in rank associated with these adjustments did not necessarily follow the expected pattern. One would expect those plans with the largest discrepancy between observed and predicted percentages would experience the largest change in rank. For example, a plan in Florida had an adjusted difference of 16% endorsing CARE & SERVICES with the case mix adjustment.. However, foor that plan, its in-state ranking actually remained the same, while the rank of another plan (in the same state) with a difference of only 3% when the case mix was added, changed by 4 positions. The plan moved from number 6 in the state to number 10; in this case, the plan appeared to have fewer enrollees prone to endorsing the CARE & SERVICES composite when the case mix was added, suggesting their population may be more difficult or complex to provide with services.

The threshold decision for determining whether to case mix adjust the reasons for disenrollment for the consumer website is a policy decision rather than a statistical decision. There is evidence that case mix adjustment does make a difference for a number of plans, but only when we ignore the manner in which the data is reported to the public. However, when we adjust the results to be compatible with the manner in which the consumer website portrays disenrollment rates and the apportionment of reasons (as a bifurcated rate), the majority of plans would not experience a change in position given the case mix adjustment. Yet, it does seem prudent to further examine case mix adjustment with additional years of data, given the evidence shown above. Lastly, we must always keep in mind that explaining case mix adjustment to consumers and plans can be a difficult task.

Concerns of TEP Members

At the February 6, 2002, third meeting of the Technical Expert Panel on the National Implementation of the CAHPS® Medicare Disenrollment Survey, a lively discussion took place on the merits of using a case-mix adjustment when reporting data from a survey like the Disenrollment Reasons Survey. There was substantial doubt among some members regarding the appropriateness of this action, given that the survey was designed to find differences across health plans in “reasons for disenrollment.” Some members felt that a case-mix adjustment would be “washing away” differences in the plans and this would be counter to the purposes of the survey.

However, consideration should also be given to the “fairness” of the representation of the plan. If in fact, some plans have more difficult or complex situations to address through their services, it might be unfair to compare them with plans serving beneficiaries who are relatively young and healthy. The results of the “practical application of the model” were not available at the time of the February 2002 TEP meeting—as a result, the discussion did not address the findings related to the practical impact. Through this analysis we have found that for some, albeit only a few, health plans there is a difference in the “characteristics of the disenrollees and their geographic location” that alters their relative standing in regard to the reasons for disenrollment from their plan.

One TEP member suggested that, if any case mix adjustment is to be used in reporting disenrollment information, then its focus should be on the potential case mix adjustment of the rates of disenrollment from the plans rather than just the reasons for disenrollment. This would imply bringing into the analysis the enrolled MMC population as well as the disenrolled MMC population. By case mix adjusting the rate of disenrollment we would be altering the observed rate of plan disenrollment and substituting an adjusted rate of disenrollment.

Another TEP member suggested that logistic models might not be adequately taking into consideration the differences in levels of the variables, i.e., individual vs. contextual. It was suggested that we further explore the results using hierarchical linear models that account for differences in the two levels (individual and contextual) for next year’s round of analysis.

A number of TEP members discussed the merits of including “health status” as a case-mix variable. There was concern that we were including a variable in our case mix that was potentially under the control of the plan and thus, was not an individual characteristic. While we agree that plans can (and should) impact the actual health of the beneficiary, we see a distinction between the self-assessed perception of health and the “health” impacts of the plan, as we discussed earlier. As we presented in the literature review, there is support in the existing research for asserting that self-reported health status is not under the plans' control, given that individuals' perceptions about their health status are unique to them, and are formed by factors other than those under the control of the plan, for example, their sense of being in control of their life, emotional distress, having a low income, etc. Other research has also shown that even when plans alter some components of managed care, such as the amount of cost sharing, there is no impact on self-reported health status even though the enrollees have gone without care for serious symptoms. Also, there is evidence that some individuals with serious chronic diseases will rate themselves as being in good health even when their caregivers would indicate their health as being poor (Rubenstein, Schairer, Wieland, and Kane, 1984; Leinonen, Heikkinen, and Jylha, 1999).

Next Steps

In response to the concerns of TEP members, we will work with CMS on the issue of investigating the desirability and feasibility of developing a case mix adjustment model for reporting disenrollment rates as an alternative strategy to work on in the next contract period. The methodology would differ depending on the level of analysis; the analysis could either be conducted at the plan level with the dependent variable as a plan-level rate, or at the individual level with a dichotomous dependent variable (disenrolled or did not disenroll). Analysis at either level would require information about both enrollees and disenrollees.

For the 2001 Disenrollment Reasons data, we propose running a test of the same series of logistic regression models we used in this analysis,[19] with data that has been pooled across two years in order to improve the stability of the results and to have an adequate sample for an analysis of the lower level reasons groupings. The individual level factor analysis derived five separate factors that were then collapsed into the two composites, CARE & SERVICES and COSTS & BENEFITS. When we attempted modeling the five consumer reason groupings using the 2000 data alone, the models were unstable for two of the composites, due to small and zero cell sizes. We may also want to examine the eight plan groupings using two years of pooled data.

We would also suggest adding perceived mental health status to the analysis, given the recent recommendation by the Harvard team. We could also examine dual-eligibility as a potential adjuster using two years of data, if cell sizes allow.

Given feedback from the TEP, we will consider conducting the case mix analysis using Hierarchical Linear Models to account for the differences in variable levels in the analysis. In hierarchical modeling we would first model the individual characteristics that lead to endorsing a specific composite and then we would use the slope and intercept of that model as the dependent variable in a model containing the contextual level variables, like CMS Region. We could examine the findings of both types of models (logistic and HLM) and make recommendations for the future as to the preferred methodology.

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[19] Prior to this analysis, we will conduct a confirmatory factor analysis of the "Reasons" data to assure that the reason groupings are consistent over time and that they are not sample specific.

We will also continue to monitor the literature for studies using the selected case-mix variables particularly with respect to the rationale for using self-perceived health status as a case mix variable and to glean whether some additional variable(s) might improve the goodness-of-fit of the models.

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APPENDICES

Appendix 1: Pre-printed Reasons Questions
2000 CAHPS® Medicare Disenrollment Survey

"Did you leave [MEDICARE HEALTH PLAN NAME] because you could not pay the monthly premium?"

"Did you leave [MEDICARE HEALTH PLAN NAME] because the plan did not include the doctors or other health care providers you wanted to see?"

"Did you leave [MEDICARE HEALTH PLAN NAME] because the doctor you wanted to see retired or left the plan? "

"Did you leave [MEDICARE HEALTH PLAN NAME] because the plan doctor or other health care provider you wanted to see was not accepting new patients? "

"Did you leave [MEDICARE HEALTH PLAN NAME] because you could not see the plan doctor or other care health provider you wanted to see on every visit? "

"Did you leave [MEDICARE HEALTH PLAN NAME] because the plan doctors or other health care providers did not explain things in a way you could understand? "

"Did you leave [MEDICARE HEALTH PLAN NAME] because you had problems with the plan doctors or other health care providers?

"Did you leave [MEDICARE HEALTH PLAN NAME] because you had problems or delays getting the plan to approve referrals to specialists?

"Did you leave [MEDICARE HEALTH PLAN NAME] because you had problems getting the care you needed when you needed it?"

"Did you leave [MEDICARE HEALTH PLAN NAME] because the plan refused to pay for emergency or other urgent care? "

"Did you leave [MEDICARE HEALTH PLAN NAME] because you could not get admitted to a hospital when you needed to? "

"Did you leave [MEDICARE HEALTH PLAN NAME] because you had to leave the hospital before you or your doctor thought you should?

"Did you leave [MEDICARE HEALTH PLAN NAME] because you could not get special medical equipment when you needed it? "

“Did you leave [MEDICARE HEALTH PLAN NAME] because you could not get home health care when you needed it? ”

***“Did you leave [MEDICARE HEALTH PLAN NAME] because you had no transportation or it was too far to the clinic or doctor’s office where you had to go for regular or routine health care? ”**

“Did you leave [MEDICARE HEALTH PLAN NAME] because you could not get an appointment for regular or routine health care as soon as you wanted? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because you had to wait too long past your appointment time to see the health care provider you went to see? ”

***“Did you leave [MEDICARE HEALTH PLAN NAME] because you wanted to be sure you could get the health care you need while you are out of town or traveling away from home?”**

“Did you leave [MEDICARE HEALTH PLAN NAME] because you thought you were given incorrect or incomplete information at the time you joined the plan? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because after you joined the plan, it wasn’t what you expected? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because information from the plan about things like benefits, services, doctors, and rules was hard to get or not very helpful? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because the maximum dollar amount the plan allowed each year (or quarter) for your prescription medicine was not enough to meet your needs? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because the plan required you to get a generic medicine when you wanted a brand name medicine? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because the plan would not pay for a medication that your doctor had prescribed? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because another plan would cost you less? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because the plan would not pay for some of the care you needed? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because another plan offered better benefits or coverage for some types of care or services? ”

“Did you leave the plan because [MEDICARE HEALTH PLAN NAME] started charging you a monthly premium, or increased the monthly premium that you pay?”

“Did you leave because [MEDICARE HEALTH PLAN NAME] increased the co-payment that you paid for office visits to your doctor and for other services?”

“Did you leave because [MEDICARE HEALTH PLAN NAME] increased the co-payment that you paid for prescription medicines? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because the plan’s customer service staff were not helpful or you were dissatisfied with the way they handled your questions or complaint? ”

“Did you leave [MEDICARE HEALTH PLAN NAME] because your doctor or other care health provider or someone from the plan told you that you could get better care elsewhere? ”

* **“Did you leave [MEDICARE HEALTH PLAN NAME] because you or your spouse, another family member, or a friend had a bad experience with that plan? ”**

* ***Dropped from the case mix analysis.***

Reasons Categories for Consumer and Plan Reports

Consumer Reporting	Plan Reporting	Survey Item (*Items dropped from the analysis)
Problems with Care or Service		
Problems with information from the plan	Problems with information from the plan	Thought you were given incorrect or incomplete information at the time you joined the plan After joining the plan, it wasn't what you expected Information from the plan about things like benefits, services, doctors, and rules was hard to get or not very helpful Plan's customer service staff were not helpful or you were dissatisfied with the way they handled your questions or complaint Insecurity about future of plan or about continued coverage
Problems getting particular doctors	Problems getting particular doctors	Plan did not include doctors or other providers you wanted to see Doctor or other provider you wanted to see retired or left the plan Doctor or other provider you wanted to see was not accepting new patients Could not see the doctor or other provider you wanted to see on every visit
Problems getting care	Problems getting care	Could not get appointment for regular or routine health care as soon as wanted Had to wait too long past your appointment time to see the health care provider you went to see Doctors or other health care providers did not explain things in a way you could understand Had problems with the plan doctors or other health care providers Had problems or delays getting the plan to approve referrals to specialists Had problems getting the care you needed when you needed it
	Problems getting particular needs met	Plan refused to pay for emergency or other urgent care Could not get admitted to a hospital when you needed to Had to leave the hospital before you or your doctor thought you should Could not get special medical equipment when you needed it Could not get home health care when you needed it Plan would not pay for some of the care you needed
	Other problems with care or service	Had no transportation or it was too far to the clinic or doctor's office where you had to go for regular or routine health care* Wanted to be sure you could get the health care you need while you are out of town or traveling away from home* Doctor or other care health provider or someone from the plan told you that you could get better care elsewhere* You or your spouse, another family member, or friend had a bad experience with that plan
Concerns about Costs		
Issues with premiums, co-payments, or coverage	Premiums or co-payments too high	Could not pay the monthly premium Another plan would cost you less Plan started charging you a monthly premium, or increased the monthly premium that you pay
	Co-payments increased and/or another plan offered better coverage	Another plan offered better benefits or coverage for some types of care or services Plan increased the co-payment that you paid for office visits to your doctor and for other services Plan increased the co-payment that you paid for prescription medicines No longer needed coverage under the plan
Problems getting or paying for prescription medicines	Problems getting or paying for prescription medicines	Maximum dollar amount the plan allowed each year (or quarter) for your prescription medicine was not enough to meet your needs Plan required you to get a generic medicine when you wanted a brand name medicine Plan would not pay for a medication that your doctor had prescribed

Appendix 2: Variable Frequencies

Variable Frequencies[20]
AGE

AGE	Frequency	Percent	Cumulative Frequency	Cumulative Percent
64 or younger	2340	10.94	2340	10.94
65-69	5854	27.38	8194	38.32
70-74	5549	25.95	13743	64.28
75-79	4036	18.88	17779	83.15
80 and older	3602	16.85	21381	100%

GENDER

GENDER	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Male	9140	42.75	9140	42.75
Female	12241	57.25	21381	100%

PERCEPTION OF GENERAL HEALTH

HEALTH STATUS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Excellent	1399	6.86	1399	6.86
Very Good	4598	22.53	5997	29.39
Good	7463	36.57	13460	65.96
Fair	5159	25.28	18619	91.25
Poor	1786	8.75	20405	100%

Frequency Missing= 976

[20] Cases were assigned to missing when they did not contain the case mix variable and we could not locate additional information from other files. No imputation was done.

EDUCATION

EDUCATION	Frequency	Percent	Cumulative Frequency	Cumulative Percent
8th grade or less	2629	13.20	2629	13.20
Some high school	3507	17.61	6136	30.81
HS Grad or GED	6791	34.10	12927	64.92
Some College or 2 Yr. Degree	4394	22.07	17321	86.98
4 Year College Grad	1306	6.56	18627	93.54
More than 4 Yr College	1286	6.46	19913	100%

Frequency Missing=1468

RACE

RACE	Frequency	Percent	Cumulative Frequency	Cumulative Percent
White	17090	80.13	17090	80.13
Black	2336	10.95	19426	91.08
Other	38	0.18	19464	91.26
Asian	317	1.49	19781	92.75
Hispanic	1284	6.02	21065	98.77
Native American	263	1`.23	21328	100%

Frequency Missing = 53

CMS REGION

CMS REGION	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1--CT, ME, MA, NH, RI, VT	1213	5.68	1213	5.68
2--NJ,NY,PR,VI	2986	13.8	4199	19.65
3--DE,D.C.,MD,PA,VA,WV	1864	8.72	6063	28.38
4--L,NC,SC,FL,GA,KY,MS,TN	4613	21.59	10676	49.97
5--IL,IN,MI,MN,OH,WI	2866	13.41	13542	63.38
6--AR,LA,NM,OK,TX	1529	7.16	15071	70.54
7--IA,KS,MO,NE	997	4.67	16068	75.20
8--CO,MT,ND,SD,UT,WY	381	1.78	16449	76.99
9--AZ,CA,HI,NV	3563	16.68	20012	93.66
10--AK,ID,OR,WA	1354	6.34	21366	100%

Frequency Missing = 15

Appendix 3: Maximum Likelihood Estimates for Models B3 and B4

Model B3

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-0.3628	0.1478	6.0257	0.0141
AGEDUM1	1	-0.5322	0.1258	17.8833	<.0001
AGEDUM3	1	-0.1451	0.0885	2.6886	0.1011
AGEDUM4	1	0.00925	0.0977	0.0090	0.9246
AGEDUM5	1	0.1350	0.1059	1.6246	0.2024
HLTHDUM2	1	-0.1472	0.1388	1.1250	0.2888
HLTHDUM3	1	-0.0989	0.1330	0.5532	0.4570
HLTHDUM4	1	-0.0969	0.1412	0.4708	0.4926
HLTHDUM5	1	0.00436	0.1756	0.0006	0.9802
EDUCDUM1	1	-0.1276	0.1133	1.2670	0.2603
EDUCDUM2	1	-0.0566	0.0962	0.3462	0.5563
EDUCDUM4	1	0.1261	0.0916	1.8925	0.1689
EDUCDUM5	1	0.3040	0.1406	4.6748	0.0306
EDUCDUM6	1	0.3267	0.1439	5.1563	0.0232
RACEDUM2	1	0.2548	0.1235	4.2606	0.0390
RACEDUM3	1	-0.8295	0.9882	0.7045	0.4013
RACEDUM4	1	0.3741	0.3369	1.2335	0.2667
RACEDUM5	1	0.3940	0.1570	6.2948	0.0121
RACEDUM6	1	-0.2375	0.3819	0.3867	0.5341
GENDUM2	1	0.1738	0.0674	6.6526	0.0099
REGDUM1	1	0.5241	0.2320	5.1037	0.0239
REGDUM2	1	0.0147	0.2057	0.0051	0.9428
REGDUM3	1	-0.3851	0.1862	4.2789	0.0386
REGDUM4	1	0.3261	0.1601	4.1467	0.0417
REGDUM5	1	-0.0841	0.1410	0.3558	0.5508
REGDUM6	1	0.9623	0.1300	54.8295	<.0001
REGDUM7	1	0.0753	0.1176	0.4098	0.5221
REGDUM8	1	-0.1156	0.1384	0.6977	0.4035
REGDUM9	1	0.2664	0.0763	12.1930	0.0005
AGEDUM1*CMSREG	1	0.0254	0.0219	1.3390	0.2472
AGEDUM3*CMSREG	1	0.0346	0.0154	5.0349	0.0248
AGEDUM4*CMSREG	1	0.0287	0.0168	2.9009	0.0885
AGEDUM5*CMSREG	1	0.0172	0.0179	0.9190	0.3377
HLTHDUM2*CMSREG	1	0.0415	0.0237	3.0667	0.0799
HLTHDUM3*CMSREG	1	0.0309	0.0228	1.8290	0.1762
HLTHDUM4*CMSREG	1	0.0457	0.0242	3.5516	0.0595
HLTHDUM5*CMSREG	1	0.0284	0.0301	0.8882	0.3460
EDUCDUM1*CMSREG	1	0.00566	0.0204	0.0768	0.7816
EDUCDUM2*CMSREG	1	-0.0134	0.0173	0.5944	0.4407
EDUCDUM4*CMSREG	1	0.00125	0.0152	0.0068	0.9341
EDUCDUM5*CMSREG	1	0.0204	0.0237	0.7393	0.3899
EDUCDUM6*CMSREG	1	0.0131	0.0240	0.2971	0.5857
RACEDUM2*CMSREG	1	-0.0336	0.0255	1.7322	0.1881
RACEDUM3*CMSREG	1	0.0568	0.1470	0.1491	0.6994
RACEDUM4*CMSREG	1	-0.1166	0.0442	6.9719	0.0083
RACEDUM5*CMSREG	1	-0.0709	0.0256	7.6738	0.0056
RACEDUM6*CMSREG	1	0.0105	0.0540	0.0379	0.8456
GENDUM2*CMSREG	1	-0.00546	0.0116	0.2224	0.6372

Model B4

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept		1	-0.2866	3.6219	0.0063	0.9369
AGEDUM1		1	-0.4745	0.1385	11.7450	0.0006
AGEDUM3		1	-0.1309	0.0973	1.8099	0.1785
AGEDUM4		1	0.0930	0.1072	0.7520	0.3859
AGEDUM5		1	0.2353	0.1167	4.0675	0.0437
HLTHDUM2		1	-0.1556	0.1524	1.0425	0.3072
HLTHDUM3		1	-0.0781	0.1460	0.2856	0.5930
HLTHDUM4		1	-0.1868	0.1549	1.4530	0.2281
HLTHDUM5		1	-0.1036	0.1929	0.2882	0.5914
EDUCDUM1		1	-0.3108	0.1246	6.2174	0.0126
EDUCDUM2		1	-0.0639	0.1056	0.3656	0.5454
EDUCDUM4		1	0.1183	0.1004	1.3881	0.2387
EDUCDUM5		1	0.2837	0.1548	3.3591	0.0668
EDUCDUM6		1	0.4072	0.1573	6.6987	0.0096
RACEDUM2		1	-0.3051	0.1453	4.4122	0.0357
RACEDUM3		1	-1.1835	1.0185	1.3505	0.2452
RACEDUM4		1	-0.2460	0.3699	0.4421	0.5061
RACEDUM5		1	0.0901	0.1820	0.2449	0.6207
RACEDUM6		1	-0.4966	0.4165	1.4215	0.2332
GENDUM2		1	0.1416	0.0736	3.6989	0.0544
REGDUM1		1	0.3349	0.3770	0.7889	0.3744
REGDUM2		1	0.5915	0.3208	3.3994	0.0652
REGDUM3		1	0.2655	0.3144	0.7130	0.3984
REGDUM4		1	0.5226	0.2662	3.8534	0.0496
REGDUM5		1	0.1690	0.2593	0.4244	0.5147
REGDUM6		1	0.2328	0.2848	0.6680	0.4137
REGDUM7		1	-0.0755	0.2772	0.0743	0.7852
REGDUM8		1	-0.5069	0.2919	3.0156	0.0825
REGDUM9		1	-0.1973	0.1810	1.1882	0.2757
CONTRACT	H0150	1	1.6566	3.6259	0.2087	0.6478
CONTRACT	H0151	1	0.0244	3.6197	0.0000	0.9946
CONTRACT	H0152	1	-0.3615	3.6217	0.0100	0.9205
CONTRACT	H0153	1	2.0639	3.6286	0.3235	0.5695
CONTRACT	H0154	1	1.0328	3.6229	0.0813	0.7756
CONTRACT	H0303	1	1.2469	3.6231	0.1184	0.7307
CONTRACT	H0307	1	0.6557	3.6206	0.0328	0.8563
CONTRACT	H0350	1	1.9943	3.6574	0.2973	0.5856
CONTRACT	H0351	1	-0.0238	3.6211	0.0000	0.9948
CONTRACT	H0354	1	1.7097	3.6249	0.2224	0.6372
CONTRACT	H0502	1	-12.2264	444.3	0.0008	0.9780
CONTRACT	H0504	1	0.7296	3.6218	0.0406	0.8403
CONTRACT	H0523	1	-0.3075	3.6202	0.0072	0.9323
CONTRACT	H0524	1	-0.0592	3.6207	0.0003	0.9870
CONTRACT	H0526	1	0.1988	3.6200	0.0030	0.9562
CONTRACT	H0529	1	0.2006	3.6253	0.0031	0.9559
CONTRACT	H0543	1	0.5000	3.6207	0.0191	0.8902
CONTRACT	H0545	1	0.8984	3.6210	0.0616	0.8041
CONTRACT	H0559	1	-0.5481	3.6234	0.0229	0.8798
CONTRACT	H0562	1	-0.1806	3.6204	0.0025	0.9602
CONTRACT	H0564	1	-0.1222	3.6199	0.0011	0.9731
CONTRACT	H0566	1	0.7679	3.6221	0.0449	0.8321
CONTRACT	H0571	1	0.5463	3.6764	0.0221	0.8819
CONTRACT	H0583	1	0.4906	3.6247	0.0183	0.8923
CONTRACT	H0584	1	0.3686	3.6220	0.0104	0.9189
CONTRACT	H0591	1	0.2101	3.6233	0.0034	0.9538
CONTRACT	H0598	1	0.1231	3.6241	0.0012	0.9729
CONTRACT	H0602	1	-0.4845	3.6267	0.0178	0.8937
CONTRACT	H0609	1	0.7530	3.6268	0.0431	0.8355
CONTRACT	H0630	1	1.0761	3.6340	0.0877	0.7671
CONTRACT	H0657	1	-11.5536	219.9	0.0028	0.9581
CONTRACT	H0752	1	0.1565	3.6373	0.0019	0.9657
CONTRACT	H0755	1	-0.7665	3.6268	0.0447	0.8326
CONTRACT	H0954	1	0.00688	3.6222	0.0000	0.9985
CONTRACT	H1010	1	-1.2439	3.6442	0.1165	0.7328
CONTRACT	H1013	1	0.6801	3.6246	0.0352	0.8512
CONTRACT	H1016	1	-0.6889	3.6196	0.0362	0.8491
CONTRACT	H1019	1	1.5841	3.6292	0.1905	0.6625
CONTRACT	H1020	1	-0.7859	3.6275	0.0469	0.8285
CONTRACT	H1026	1	-0.5593	3.6198	0.0239	0.8772
CONTRACT	H1027	1	0.0579	3.6230	0.0003	0.9873
CONTRACT	H1035	1	-0.4041	3.6192	0.0125	0.9111
CONTRACT	H1036	1	-0.1591	3.6203	0.0019	0.9650
CONTRACT	H1057	1	-2.2449	3.6259	0.3833	0.5358

CONTRACT	H1059	1	-1.7554	3.6292	0.2340	0.6286
CONTRACT	H1061	1	-1.7854	3.6301	0.2419	0.6228
CONTRACT	H1062	1	-2.2193	3.6292	0.3740	0.5409
CONTRACT	H1071	1	-0.6194	3.6202	0.0293	0.8641
CONTRACT	H1076	1	-1.1352	3.6203	0.0983	0.7538
CONTRACT	H1078	1	-0.0249	3.6213	0.0000	0.9945
CONTRACT	H1080	1	-0.4898	3.6208	0.0183	0.8924
CONTRACT	H1082	1	-0.4110	3.6191	0.0129	0.9096
CONTRACT	H1095	1	-1.0309	3.6233	0.0810	0.7760
CONTRACT	H1099	1	-1.0091	3.6197	0.0777	0.7804
CONTRACT	H1168	1	0.7094	3.6208	0.0384	0.8447
CONTRACT	H1170	1	0.5451	3.6209	0.0227	0.8803
CONTRACT	H1230	1	0.0162	3.6299	0.0000	0.9964
CONTRACT	H1251	1	-0.6951	3.6316	0.0366	0.8482
CONTRACT	H1349	1	-1.0015	3.6234	0.0764	0.7822
CONTRACT	H1350	1	-0.5760	3.6268	0.0252	0.8738
CONTRACT	H1406	1	0.5326	3.6220	0.0216	0.8831
CONTRACT	H1463	1	-0.0253	3.6235	0.0000	0.9944
CONTRACT	H1472	1	-0.3981	3.6746	0.0117	0.9137
CONTRACT	H1553	1	0.1271	3.6267	0.0012	0.9721
CONTRACT	H1555	1	-0.0617	3.6473	0.0003	0.9865
CONTRACT	H1558	1	0.6153	3.6352	0.0286	0.8656
CONTRACT	H1651	1	0.4374	3.8186	0.0131	0.9088
CONTRACT	H1751	1	2.2056	3.6332	0.3685	0.5438
CONTRACT	H1849	1	0.9204	3.6265	0.0644	0.7997
CONTRACT	H1951	1	1.2487	3.6331	0.1181	0.7311
CONTRACT	H1958	1	0.3625	3.6243	0.0100	0.9203
CONTRACT	H1961	1	1.3376	3.6268	0.1360	0.7123
CONTRACT	H2204	1	1.9379	3.6516	0.2816	0.5956
CONTRACT	H2206	1	1.3923	3.6292	0.1472	0.7012
CONTRACT	H2256	1	1.4285	3.6264	0.1552	0.6936
CONTRACT	H2261	1	-1.5234	3.6265	0.1765	0.6744
CONTRACT	H2312	1	-0.1619	3.6232	0.0020	0.9644
CONTRACT	H2353	1	0.7002	3.6225	0.0374	0.8467
CONTRACT	H2354	1	-0.8980	3.6249	0.0614	0.8043
CONTRACT	H2459	1	-0.6982	3.6223	0.0372	0.8472
CONTRACT	H2461	1	-0.7772	3.6608	0.0451	0.8319
CONTRACT	H2462	1	-1.0155	3.6233	0.0786	0.7793
CONTRACT	H2649	1	-0.0149	3.6236	0.0000	0.9967
CONTRACT	H2654	1	0.9083	3.6230	0.0629	0.8020
CONTRACT	H2663	1	-0.7020	3.6212	0.0376	0.8463
CONTRACT	H2666	1	-0.3107	3.6226	0.0074	0.9317
CONTRACT	H2667	1	-0.7187	3.6324	0.0391	0.8432
CONTRACT	H2668	1	-0.4115	3.6278	0.0129	0.9097
CONTRACT	H2802	1	0.2706	3.6236	0.0056	0.9405
CONTRACT	H2931	1	0.5846	3.6251	0.0260	0.8719
CONTRACT	H2949	1	1.1662	3.6229	0.1036	0.7475
CONTRACT	H2960	1	0.3372	3.6220	0.0087	0.9258
CONTRACT	H2961	1	1.3417	3.6247	0.1370	0.7113
CONTRACT	H3107	1	0.0107	3.6272	0.0000	0.9976
CONTRACT	H3152	1	-1.5610	3.6220	0.1857	0.6665
CONTRACT	H3154	1	-0.6639	3.6208	0.0336	0.8545
CONTRACT	H3156	1	-1.5673	3.6214	0.1873	0.6652
CONTRACT	H3164	1	1.2037	3.6770	0.1072	0.7434
CONTRACT	H3204	1	0.8835	3.6256	0.0594	0.8075
CONTRACT	H3251	1	-0.2364	3.6264	0.0043	0.9480
CONTRACT	H3305	1	-0.6239	3.6218	0.0297	0.8632
CONTRACT	H3307	1	-0.2354	3.6234	0.0042	0.9482
CONTRACT	H3312	1	-1.1607	3.6256	0.1025	0.7489
CONTRACT	H3330	1	-0.5447	3.6229	0.0226	0.8805
CONTRACT	H3351	1	-1.3633	3.6214	0.1417	0.7066
CONTRACT	H3356	1	-3.1921	3.6536	0.7633	0.3823
CONTRACT	H3359	1	1.4180	3.6308	0.1525	0.6961
CONTRACT	H3361	1	-0.2798	3.6206	0.0060	0.9384
CONTRACT	H3362	1	-0.2814	3.6215	0.0060	0.9381
CONTRACT	H3366	1	0.6192	3.6240	0.0292	0.8643
CONTRACT	H3370	1	0.1690	3.6220	0.0022	0.9628
CONTRACT	H3379	1	0.4895	3.6233	0.0182	0.8925
CONTRACT	H3384	1	-1.6506	3.6217	0.2077	0.6486
CONTRACT	H3385	1	-0.0538	3.6251	0.0002	0.9882
CONTRACT	H3387	1	1.2866	3.7976	0.1148	0.7348
CONTRACT	H3449	1	-0.7282	3.6194	0.0405	0.8405
CONTRACT	H3455	1	-0.3510	3.6195	0.0094	0.9227
CONTRACT	H3456	1	0.6902	3.6205	0.0363	0.8488
CONTRACT	H3503	1	12.8289	313.7	0.0017	0.9674
CONTRACT	H3607	1	-0.6402	3.6216	0.0312	0.8597
CONTRACT	H3653	1	-0.9760	3.6252	0.0725	0.7877
CONTRACT	H3655	1	-0.0848	3.6213	0.0005	0.9813
CONTRACT	H3657	1	-0.3581	3.6209	0.0098	0.9212
CONTRACT	H3659	1	-0.1081	3.6204	0.0009	0.9762
CONTRACT	H3660	1	-0.1897	3.6219	0.0027	0.9582
CONTRACT	H3664	1	0.8327	3.6331	0.0525	0.8187

CONTRACT	H3668	1	-1.2885	3.6226	0.1265	0.7221
CONTRACT	H3672	1	0.1972	3.6199	0.0030	0.9566
CONTRACT	H3673	1	0.6664	3.6684	0.0330	0.8559
CONTRACT	H3749	1	0.7987	3.6249	0.0485	0.8256
CONTRACT	H3755	1	1.1632	3.6311	0.1026	0.7487
CONTRACT	H3756	1	1.5635	3.6296	0.1856	0.6666
CONTRACT	H3805	1	0.5418	3.6232	0.0224	0.8811
CONTRACT	H3851	1	-0.3629	3.6241	0.0100	0.9202
CONTRACT	H3856	1	0.0943	3.6256	0.0007	0.9792
CONTRACT	H3858	1	-0.6040	3.6307	0.0277	0.8679
CONTRACT	H3862	1	-0.2367	3.6261	0.0043	0.9480
CONTRACT	H3864	1	0.2635	3.6263	0.0053	0.9421
CONTRACT	H3931	1	-1.1931	3.6242	0.1084	0.7420
CONTRACT	H3949	1	-0.1740	3.6239	0.0023	0.9617
CONTRACT	H3951	1	-1.1885	3.6267	0.1074	0.7431
CONTRACT	H3952	1	-1.3886	3.6241	0.1468	0.7016
CONTRACT	H3954	1	0.4743	3.6235	0.0171	0.8959
CONTRACT	H3957	1	-0.6960	3.6225	0.0369	0.8476
CONTRACT	H3959	1	-1.2835	3.6235	0.1255	0.7232
CONTRACT	H3960	1	-1.3473	3.6282	0.1379	0.7104
CONTRACT	H3962	1	-0.6819	3.6225	0.0354	0.8507
CONTRACT	H3963	1	-2.0191	3.6308	0.3092	0.5781
CONTRACT	H3964	1	1.1554	3.6260	0.1015	0.7500
CONTRACT	H4102	1	0.0701	3.6247	0.0004	0.9846
CONTRACT	H4152	1	-0.8542	3.6268	0.0555	0.8138
CONTRACT	H4153	1	-0.1620	3.6319	0.0020	0.9644
CONTRACT	H4454	1	0.6133	3.6215	0.0287	0.8655
CONTRACT	H4456	1	-0.1131	3.6208	0.0010	0.9751
CONTRACT	H4461	1	0.3659	3.6231	0.0102	0.9196
CONTRACT	H4504	1	-0.0961	3.6284	0.0007	0.9789
CONTRACT	H4510	1	0.8292	3.6276	0.0522	0.8192
CONTRACT	H4564	1	-0.6013	3.6261	0.0275	0.8683
CONTRACT	H4572	1	1.8038	3.6421	0.2453	0.6204
CONTRACT	H4590	1	1.9824	3.6313	0.2980	0.5851
CONTRACT	H5005	1	0.7792	3.6239	0.0462	0.8298
CONTRACT	H5050	1	-0.4064	3.6272	0.0126	0.9108
CONTRACT	H5063	1	0.1233	3.6246	0.0012	0.9729
CONTRACT	H5102	1	-1.8712	3.6688	0.2601	0.6100
CONTRACT	H5149	1	-0.5839	3.6633	0.0254	0.8734
CONTRACT	H5253	1	-1.2342	3.6216	0.1161	0.7333
CONTRACT	H5254	1	0.7090	3.6331	0.0381	0.8453
CONTRACT	H5264	1	-0.0892	3.6684	0.0006	0.9806
CONTRACT	H9001	1	2.0332	3.6348	0.3129	0.5759
CONTRACT	H9003	1	-0.1010	3.6291	0.0008	0.9778
CONTRACT	H9005	1	-0.7719	3.6228	0.0454	0.8313
CONTRACT	H9011	1	-0.2652	3.6219	0.0054	0.9416
CONTRACT	H9016	1	1.5729	3.6249	0.1883	0.6644
CONTRACT	H9047	1	-0.4274	3.6272	0.0139	0.9062
CONTRACT	H9049	1	12.0647	255.6	0.0022	0.9624
CONTRACT	H9101	1	1.0977	3.6294	0.0915	0.7623
CONTRACT	H9103	1	-1.2998	3.6652	0.1258	0.7229
AGEDUM1*CMSREG		1	0.00783	0.0239	0.1077	0.7428
AGEDUM3*CMSREG		1	0.0320	0.0166	3.7004	0.0544
AGEDUM4*CMSREG		1	0.0191	0.0182	1.1079	0.2925
AGEDUM5*CMSREG		1	0.00996	0.0194	0.2629	0.6082
HLTHDUM2*CMSREG		1	0.0406	0.0256	2.5159	0.1127
HLTHDUM3*CMSREG		1	0.0253	0.0246	1.0552	0.3043
HLTHDUM4*CMSREG		1	0.0541	0.0261	4.2806	0.0386
HLTHDUM5*CMSREG		1	0.0368	0.0326	1.2789	0.2581
EDUCDUM1*CMSREG		1	0.0296	0.0221	1.7979	0.1800
EDUCDUM2*CMSREG		1	-0.0120	0.0187	0.4127	0.5206
EDUCDUM4*CMSREG		1	0.00399	0.0163	0.0596	0.8072
EDUCDUM5*CMSREG		1	0.0198	0.0255	0.6039	0.4371
EDUCDUM6*CMSREG		1	0.00425	0.0258	0.0273	0.8689
RACEDUM2*CMSREG		1	0.0197	0.0287	0.4718	0.4922
RACEDUM3*CMSREG		1	0.1058	0.1498	0.4988	0.4800
RACEDUM4*CMSREG		1	-0.0309	0.0491	0.3975	0.5284
RACEDUM5*CMSREG		1	-0.0381	0.0286	1.7717	0.1832
RACEDUM6*CMSREG		1	0.0483	0.0581	0.6906	0.4059
GENDUM2*CMSREG		1	-0.00226	0.0124	0.0328	0.8562

Appendix 4

Model Statistics

CARE & SERVICES Composite

Models	AIC	Max R^2	Likelihood Ratio	df	Pr	C-Statistic	Hosmer-Lemeshow	df	Pr
B1	25631.126 25510.131	0.0098	136.9957	8	<.0001	0.546	2.8787	7	0.8960
B2	24575.207 23863.934	0.0598	813.2725	51	<.0001	0.621	18.7241	8	0.0164
B3	24575.207 23865.419	0.0591	803.7884	47	<.0001	0.620	14.1181	8	0.0878
B4	24575.207 21796.433	0.2219	3226.7735	224	<.0001	0.736	5.0726	8	0.7498

Likelihood Ratio Tests for Competing Models

CARE & SERVICES Composite

Models	Comparisons	Δ Likelihood Ratio	df	P=	
(B1) Age & Health Status					Base Model
(B2) Age, Health, Gender, Race, Education, Proxy, Ansproxy, Region, Region Interactions	B1 & B2	676.2793	43	<.0001	
(B3) Backward Selection of (B2)	B1 & B3	666.7927	39	<.0001	Final Model
(B4) Added contract (Plan) to Model (B3)	B1 & B4	2422.9851	177	<.0001	Plan Effect

Classification Table
CARE & SERVICES Composite

Models B3 & B4

		Correct		Incorrect		Percentages				
	Prob Level	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
Model B3	0.490	6129	4245	4385	2976	58.5	67.3	49.2	41.7	41.2
Model B4	0.490	6237	5458	3172	2868	65.9	68.5	63.2	33.7	34.4

Appendix 5: Model B4 Plan Coefficients and Odds Ratios

CARE & SERVICES Composite

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
CONTRACT H0150 vs H9104 [21]	1.925	0.931	3.982
CONTRACT H0151 vs H9104	0.376	0.208	0.680
CONTRACT H0152 vs H9104	0.258	0.136	0.489
CONTRACT H0153 vs H9104	2.900	1.334	6.304
CONTRACT H0154 vs H9104	1.029	0.529	2.004
CONTRACT H0303 vs H9104	1.130	0.598	2.134
CONTRACT H0307 vs H9104	0.645	0.360	1.154
CONTRACT H0350 vs H9104	2.390	0.743	7.691
CONTRACT H0351 vs H9104	0.320	0.178	0.578
CONTRACT H0354 vs H9104	1.763	0.901	3.451
CONTRACT H0502 vs H9104	<0.001	<0.001	>999.999
CONTRACT H0504 vs H9104	0.645	0.356	1.168
CONTRACT H0523 vs H9104	0.236	0.135	0.412
CONTRACT H0524 vs H9104	0.299	0.169	0.530
CONTRACT H0526 vs H9104	0.388	0.223	0.675
CONTRACT H0529 vs H9104	0.407	0.208	0.798
CONTRACT H0543 vs H9104	0.534	0.302	0.945
CONTRACT H0545 vs H9104	0.776	0.436	1.379
CONTRACT H0559 vs H9104	0.187	0.099	0.351
CONTRACT H0562 vs H9104	0.272	0.155	0.476
CONTRACT H0564 vs H9104	0.290	0.166	0.504
CONTRACT H0566 vs H9104	0.703	0.384	1.285
CONTRACT H0571 vs H9104	0.509	0.131	1.985
CONTRACT H0583 vs H9104	0.519	0.268	1.008
CONTRACT H0584 vs H9104	0.449	0.247	0.818
CONTRACT H0591 vs H9104	0.398	0.211	0.751
CONTRACT H0598 vs H9104	0.362	0.189	0.691
CONTRACT H0602 vs H9104	0.148	0.081	0.272
CONTRACT H0609 vs H9104	0.497	0.278	0.889
CONTRACT H0630 vs H9104	0.664	0.322	1.367
CONTRACT H0657 vs H9104	<0.001	<0.001	>999.999
CONTRACT H0752 vs H9104	0.426	0.188	0.968
CONTRACT H0755 vs H9104	0.172	0.093	0.317
CONTRACT H0954 vs H9104	0.375	0.214	0.658
CONTRACT H1010 vs H9104	0.107	0.039	0.297
CONTRACT H1013 vs H9104	0.720	0.357	1.449
CONTRACT H1016 vs H9104	0.183	0.101	0.331
CONTRACT H1019 vs H9104	1.780	0.810	3.913
CONTRACT H1020 vs H9104	0.169	0.079	0.360
CONTRACT H1026 vs H9104	0.209	0.115	0.379
CONTRACT H1027 vs H9104	0.383	0.197	0.744
CONTRACT H1035 vs H9104	0.246	0.138	0.440
CONTRACT H1036 vs H9104	0.316	0.172	0.579
CONTRACT H1057 vs H9104	0.039	0.019	0.081
CONTRACT H1059 vs H9104	0.063	0.029	0.139
CONTRACT H1061 vs H9104	0.061	0.027	0.136
CONTRACT H1062 vs H9104	0.040	0.018	0.088
CONTRACT H1071 vs H9104	0.197	0.107	0.362
CONTRACT H1076 vs H9104	0.117	0.064	0.214
CONTRACT H1078 vs H9104	0.345	0.185	0.644
CONTRACT H1080 vs H9104	0.225	0.121	0.417
CONTRACT H1082 vs H9104	0.243	0.137	0.433
CONTRACT H1095 vs H9104	0.130	0.066	0.254
CONTRACT H1099 vs H9104	0.134	0.074	0.243
CONTRACT H1168 vs H9104	0.751	0.404	1.396
CONTRACT H1170 vs H9104	0.630	0.338	1.174
CONTRACT H1230 vs H9104	0.334	0.157	0.713
CONTRACT H1251 vs H9104	0.157	0.072	0.344
CONTRACT H1349 vs H9104	0.145	0.080	0.263
CONTRACT H1350 vs H9104	0.229	0.117	0.448
CONTRACT H1406 vs H9104	0.647	0.355	1.179
CONTRACT H1463 vs H9104	0.374	0.199	0.703
CONTRACT H1472 vs H9104	0.232	0.060	0.893
CONTRACT H1553 vs H9104	0.432	0.215	0.868

[21] Contract H9104 is the reference variable used for relative comparisons—H9104 has 133 disenrollees

CONTRACT H1555 vs H9104	0.356	0.126	1.001
CONTRACT H1558 vs H9104	0.709	0.302	1.666
CONTRACT H1651 vs H9104	0.572	0.049	6.742
CONTRACT H1751 vs H9104	3.037	1.398	6.600
CONTRACT H1849 vs H9104	0.927	0.444	1.937
CONTRACT H1951 vs H9104	1.512	0.705	3.241
CONTRACT H1958 vs H9104	0.625	0.351	1.113
CONTRACT H1961 vs H9104	1.655	0.874	3.132
CONTRACT H2204 vs H9104	2.519	0.892	7.117
CONTRACT H2206 vs H9104	1.452	0.752	2.806
CONTRACT H2256 vs H9104	1.506	0.821	2.761
CONTRACT H2261 vs H9104	0.081	0.044	0.149
CONTRACT H2312 vs H9104	0.326	0.174	0.610
CONTRACT H2353 vs H9104	0.773	0.420	1.421
CONTRACT H2354 vs H9104	0.153	0.079	0.297
CONTRACT H2459 vs H9104	0.187	0.102	0.343
CONTRACT H2461 vs H9104	0.172	0.051	0.575
CONTRACT H2462 vs H9104	0.139	0.074	0.258
CONTRACT H2649 vs H9104	0.330	0.187	0.581
CONTRACT H2654 vs H9104	0.872	0.479	1.586
CONTRACT H2663 vs H9104	0.173	0.099	0.303
CONTRACT H2666 vs H9104	0.243	0.142	0.418
CONTRACT H2667 vs H9104	0.162	0.075	0.348
CONTRACT H2668 vs H9104	0.232	0.114	0.473
CONTRACT H2802 vs H9104	0.437	0.247	0.772
CONTRACT H2931 vs H9104	0.596	0.303	1.172
CONTRACT H2949 vs H9104	1.071	0.569	2.016
CONTRACT H2960 vs H9104	0.461	0.253	0.840
CONTRACT H2961 vs H9104	1.260	0.645	2.459
CONTRACT H3107 vs H9104	0.374	0.176	0.797
CONTRACT H3152 vs H9104	0.077	0.040	0.148
CONTRACT H3154 vs H9104	0.188	0.101	0.351
CONTRACT H3156 vs H9104	0.076	0.040	0.145
CONTRACT H3164 vs H9104	1.206	0.296	4.906
CONTRACT H3204 vs H9104	0.996	0.533	1.861
CONTRACT H3251 vs H9104	0.324	0.171	0.615
CONTRACT H3305 vs H9104	0.196	0.103	0.374
CONTRACT H3307 vs H9104	0.290	0.147	0.572
CONTRACT H3312 vs H9104	0.115	0.056	0.239
CONTRACT H3330 vs H9104	0.211	0.108	0.413
CONTRACT H3351 vs H9104	0.094	0.050	0.178
CONTRACT H3356 vs H9104	0.015	0.005	0.049
CONTRACT H3359 vs H9104	1.477	0.653	3.338
CONTRACT H3361 vs H9104	0.276	0.149	0.514
CONTRACT H3362 vs H9104	0.276	0.146	0.524
CONTRACT H3366 vs H9104	0.685	0.342	1.371
CONTRACT H3370 vs H9104	0.436	0.228	0.837
CONTRACT H3379 vs H9104	0.588	0.299	1.158
CONTRACT H3384 vs H9104	0.071	0.037	0.135
CONTRACT H3385 vs H9104	0.354	0.173	0.724
CONTRACT H3387 vs H9104	1.266	0.122	13.108
CONTRACT H3449 vs H9104	0.177	0.099	0.318
CONTRACT H3455 vs H9104	0.261	0.145	0.469
CONTRACT H3456 vs H9104	0.730	0.396	1.346
CONTRACT H3503 vs H9104	>999.999	<0.001	>999.999
CONTRACT H3607 vs H9104	0.201	0.112	0.363
CONTRACT H3653 vs H9104	0.142	0.073	0.276
CONTRACT H3655 vs H9104	0.353	0.197	0.630
CONTRACT H3657 vs H9104	0.267	0.151	0.473
CONTRACT H3659 vs H9104	0.343	0.197	0.598
CONTRACT H3660 vs H9104	0.315	0.174	0.571
CONTRACT H3664 vs H9104	0.881	0.389	1.995
CONTRACT H3668 vs H9104	0.105	0.057	0.194
CONTRACT H3672 vs H9104	0.463	0.268	0.798
CONTRACT H3673 vs H9104	0.757	0.208	2.751
CONTRACT H3749 vs H9104	0.921	0.508	1.671
CONTRACT H3755 vs H9104	1.322	0.636	2.747
CONTRACT H3756 vs H9104	2.027	1.007	4.082
CONTRACT H3805 vs H9104	0.713	0.403	1.263
CONTRACT H3851 vs H9104	0.281	0.153	0.515
CONTRACT H3856 vs H9104	0.448	0.239	0.841
CONTRACT H3858 vs H9104	0.219	0.105	0.458
CONTRACT H3862 vs H9104	0.325	0.169	0.623
CONTRACT H3864 vs H9104	0.509	0.267	0.973
CONTRACT H3931 vs H9104	0.115	0.063	0.212
CONTRACT H3949 vs H9104	0.309	0.170	0.563
CONTRACT H3951 vs H9104	0.115	0.059	0.223
CONTRACT H3952 vs H9104	0.094	0.051	0.172
CONTRACT H3954 vs H9104	0.607	0.335	1.101
CONTRACT H3957 vs H9104	0.189	0.107	0.334
CONTRACT H3959 vs H9104	0.105	0.058	0.189
CONTRACT H3960 vs H9104	0.099	0.050	0.198

CONTRACT H3962 vs H9104	0.193	0.109	0.340
CONTRACT H3963 vs H9104	0.050	0.024	0.106
CONTRACT H3964 vs H9104	1.165	0.610	2.225
CONTRACT H4102 vs H9104	0.390	0.223	0.682
CONTRACT H4152 vs H9104	0.157	0.085	0.291
CONTRACT H4153 vs H9104	0.309	0.152	0.628
CONTRACT H4454 vs H9104	0.680	0.361	1.282
CONTRACT H4456 vs H9104	0.334	0.181	0.616
CONTRACT H4461 vs H9104	0.530	0.272	1.035
CONTRACT H4504 vs H9104	0.366	0.188	0.712
CONTRACT H4510 vs H9104	0.923	0.479	1.776
CONTRACT H4564 vs H9104	0.228	0.121	0.429
CONTRACT H4572 vs H9104	2.591	1.033	6.498
CONTRACT H4590 vs H9104	3.065	1.472	6.385
CONTRACT H5005 vs H9104	0.887	0.488	1.611
CONTRACT H5050 vs H9104	0.280	0.144	0.541
CONTRACT H5063 vs H9104	0.441	0.239	0.813
CONTRACT H5102 vs H9104	0.059	0.016	0.216
CONTRACT H5149 vs H9104	0.213	0.063	0.714
CONTRACT H5253 vs H9104	0.111	0.062	0.199
CONTRACT H5254 vs H9104	0.765	0.336	1.740
CONTRACT H5264 vs H9104	0.333	0.092	1.205
CONTRACT H9001 vs H9104	2.830	1.302	6.151
CONTRACT H9003 vs H9104	0.378	0.188	0.761
CONTRACT H9005 vs H9104	0.177	0.096	0.327
CONTRACT H9011 vs H9104	0.278	0.147	0.527
CONTRACT H9016 vs H9104	1.486	0.769	2.871
CONTRACT H9047 vs H9104	0.273	0.141	0.530
CONTRACT H9049 vs H9104	>999.999	<0.001	>999.999
CONTRACT H9101 vs H9104	1.058	0.479	2.336
CONTRACT H9103 vs H9104	0.110	0.032	0.373

Appendix 6: Application of Case Mix Adjustment

Potential Impact of Case Mix Adjustment on 2000 Disenrollment Reason Information Reported to Consumers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Plan Contract	Observed Percent of Respondents citing Care & Service MIR	Predicted Percent of Respondents citing Care & Service MIR (B3)	Difference Between Observed and Predicted Percent of Respondents citing Care & Service MIR	AdjustedDisenrollment Rate [22]	Percent of Enrollees Reporting Disenrollment Due to Care & Service (without case mix adjustment)	Percent of Enrollees Reporting Disenrollment Due to Care & Service (with case mix adjustment)	Difference between no case mix and case mix reports
H1016	24%	54%	-30%	39%	9%	21%	-12%
H1076	34%	54%	-20%	45%	15%	24%	-9%
H2663	34%	50%	-16%	38%	13%	19%	-6%
H3156	23%	45%	-22%	28%	6%	12%	-6%
H3152	22%	45%	-23%	19%	4%	9%	-4%
H0523	44%	60%	-16%	22%	10%	13%	-3%
H1349	30%	54%	-24%	14%	4%	8%	-3%
H1082	43%	54%	-11%	28%	12%	15%	-3%
H3959	22%	36%	-14%	14%	3%	5%	-2%
H0564	50%	58%	-8%	23%	12%	13%	-2%
H1026	45%	54%	-9%	20%	9%	11%	-2%
H1099	36%	54%	-18%	9%	3%	5%	-2%
H3931	22%	36%	-14%	11%	2%	4%	-2%
H0562	47%	61%	-14%	11%	5%	7%	-2%
H0755	36%	57%	-21%	7%	3%	4%	-1%
H0351	47%	58%	-11%	14%	7%	8%	-1%
H9047	42%	55%	-13%	10%	4%	6%	-1%
H1071	40%	55%	-15%	8%	3%	4%	-1%
H1958	57%	67%	-10%	11%	6%	7%	-1%
H3384	33%	45%	-12%	9%	3%	4%	-1%
H3351	28%	44%	-16%	6%	2%	3%	-1%
H3449	40%	52%	-12%	7%	3%	4%	-1%
H0543	53%	60%	-7%	12%	6%	7%	-1%
H5253	25%	47%	-22%	3%	1%	1%	-1%
H2666	41%	52%	-11%	6%	2%	3%	-1%
H1080	48%	53%	-5%	12%	6%	6%	-1%
H0151	51%	55%	-4%	16%	8%	9%	-1%

[22] In this table, we combine case mix adjusted reasons with disenrollment rates that were not case mix adjusted, for the purpose of illustration only. The “adjusted” here refers to the fact that publicly reported disenrollment rates are “adjusted” to remove disenrollees who leave a M+C plan when their current or former employer stops offering that plan.

Plan Contract	(1) Observed Percent of Respondents citing Care & Service MIR	(2) Predicted Percent of Respondents citing Care & Service MIR (B3)	(3) Difference Between Observed and Predicted Percent of Respondents citing Care & Service MIR	(4) Disenrollment Rate Adjusted	(5) Percent of Enrollees Reporting Disenrollment Due to Care & Service (without case mix adjustment)	(6) Percent of Enrollees Reporting Disenrollment Due to Care & Service (with case mix adjustment)	(7) Difference between no case mix and case mix reports
H2459	36%	45%	-9%	6%	2%	3%	-1%
H0524	47%	58%	-11%	4%	2%	2%	0%
H3607	36%	47%	-11%	4%	1%	2%	0%
H3330	44%	46%	-2%	18%	8%	8%	0%
H1035	49%	53%	-4%	8%	4%	4%	0%
H0526	53%	58%	-5%	7%	4%	4%	0%
H3154	42%	44%	-2%	20%	8%	9%	0%
H3455	49%	53%	-4%	8%	4%	4%	0%
H4102	51%	54%	-3%	9%	5%	5%	0%
H3851	47%	54%	-7%	4%	2%	2%	0%
H2960	56%	60%	-4%	7%	4%	4%	0%
H2649	49%	51%	-2%	15%	7%	8%	0%
H0584	56%	58%	-2%	9%	5%	5%	0%
H3657	46%	48%	-2%	9%	4%	4%	0%
H3957	32%	38%	-6%	3%	1%	1%	0%
H3305	44%	46%	-2%	6%	3%	3%	0%
H4510	68%	69%	-1%	14%	10%	10%	0%
H0630		47%		3%		1%	
H1463		45%		8%		4%	
H1849		52%		2%		1%	
H1951		70%		6%		4%	
H2204		57%		14%		8%	
H2931		58%		8%		5%	
H3251		70%		38%		26%	
H3359		47%		17%		8%	
H3755		71%		4%		3%	
H3864		51%		5%		3%	
H9101		47%		11%		5%	
H9011	53%	53%	0%	22%	12%	12%	0%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Plan Contract	Observed Percent of Respondents citing Care & Service MIR	Predicted Percent of Respondents citing Care & Service MIR (B3)	Difference Between Observed and Predicted Percent of Respondents citing Care & Service MIR	Disenrollment Rate Adjusted	Percent of Enrollees Reporting Disenrollment Due to Care & Service (without case mix adjustment)	Percent of Enrollees Reporting Disenrollment Due to Care & Service (with case mix adjustment)	Difference between no case mix and case mix reports
H3856	56%	55%	1%	4%	2%	2%	0%
H3749	71%	70%	1%	6%	4%	4%	0%
H4456	54%	51%	3%	2%	1%	1%	0%
H3962	35%	34%	1%	11%	4%	4%	0%
H2312	48%	45%	3%	3%	1%	1%	0%
H3655	48%	45%	3%	4%	2%	2%	0%
H3660	47%	45%	2%	7%	3%	3%	0%
H2802	57%	53%	4%	6%	3%	3%	0%
H0566	68%	61%	7%	4%	3%	2%	0%
H1078	57%	55%	2%	16%	9%	9%	0%
H1036	55%	53%	2%	17%	9%	9%	0%
H3362	51%	43%	8%	4%	2%	2%	0%
H4454	74%	56%	18%	2%	1%	1%	0%
H5063	59%	55%	4%	10%	6%	6%	0%
H4461	64%	53%	11%	4%	3%	2%	0%
H3204	76%	72%	4%	12%	9%	9%	0%
H3307	53%	45%	8%	7%	4%	3%	1%
H0504	65%	60%	5%	12%	8%	7%	1%
H3659	51%	45%	6%	10%	5%	4%	1%
H4152	33%			2%	1%		
H3963	12%			6%	1%		
H0307	65%	56%	9%	9%	6%	5%	1%
H2353	68%	47%	21%	4%	3%	2%	1%
H0545	69%	59%	10%	9%	6%	5%	1%
H1170	68%	54%	14%	7%	5%	4%	1%
H9001	88%	56%	32%	3%	3%	2%	1%
H9005	35%			3%	1%		
H3949	42%	36%	6%	18%	8%	7%	1%
H1961	79%	69%	10%	11%	9%	8%	1%

Plan Contract	(1) Observed Percent of Respondents citing Care & Service MIR	(2) Predicted Percent of Respondents citing Care & Service MIR (B3)	(3) Difference Between Observed and Predicted Percent of Respondents citing Care & Service MIR	(4) Disenrollment Rate Adjusted	(5) Percent of Enrollees Reporting Disenrollment Due to Care & Service (without case mix adjustment)	(6) Percent of Enrollees Reporting Disenrollment Due to Care & Service (with case mix adjustment)	(7) Difference between no case mix and case mix reports
H0303	76%	58%	18%	6%	5%	3%	1%
H4564	38%			3%	1%		
H3361	53%	45%	8%	14%	7%	6%	1%
H2261	20%			6%	1%		
H3805	65%	56%	9%	14%	9%	8%	1%
H0609	61%	51%	10%	13%	8%	7%	1%
H2654	70%	49%	21%	7%	5%	3%	1%
H9104	75%	60%	15%	10%	8%	6%	2%
H4590	88%	71%	17%	9%	8%	6%	2%
H1406	62%	47%	15%	10%	6%	5%	2%
H3954	62%	36%	26%	6%	4%	2%	2%
H3952	20%			8%	2%		
H2961	75%	57%	18%	9%	7%	5%	2%
H1168	72%	54%	18%	9%	6%	5%	2%
H5005	74%	56%	18%	9%	7%	5%	2%
H2462	33%		33%	5%	2%		
H2949	75%	56%	19%	9%	7%	5%	2%
H2667	35%		35%	5%	2%		
H0154	77%	54%	23%	8%	6%	4%	2%
H0602	31%			6%	2%	0%	
H3456	73%	54%	19%	10%	7%	5%	2%
H3668	23%			9%	2%		
H1027	60%	55%	5%	44%	26%	24%	2%
H3756	84%	71%	13%	18%	15%	13%	2%
H2256	81%	55%	26%	9%	7%	5%	2%
H0954	51%	38%	13%	18%	9%	7%	2%
H3370	65%	45%	20%	13%	8%	6%	3%
H1751	87%	53%	34%	8%	7%	4%	3%
H3672	55%	43%	12%	23%	13%	10%	3%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Plan Contract	Observed Percent of Respondents citing Care & Service MIR	Predicted Percent of Respondents citing Care & Service MIR (B3)	Difference Between Observed and Predicted Percent of Respondents citing Care & Service MIR	Disenrollment Rate Adjusted	Percent of Enrollees Reporting Disenrollment Due to Care & Service (without case mix adjustment)	Percent of Enrollees Reporting Disenrollment Due to Care & Service (with case mix adjustment)	Difference between no case mix and case mix reports
H1013	74%	54%	20%	15%	11%	8%	3%
H3964	74%	37%	37%	8%	6%	3%	3%
H3653	27%			12%	3%		
H3379	67%	46%	21%	18%	12%	8%	4%
H2206	83%	57%	26%	15%	12%	9%	4%
H0150	89%	54%	35%	12%	11%	6%	4%
H0354	84%	58%	26%	18%	15%	10%	5%
H9016	81%	54%	27%	18%	15%	10%	5%
H3366	71%	44%	27%	18%	13%	8%	5%
H1019	86%	54%	32%	51%	44%	28%	16%
					(1)*(4)	**(2)*(4)**	**(5)-(6)**