CDPS-Medicare:
The Chronic Illness and Disability Payment System Modified to Predict Expenditures for Medicare Beneficiaries

Submitted by:

Richard Kronick, Ph.D. [1]
Todd P. Gilmer, Ph.D. [1]
Tony Dreyfus, M.C.P. [2]
Theodore G. Ganiats, M.D. [1]

Affiliations: [1]Department of Family and Preventive Medicine, UCSD School of Medicine
[2] Independent Consultant, Boston, MA

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Richard Kronick, Ph.D.
Project Director

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Executive Summary

The Chronic Illness and Disability Payment System (CDPS) was originally developed for states to use in adjusting capitated payments for Medicaid beneficiaries. This report presents our work to revise CDPS for use in adjusting capitated Medicare payments to health plans. We describe the development of the original CDPS model and its modification to create the CDPS-Medicare model, and provide regression results for six variants of CDPS-Medicare. We examine the prediction of expenditures for various subsets of beneficiaries, including diagnostically defined groups, functionally impaired beneficiaries and institutionalized beneficiaries. The report also compares CDPS-Medicare with the Hierarchical Condition Category (HCC) model. Finally, we analyze the effects of mortality on HMO resource needs and analyze how changes in disease burden will affect implementation of diagnosis-based payment.

Chapter 1: The Original CDPS Model and Its Application to Medicare Data

Eight state Medicaid programs have begun using one of our models, the Disability Payment System or its newer version, CDPS, and others are evaluating its use.

To create CDPS, we used claims for nearly four million Medicaid beneficiaries from seven states to analyze effects of diagnoses on future expenditures for all the 15,000 diagnosis codes in the *International Classification of Diseases* (ICD). The CDPS model for Medicaid (or "CDPS-Medicaid") includes 20 major categories of diagnoses, which correspond to body systems or type of diagnosis. Most of the major categories are further divided into several subcategories according to the degree of the increased expenditures associated with the diagnoses. For example, diagnoses of the nervous system are divided into three subcategories for high cost, medium cost, and low cost conditions.

Physician specialists were consulted extensively to help us determine the organization of diagnoses and exclude ill-defined diagnoses from the model. In each of the major categories in CDPS-Medicaid, only the single most severe diagnosis within the major category is counted. Such "hierarchical" counting and reliance on well-defined diagnoses strengthen the model's resistance to aggressive plan efforts to increase diagnostic reporting.

Most of the subcategories of CDPS-Medicaid appear to be good predictors of increased future expenditures among Medicare beneficiaries. Most of the categories that are predictive of high costs in the Medicaid population are also predictive of high costs in the Medicare population. The R^2 for CDPS-Medicaid applied to Medicare data was 0.105.

Chapter 2: Reassigning Diagnoses, Creating New Subcategories and Changing Counting Rules to Create the CDPS-Medicare Model

At the request of CMS, we substantially modified CDPS in order to produce "CDPS-Medicare," a model which is more appropriate for use in making payments for Medicare beneficiaries.

To develop the new model, we used Medicare claims data to determine whether diagnoses were assigned to the appropriate payment levels, and we reassigned a number of diagnoses. We also reconsidered whether diagnoses were adequately well-defined to be included in the model. For cardiovascular, pulmonary and nervous system conditions, we made new subcategories and modified the rules for counting diagnoses. Finally, we also made significant changes in the major category for diabetes and made a new major category for delirium and dementia.

Diagnoses were evaluated for reassignment or removal from the model in small groups of ICD codes called "stage one groups." We promoted 51 stage one groups from a lower to a higher subcategory, and demoted 42 stage one groups from a higher subcategory to a lower one. Many diagnoses were also removed from the payment model, either because of insignificant cost effects among Medicare beneficiaries or because of our heightened concern about excluding ill-defined diagnoses. Some entire subcategories were also cut from the payment model in final model testing. Overall, the number of stage one groups was reduced from 451 to 389, which makes the model more resistant to increased coding of diagnoses.

Within most major diagnostic categories of CDPS-Medicare, only the single highest-cost subcategory is counted, but we changed the counting rules in order to allow multiple counting among cardiovascular, pulmonary and nervous system diagnoses. Multiple counting should allow more accurate predictions for beneficiaries with more than one type of disease within these important major categories.

After the reassigment of some diagnoses, the exclusion of others, and the increased counting allowed in several areas, the R^2 of the CDPS-Medicare model is 0.110, only modestly better than the CDPS-Medicaid R^2 0.105. This modest improvement reflects our effort to balance the goals of modifying the classification so it better corresponds to Medicare expenditures and excluding diagnoses from the model so it better resists proliferative coding. The work increases our confidence that the model is rewarding solid diagnoses to the right degree.

Chapter 3: Regression Results for Six CDPS-Medicare Models

We created six variants of the CDPS-Medicare model to explore different ways to expand, simplify or improve the model. The base model includes all the diagnostic subcategories and a set of demographic variables. The second, or "disabled interaction model," adds interactions between disability status and selected diagnostic categories. The third or "full" model adds interactions among selected disease categories and variables for beneficiaries with four or more high-cost subcategories. The fourth model uses only inpatient data, the fifth uses a restricted set of CDPS subcategories, and the sixth incorporates information on death. (See Table S-1 for a comparison of R^2 statistics for CDPS-Medicaid and the CDPS-Medicare

model variants. See Table S-2 for the frequencies and expenditure effects of the variables for all six model variants.)

The base, disability interaction and full models

Each of the diagnostic subcategories of the base model appears to be a good predictor of increased future expenditures among Medicare beneficiaries. Of the 66 CDPS-Medicare diagnostic subcategories, all work well as predictive variables and the vast majority have estimated coefficients at least 20 times larger than their standard error.

A few subcategories are predictive of very large increased expenditures in the following year. Seven subcategories were predictive of more than $7,000 of increased expenditures in the following year; most of these had very low frequencies, under one-half of one percent of the Medicare population, while two had approximately one percent. An additional seven subcategories were predictive of more than $4,000 in additional expenditures and also had frequencies of one percent or less. The remaining subcategories are associated with smaller increased expenditures but much larger numbers of beneficiaries. Fifteen of the subcategories have frequencies of five percent or more.

The intercept for the regression is the estimated expenditures for someone with no CDPS diagnosis who is male and aged 70 to 74 (the reference demographic category). For such a person, we predict expenditures of $1,760, which is 33 percent of the average expenditure for all beneficiaries of $5,314. Estimated expenditures for other beneficiaries can be calculated by adding to the intercept additional coefficients, one from the appropriate age-gender category and others from diagnostic subcategories in which the beneficiary has a diagnosis. The addition of diagnostic coefficients, however, is limited by the counting rules described earlier.

The disability interaction model adds to the base model a set of interaction variables, each of which indicates whether a beneficiary began Medicare coverage because of disability *and* has a diagnosis in one of various CDPS-Medicare subcategories. Unlike the disability interactions used in the HCC model, which count only beneficiaries under age 65, our disability interactions count those of all ages who became eligible because of disability.

The full model adds two sets of additional variables, one set for beneficiaries with diagnoses in four or more high-cost subcategories and a second for beneficiaries with specified combinations of diagnoses. We added the first set of variables because we found significant underpredictions for individuals with high numbers of high-cost subcategories.

The inpatient, restricted and end-of-life models

The remaining three alternative models may help consideration of payment policy options.

Because CMS already receives inpatient diagnoses, we explored using CDPS-Medicare with inpatient data only.[1] The majority of the coefficients are higher in the inpatient regression

[1] We used all diagnoses found on the inpatient record, not just the primary inpatient diagnosis, which is the basis for the PIP-DCG model.

than in regressions using both ambulatory and inpatient data, many substantially higher. The R^2 using only inpatient data is 0.085.

Yet extended use of only inpatient data would encourage hospitalization of beneficiaries and will penalize plans that have reduced hospitalization. We calculated for each diagnostic subcategory the ratio of inpatient diagnoses to all diagnoses, and found that for 55 of 66 subcategories fewer than 40 percent of the beneficiaries would be identified using only inpatient diagnoses. The high proportions of non-inpatient diagnoses indicate that an inpatient-only system will create strong incentives to hospitalize, especially when plans face substantial costs to serve beneficiaries with home, community-based or outpatient services.[2]

A possible alternative to the inpatient model is a "restricted" model, where diagnoses are used from both inpatient and ambulatory sources, but payment is made only for subcategories with substantial coefficients and relatively few beneficiaries. A restricted model might lower the reporting burden on plans without offering inappropriate incentives to hospitalize beneficiaries.

For an illustrative restricted model, we selected 29 CDPS subcategories based on their coefficients in the base model and their frequencies. Most of the selected subcategories have coefficients of $3,000 or more and frequencies of three percent or less.[3] With fewer subcategories, diagnoses would affect payments for many fewer beneficiaries: in the base and full models, 70 percent; in the restricted model, only 27 percent. The R^2 of the restricted model is 0.089. Yet it is hard to imagine that a restricted model of this type would in practice reduce the burden of data collection, since plans would still have to gather and submit data on a large number of enrollees.

The end-of-life model supplements the full model with variables indicating how close a beneficiary is to the end of life. Because health care expenditures increase in the last years of life, the incorporation of information on when people die improves predictive accuracy far beyond what can be obtained using diagnoses alone. (Chapter 6 examines the components of end-of-life care and policy implications.)

Our most important finding is that the period before death is expensive even when we control for the effects of diagnosis. Compared with beneficiaries with similar diagnoses who do not die, beneficiaries who die in the first half of 1997 are estimated to have additional 1997 expenditures on average of $9,900, while those dying in the second half of 1997 are estimated to have additional expenditures of $15,800. We also found that the association between the end of life and increased expenditures, still controlling for diagnosis, extends back from the end of life for several years. People who are going to die are much more costly than people with similar diagnoses who are not going to die.

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[2] T. Dreyfus and R. Kronick, "Paying Plans to Care for People with Chronic Illness," pp. 40-41, in R. Kronick and J. de Beyer, *Medicare HMOs; Making Them Work for the Chronically Ill,* Chicago: Health Administration Press, 1999.

[3] We also included high-cost ischemic heart disease (congestive heart failure), with a base model coefficient of $2,800 and a frequency of 10 percent, because of its significance as a cause of morbidity among Medicare beneficiaries, the proliferation of disease management programs designed to improve the care of beneficiaries with CHF, and its prominence in discussions about supplementing the diagnostic reporting of the PIP-DCG system with non-inpatient diagnoses.

The costs of end-of-life care are so significant that the inclusion of the end-of-life variables leads to a much higher predictive accuracy than we have seen before. The end-of-life model has an R^2 of 0.193.

The inclusion of the end-of-life variables also has a striking effect on the coefficients of the age-gender variables, especially for men: the normal increase of expenditures with age is sharply reduced and for older men actually reversed. In the full model, the age-gender coefficients rise from $1,140 for men age 80-84 to $2,570 for men aged 90-94; in the end-of-life model, the coefficients fall, from $50 for ages 80-84, to –$280 for age 85-89 and –$1,100 for age 90-94.[4] The additional expenditures for older beneficiaries appear to be associated not with aging itself but to result from increasing incidence of illness and from reaching the final few years of life. (See Figure S-1 for a comparison of the male age group coefficients in the full model and the end-of-life model.)

Chapter 4: Predicting Expenditures for Various Biased Groups and for Functionally Impaired Beneficiaries

Predicting Expenditures for Various Biased Groups

To test our models' performance, we calculated the ratio of predicted to actual expenditures for various groups of beneficiaries. (See Table S-3 for selected predictive ratios.)

The predictive ratios of diagnostically-defined groups highlight the advantages and disadvantages of certain models. The ratios show the advantage of the full model over the base and disabled interaction models for groups defined by diagnostic combinations, such as diabetes and cerebrovascular disease. The restricted and inpatient models perform much less well than the other models in making accurate predictions for most diagnostic groups.

More difficult tests for a diagnostic model are posed by groups defined without reference to diagnosis. For groups of beneficiaries defined by their level of expenditure in the base year, the first four CDPS models under-predict for the most expensive fifth of beneficiaries and over-predict for the other four quintiles.

Additional tests are posed by groups defined by levels of spending on home health services or durable medical equipment. For all beneficiaries with home health costs in the base year taken as a single group, the CDPS models predict only three-quarters of expenditures. Among these beneficiaries with some use, predictions for the first four CDPS models are good for those in the lower quintiles of home health expenditures, but poor for the fourth and fifth quintiles. Use of home health services appears to be an indicator of frailty or poor health status that is not captured by diagnoses.

[4] The reference category is men age 70 to 74.

Predicting Expenditures for Functionally Impaired Beneficiaries

Diagnosis-based payment may not pay accurately for beneficiaries with significant functional impairments, which might signal declines in health status and additional future expenditures not predicted by diagnoses alone. These unpredicted expenditures would concern programs designed to attract beneficiaries with significant functional impairments, such as the Program of All-Inclusive Care for the Elderly (PACE).

We used data from the Medicare Current Beneficiary Survey on activities of daily living (ADLs) linked to claims data on diagnoses and expenditures. We grouped beneficiaries by their number of ADL impairments in 1996, from none to six. Separately, we used 1996 diagnostic data for each beneficiary and the diagnostic subcategory weights from the full CDPS model to calculate 1997 individual predicted expenditure amounts. These predicted expenditures can then be compared with the actual expenditures for each group defined by number of ADL impairments (see Table S-4).

Actual expenditures were lower than predicted for beneficiaries with no impairments or one impairment and higher than predicted for those with two to six impairments. Normalized predictive ratios ranged from 1.16 for the beneficiaries with no impairments to 0.69 for beneficiaries with five impairments.

Currently, reliable information on functional status is available for few beneficiaries and would be costly to add to the diagnostic record, since physicians do not routinely gather such data. As a result, widespread adjustment of payments with information on functional status seems impractical in the near future. Yet our analysis supports the view that payments adjusted only by diagnosis could be unfair to programs designed to serve beneficiaries with high levels of functional impairment.

We also investigated whether the end-of-life model better accounts for the high costs of beneficiaries with functional impairments, but found that it under-predicts expenditures for those with three to five ADL impairments. The high costs of the functionally impaired are only partially accounted for by their greater likelihood of death.

Predicting Expenditures for Institutionalized Beneficiaries

We investigate whether institutional status should be used as an adjuster as part of the payment system. The traditional demographically-based system does adjust for institutional status, while the PIP-DCG system implemented by CMS does not adjust for institutional status. But our work on the relationship between institutional status, diagnoses, and expenditures indicates that adjustment for institutional status *is* desirable.

The high mortality rate for the institutionalized and the high cost of end-of-life care would suggest that the high costs of the institutionalized cannot be fully accounted for by diagnoses. Hogan and colleagues report a mortality rate of 21 percent among beneficiaries in a facility at some point during the year, compared to approximately three percent for beneficiaries residing in the community throughout the year. Our results in Chapter 3 show that actual expenditures for decedents are much higher than the expenditures predicted by a diagnostic model. Given the much higher mortality rate of the institutionalized and the higher than predicted expenditures for decedents, we expect that diagnostic adjustment should substantially underpredict expenditures in the last twelve months of life for the institutionalized.

We use the MCBS data to investigate the relationships among mortality, Medicaid status, diagnoses, institutional status, and expenditures. We find that the CDPS-Medicare model substantially underpredicts expenditures for the institutionalized, with a predictive ratio of 0.72. As expected, the end-of-life model does much better, but the predictive ratio of 0.88 shows that it still somewhat underpredicts the expenditures of the institutionalized. Thus, a prospective diagnostic model without adjustment for mortality will result in payments for the institutionalized that are substantially below expected expenditures. A prospective model that does adjust for mortality will account much better for expenditures made on the institutionalized, but may still result in payments that are lower than expenditures, especially for non-Medicaid institutionalized survivors.

Our results differ from similar analyses conducted by HER.[5] The important difference is not in our estimates of predicted expenditures but rather in our estimates of actual expenditures for the institutionalized. HER estimates that actual expenditures for the institutionalized are 1.67 times expenditures for all beneficiaries, and finds that the PIP-DCG model predicts that expenditures for this group should be 1.67 times average. The CDPS-Medicare model similarly predicts expenditures for the institutionalized at 1.70 times the average for all beneficiaries. But we estimate the actual expenditures for the institutionalized at 2.3 times the average for all beneficiaries, and find that diagnostic adjustment does not account for this elevated expenditure level. We cannot be sure whether our results or HER's are closer to the truth. However, given the very high mortality among the institutionalized and the inability of diagnostic adjustment to account for the high costs of end-of-life care, our results showing that diagnostic adjustment cannot fully account for the high costs of the institutionalized make intuitive sense.

Chapter 5: Comparison of CDPS-Medicare with HCCs

A comparison of CDPS-Medicare with the HCCs reveals important similarities in basic approach and important differences in the final models, both in the overall approach to counting diagnoses and in the classification of certain diagnoses. Compared with other approaches to diagnosis-based risk adjustment, e.g. the ACG models, the HCC and CDPS models are very similar. The HCC and CDPS models use similar approaches to define individual diagnoses, to assign individual diagnoses to categories of diagnoses, and to group these diagnostic categories into larger areas according to body system or type of disease.

Differences in counting diagnoses

Perhaps the most important difference between the HCC and CDPS models is that the CDPS model is much more conservative in counting diagnoses. One reason for this difference is that the HCCs have been expanded to include 101 separate diagnostic categories in their recommended payment model. CDPS-Medicare has only 66 diagnostic categories. In even greater contrast is the maximum number of categories that can be counted according to the counting rules for each model: for the HCCs, 63; for CDPS-Medicare, 25.

[5] See Chapter 7 in Gregory C. Pope, Chuan-Fen Liu and others, *Principal Inpatient Diagnostic Cost Group Models for Medicare Risk Adjustment*, final report, February 24, 1999.

Some of the greater possible counting in the HCC model comes from having more major areas. The HCCs have 32 groups of categories while CDPS has only 16. But much of the greater possible counting results from the HCCs' much more liberal counting rules. In the HCCs, only 13 of 32 major areas use full hierarchy, by which only the single highest-cost subcategory is counted. In CDPS-Medicare, 13 of 16 major areas use full hierarchy and only three areas allow multiple counting within the category.

Although each model's counting rules appear reasonable, we believe that the CDPS rules are more appropriate for use in making payment. The HCCs may show some advantage in modeling exercises, because its greater number of categories and more liberal counting rules produce higher R^2 statistics. But in use for payment, the many HCC diagnostic categories may counter the goal of making equitable payments, because they offer so many more rewards to proliferative coding. With either model, of course, the plan that codes more completely will get more money. Using CDPS rather than the HCCs, however, we suspect that more of the variation across plans in case mix scores should be due to true variation in acuity and less to variation in coding practices.

Differences in classification

The models differ in how they group diagnoses and in whether or not they include certain diagnoses in the payment model. We think that the HCC model draws a number of distinctions that may not hold up well in implementation.

We see problems with the HCC classification of diabetes diagnoses, in which large additional payments are proposed for diabetic complications that are very common and variable in cost-effect. The drawback with the HCC classification in diabetes is that it is unusually vulnerable to increased coding expected under diagnosis-based payment. At least 20 times more Medicare beneficiaries could be legitimately coded with complications than are indicated in fee-for-service data, and these large additional payments are probably not the right amounts for those who will be coded with complications in the future.

We see similar problems with the HCC classification of diagnoses for drug and alcohol problems. The HCCs do not distinguish between drug and alcohol use, but instead place these diagnoses into three categories according to whether the diagnosis is drug psychosis, dependence, or abuse without dependence. The distinction between dependence and abuse without dependence is probably not relevant for clinicians or clear enough for payment purposes. CDPS instead separates diagnoses in this area into categories for drug use and alcohol use. Our coefficients for the Medicare sample were not significantly different, but this distinction appears much more practical for physicians to make and should prove useful when the true costs of fuller treatment of substance abuse come to light.

Many more differences in classification of individual diagnoses exist between the two models, some of minor importance, some perhaps more significant. For example, we think that the HCC model goes too far in including cerebral atherosclerosis (in HCC 98) and unspecified cerebrovascular disease (in HCC 99). We grouped codes for these conditions (437.0 and 437.9) with other generalized ischemic cerebrovascular disease (437.1) and other cerebrovascular disease (437.8), and placed them in our category of not well-defined cerebrovascular diagnoses, which we do not recommend for use in a payment model.

Even with all these differences between the HCCs and CDPS-Medicare, both models work well and could be used CMS to implement comprehensive risk adjustment. The CDPS-Medicare model, however, should give more stable results and be less affected by the increased coding that risk adjusted payment will encourage.

Chapter 6: Estimating Effects of Mortality on HMO Resource Needs

It is well known that expenditures for Medicare beneficiaries rise substantially in their last year of life.[6] If the mortality rate among HMO enrollees is different from that of fee-for-service beneficiaries, payments to HMOs will not reflect the expected health care costs of the enrolled population. We estimate the effect of differential mortality among HMO beneficiaries on the expected resource needs of HMO enrollees, and discuss implications for payment policy.

Riley, Lubitz and Rabey analyzed mortality rates of non-institutionalized beneficiaries enrolled in HMOs in 1987 compared with the mortality rates of "similar" beneficiaries in fee-for-service, controlling for age, gender, county, Medicaid buy-in status and institutional status.[7] The authors conclude that HMO enrollees died at 80 percent of the rate of similar beneficiaries in FFS. Two more recent studies suggest that the mortality rate of HMO enrollees in January, 1998 was 85 percent of the mortality rate of FFS beneficiaries of the same age, gender, and Medicaid status.[8] Unlike Riley, Lubitz and Rabey's earlier analysis, these more recent studies do not adjust for institutional status.

Using the 20-perecent sample of the 1997 denominator file, we show that Medicare beneficiaries enrolled in HMOs in 1997 died at 85 percent of the rate of FFS beneficiaries of the same age, gender, county of residence, and Medicaid buy-in status. In 2000, when HMO enrollment was stable or declining in many areas, HMO beneficiaries died at 89 percent of the rate of "similar" FFS beneficiaries. (See Table S-6.)

These relative mortality rates are not adjusted for institutional status, and include both hospice and non-hospice decedents. If we could directly compare the mortality rates of community-based HMO and FFS beneficiaries, the relative mortality rates would certainly be much closer to 1.0. Conversely, if we compared the relative mortality rate of decedents who do not use hospice services at the end of life, the relative mortality rate would be even lower than the estimates presented here. We do not have the data needed to precisely estimate the size of the institutional and hospice adjustments, but suspect that the two adjustments would likely cancel each other out.

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[6] J.D. Lubitz and G.F. Riley, "Trends in Medicare Payments in the Last Year of Life. *New England Journal of Medicine*, vol. 328, no. 15, pp. 1092-1096, April 15, 1993; B.C. Spillman and J. Lubitz, "The Effect of Longevity on Spending for Acute and Long-Term Care," *New England Journal of Medicine,* vol. 342, no. 19, pp. 1409-15, May 11, 2000.

[7] G. Riley, J. Lubitz and E. Rabey, "Enrollee Health Status under Medicare Risk Contracts: an Analysis of Mortality Rates," *Health Services Research* vol. 26, no. 2, pp. 137-163, June, 1991.

[8] G. Riley and C. Herboldsheimer, "Including hospice care in capitation payments to risk-based HMOs - would it save money for Medicare?," *Health Care Financing Review*, Fall, 2001; and Medicare Payment Advisory Commission, *Improving Risk Adjustment in Medicare*, Report to the Congress, November, 2000, Washington DC.

We also show that decedents have expenditures in their four years before death that are $33,400 greater than expenditures of survivors who are similar in age, gender, and Medicaid buy-in status. Even controlling for diagnoses, we find that the decedents have additional expenditures of $25,300 in the last four years of life (see Table S-7). Given the estimate that HMO beneficiaries die at 89 percent of the rate of FFS beneficiaries (the estimate for relative mortality in 2000), and the estimate that decedents have an extra $25,300 to $33,400 of costs in their last four years of life, differential mortality of HMO beneficiaries results in HMO resource needs that are approximately 2.1 percent to 2.8 percent lower than they would be if HMO mortality rates were equal to FFS mortality rates. (See Table S-8.)

Regardless of the relative mortality rates of HMO and FFS beneficiaries, it is certain that HMOs experience significant losses from serving enrollees who die and can make large gains from *avoiding* the enrollment of beneficiaries with greater-than-average mortality. If CMS wants health plans to do a good job of providing end-of-life care and to market themselves on the quality of their end-of-life care, then a payment system that rewards end-of-life care is important. We make suggestions for how such a system could be implemented. Regardless of whether CMS changes the HMO payment system to pay for end-of-life care, it should work towards establishing clear expectations for how end-of-life care should be delivered, for both HMO and FFS providers.

Chapter 7: Estimating Normal Disease Progression

If diagnosis-based risk adjustment is implemented widely, diagnostic reporting will likely become much more complete. Increased intensity of diagnostic reporting will create challenges for the equitable implementation of health-based payment, and could cause overall increases in federal expenditures.

Several responses are possible. One approach is to follow the lead of most Medicaid programs: make health-based payment budget neutral, audit diagnostic information to detect clearly fraudulent behavior, and trust that relatively equal rates of increase in the intensity of diagnostic reporting across health plans will create an equitable payment system.

A key response may be to measure change in the intensity of plans' diagnostic reporting through measuring the change in disease burden reported for members enrolled for two consecutive years. If reported disease burden grows unusually fast, CMS could correspondingly adjust case-mix factors downwards. To implement such a "data reporting adjustment," a technical question needs resolution: what is the normal annual increase in diagnostic burden?

We use CDPS-Medicare and diagnostic data of fee-for-service beneficiaries to assess how much sicker beneficiaries get as they age. For the 1.4 million beneficiaries in the five-percent sample, the average disease burden computed using 1996 diagnoses is approximately $5,300, while the average disease burden using 1997 diagnoses for this same group of people is $6,000, or an increase of 13 percent.

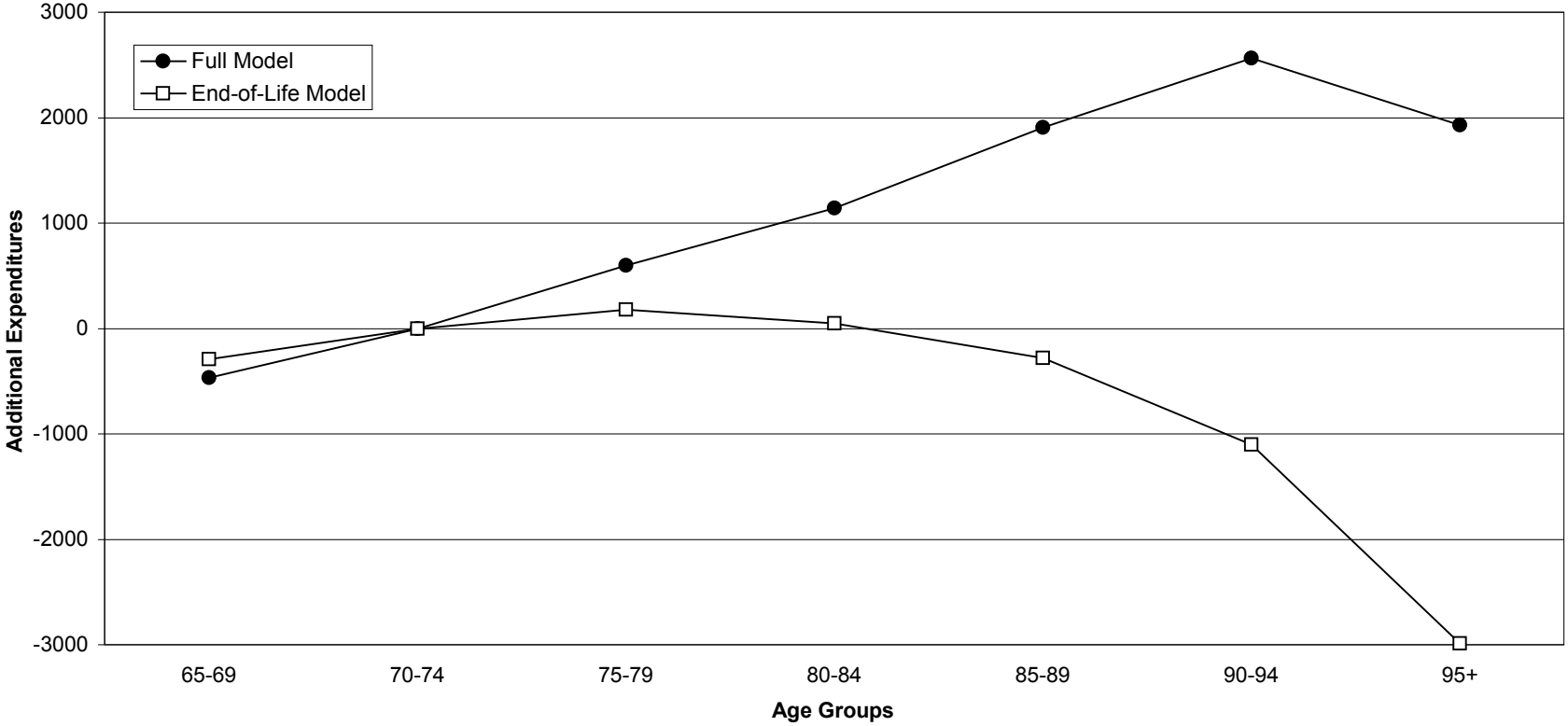
This result seems large and hard to reconcile with comparisons of disease burden calculated for successive five-year age cohorts. When comparing a group of 75-year-olds with a group of 80-year-olds, it appears that the disease burden of the 80-year-olds has increased at two to

three percent per year. Yet when we compare an individual 75-year-old with the same person at age 76 the disease burden increases by approximately 13 percent.

Some of the difference between these two estimates is due to differences in how people are selected into the analysis. In the comparison of a single individual at age 75 and at age 76, the person at age 76 has survived his or her seventy-fifth year and is certainly one year closer to death. A comparison of a cohort of 75-year-olds to a cohort of 80-year-olds is quite different. Life table data indicate that a cohort of 80-year-olds is only approximately 2.5 years closer to death than a cohort of 75-year-olds, for an average increase per year of proximity to death of only one-half year. In following individuals, we find that the effect of increasing proximity to death is associated with substantial increases in disease burden. Chapter 7 and its appendix show in detail how disease burden increases over time even for people many years from death.

On average, however, the effect of greater proximity to death on disease burden accounts for only 40 percent of the actual amount of change. Understanding why individual beneficiaries appear to get so much sicker from one year to the next while cohorts of beneficiaries five years apart appear to get sicker at a much more moderate rate remains an unresolved puzzle. Because we cannot fully explain the difference between the individual-based estimate of baseline change and the cohort-based estimate, we recommend additional analysis in order to establish a good estimate of the baseline rate of change needed to implement a data reporting adjustment.

Figure S-1
Additional Expenditures for Males, Age 65 and Over, for Full and End-of-Life Models



Note: The additional expenditures shown for the age groups in the full and end-of-life models are coefficients from regressions of the full CDPS-Medicare model and the full model supplemented with eight variables indicating death in the eight half years of 1997-2000. Both the full model and end-of-life model include diagnostic subcategories, interaction variables between disability and selected diagnostic subcategories, interactions among selected diagnoses, variables for beneficiaries with four or more high-cost subcategories, and demographic variables. In both regressions males age 70-74 are the omitted, or reference, category. Estimates of additional expenditures are relative to the reference category.
Source: Table 3-7, authors' analysis of 1996 diagnoses and 1997 expenditures.

Table S-2
Subsequent-Year Annual Expenditure Effects of CDPS-Medicare Subcategories and Other Variables for Medicare Population for Six Model Variants

CDPS Category	Frequency[1]	Base Model	Disability Interaction Model	Full Model	Inpatient Model	Restricted Model	End-of-Life Model
Cardiovascular							
Very high	0.002	$8,795	$8,662	**$7,628**	$8,381	$10,525	$7,263
Ischemic heart disease, high	0.101	2,788	2,804	**2,140**	4,143	5,006	1,379
Ischemic heart disease, low	0.082	1,202	1,210	**1,198**	877		1,398
Valvular, conductive and other heart disease, medium	0.003	2,453	2,450	**2,078**	1,643		1,948
Valvular, conductive and other heart disease, low	0.121	1,288	1,297	**1,329**	1,398		1,213
Valvular, conductive and other heart disease, very low	0.062	611	606	**643**	463		767
Peripheral vascular, medium	0.094	1,591	1,598	**1,607**	2,547		1,388
Psychiatric							
High	0.016	2,508	2,497	**2,357**	5,530	3,641	2,337
Medium	0.026	2,508	2,497	**2,357**	5,530	3,641	2,337
Low	0.052	628	645	**669**	2,228		383
Skeletal and connective							
Medium	0.060	1,962	1,966	**1,984**	2,029		1,917
Very Low	0.075	858	863	**887**	2,584		930
Extra Low	0.090	568	575	**594**	921		743
Nervous system							
High	0.003	7,861	7,434	**7,217**	10,952	8,239	6,817
Peripheral, high	0.018	2,103	2,101	**2,054**	3,838	3,410	2,145
Peripheral, low	0.014	714	715	**732**	3,411		946
Multiple sclerosis, muscular dystrophy and others	0.008	2,685	2,212	**2,014**	3,068	3,597	1,776
Parkinson's disease	0.013	2,152	2,176	**2,060**	3,681	3,103	1,194
Convulsions and epilepsy	0.024	1,352	1,328	**1,320**	2,797		1,203
Low	0.022	1,160	1,141	**1,116**	1,745		1,151
Delirum and dementia							
Delirium	0.006	1,339	1,419	**1,407**	2,283		614
Dementia	0.040	639	681	**685**	1,134		-637
Pulmonary							
High	0.012	8,655	7,938	**7,566**	7,537	9,023	6,283
Medium	0.039	1,582	1,584	**1,575**	2,097		1,163
Pneumonia, high	0.006	3,341	3,350	**2,889**	2,632		1,838
Pneumonia, low	0.052	1,154	1,152	**1,157**	868		806
Chronic obstructive disease, high	0.109	1,967	1,973	**1,778**	3,448		1,348
Gastrointestinal							
High	0.005	4,503	3,938	**3,612**	4,959	5,641	2,879
Ostomy	0.004	3,146	2,440	**1,958**	3,295	4,460	1,137
Medium	0.027	1,779	1,778	**1,620**	1,806		1,518
Low	0.062	848	849	**874**	1,132		938
Diabetes							
Type 1 or 2 with rare complications	0.008	5,050	5,007	**4,477**	5,419	5,401	4,050
Type 1 with common complications	0.006	3,829	3,822	**3,322**	6,698	4,136	2,992
Type1	0.031	3,829	3,822	**3,322**	6,698	4,136	2,992
Type 2 with common complications	0.009	1,353	1,358	**1,126**	2,747		1,022
Type 2	0.090	1,353	1,358	**1,126**	2,747		1,022
Skin							
High	0.010	4,786	4,192	**3,751**	7,388	6,510	2,504
Low	0.023	2,669	2,657	**2,515**	6,649	3,858	2,172
Renal							
Extra high	0.000[3]	13,002	12,949	**12,418**	20,584	14,555	11,869
Very high	0.007	4,332	3,695	**2,649**	5,159	5,459	1,826
Medium	0.008	2,734	2,738	**2,101**	3,462	4,326	1,824
Low	0.005	2,734	2,738	**2,101**	3,462	4,326	1,824
Very low	0.053	756	758	**783**	786		839
Substance abuse							
Low	0.004	3,788	1,728	**1,732**	1,873		1,721
Very low	0.008	1,529	876	**947**	739		602
Cancer							
Very high	0.009	7,900	7,968	**7,896**	13,000	9,302	4,389
High	0.011	3,661	3,688	**3,622**	8,534	4,910	1,993
Medium	0.021	2,066	2,084	**2,038**	6,170	2,805	1,574
Low	0.032	1,012	1,019	**1,041**	873		1,021
Very low	0.050	297	294	**305**	713		363

Metabolic							
High	0.018	3,051	3,048	**2,524**	3,093		1,878
Low	0.023	562	566	**593**	1,602		619
Cerebrovascular							
High	0.010	4,065	4,093	**3,713**	4,506	5,647	3,053
Medium	0.033	1,926	1,947	**1,662**	1,759		1,254
Low	0.037	1,123	1,131	**1,018**	2,167		988
Very low	0.005	1,123	1,131	**1,018**	2,167		988
Extra low	0.013	801	809	**718**	1,301		831
Infectious disease							
AIDS	0.001	4,839	4,639	**3,997**	5,454	5,904	3,483
High	0.002	4,839	4,639	**3,997**	5,454		3,483
HIV	0.000	2,824	2,820	**2,339**	2,125	1,651	2,118
Medium	0.013	2,824	2,820	**2,339**	2,125		2,118
Hematological							
Very high	0.000	7,404	6,910	**6,536**	9,088	8,292	4,819
High	0.002	7,404	6,910	**6,536**	9,088	8,292	4,819
Medium	0.005	4,074	3,602	**3,408**	4,596	4,543	2,539
Low	0.012	1,704	1,338	**1,335**	2,276		1,216
Anemia	0.083	891	899	**920**	890		794
Interactions with disabled							
Disabled and Psychiatric high	0.013		465	**555**	467	-262	611
Disabled and Psychiatric medium	0.011		-543	**-500**	-609	-785	-415
Disabled and M.S., muscular dystrophy, and others	0.004		1,025	**1,105**	3,024	290	1,136
Disabled and Pulmonary high	0.003		2,911	**2,785**	3,727	2,727	2,367
Disabled and Gastrointestinal high	0.001		1,949	**1,885**	2,976	1,830	1,529
Disabled and Ostomy	0.001		2,740	**2,695**	2,799	2,532	2,727
Disabled and Skin high	0.002		2,640	**2,565**	1,003	2,396	2,914
Disabled and Renal very high	0.002		2,671	**2,507**	3,085	2,447	2,504
Disabled and Substance Abuse low	0.003		3,014	**3,071**	1,981		2,953
Disabled and Substance Abuse very low	0.004		1,200	**1,181**	358		1,195
Disabled and Hematological very high	0.000		7,052	**7,335**	14,194	7,056	8,857
Disabled and Hematological medium	0.001		2,162	**2,064**	3,667	2,606	2,122
Disabled and Hematological low	0.002		1,869	**1,809**	3,006	4,981	1,769
Interactions between disease categories							
Diabetes and Ischemic heart disease high	0.030			**1,042**			891
Diabetes and Cerebrovascular	0.024			**632**			507
Ischemic high and Chronic obstructive disease high	0.027			**1,074**			903
Renal very high and Ischemic high	0.007			**786**			1
Renal very high, Ischemic high and diabetes	0.003			**1,308**			1,283
Four high-cost subcategories[2]	0.008			**1,479**			1,278
Five high-cost subcategories	0.003			**2,896**			2,826
Six high-cost subcategories	0.001			**4,099**			4,031
Seven or more high-cost	0.001			**6,294**			6,540
Died during the first six months of 1997	0.021						39,546
Died during the last six months of 1997	0.022						21,056
Died during the first six months of 1998	0.022						8,129
Died during the last six months of 1998	0.021						4,278
Died during the first six months of 1999	0.020						3,056
Died during the last six months of 1999	0.020						2,296
Died during the first six months of 2000	0.020						1,842
Died during the last six months of 2000	0.020						1,630
Originally disabled	0.063	1,387	1,167	**1,191**	2,038	1,690	642
Medicaid beneficiary	0.144	943	937	**951**	1,631	1,377	921
Medicaid beneficiary, age < 45	0.024	-273	-363	**-351**	-593	-407	-272

Male, age 0 to 34	0.008	-1,398	-1,558	**-1,573**	-2,204	-2,379	-1,108
Male, age 35 to 44	0.016	-1,287	-1,482	**-1,478**	-1,686	-1,998	-1,070
Male, age 45 to 54	0.019	-1,111	-1,322	**-1,307**	-1,419	-1,662	-1,018
Male, age 55 to 59	0.010	-760	-946	**-923**	-834	-1,025	-801
Male, age 60 to 64	0.013	-302	-492	**-466**	-179	-451	-534
Male, age 65 to 69	0.076	-460	-459	**-469**	-833	-732	-292
Male, age 70 to 74*	0.140	0	0	**0**	0	0	0
Male, age 75 to 79	0.077	582	589	**598**	948	838	178
Male, age 80 to 84	0.048	1,110	1,118	**1,140**	1,798	1,611	47
Male, age 85 to 89	0.022	1,857	1,872	**1,907**	2,776	2,495	-283
Male, age 90 to 94	0.007	2,474	2,496	**2,566**	3,494	3,146	-1,101
Male, age 95 and older	0.002	1,801	1,827	**1,930**	2,721	2,229	-2,986
Female, age 0 to 34	0.005	-1,247	-1,382	**-1,391**	-1,994	-2,123	-838
Female, age 35 to 44	0.010	-1,100	-1,245	**-1,239**	-1,367	-1,725	-703
Female, age 45 to 54	0.013	-1,033	-1,208	**-1,183**	-1,037	-1,457	-681
Female, age 55 to 59	0.008	-807	-979	**-938**	-577	-1,000	-459
Female, age 60 to 64	0.010	-186	-374	**-342**	210	-249	84
Female, age 65 to 69	0.094	-800	-806	**-820**	-1,124	-1,104	-307
Female, age 70 to 74	0.134	-406	-409	**-415**	-472	-508	43
Female, age 75 to 79	0.116	150	149	**153**	343	242	488
Female, age 80 to 84	0.087	681	684	**707**	1,137	975	787
Female, age 85 to 89	0.053	1,249	1,258	**1,311**	1,939	1,677	976
Female, age 90 to 94	0.024	1,594	1,607	**1,697**	2,463	2,029	777
Female, age 95 and older	0.008	867	881	**994**	1,776	1,146	-524
Intercept		1,760	1,789	**1,870**	3,483	3,055	1,367
R^2		0.110	0.111	**0.111**	0.085	0.089	0.193
Percent with no CDPS Category		29.8%	29.8%	**29.8%**	83.2%	72.6%	29.8%

* The age-gender group "Male, age 70 to 74" is the reference category.

[1] The frequencies shown are for the end-of-life model. The frequencies are the same for the variables included in the other models except for the inpatient model, whose frequencies are shown in Table 3-4.

[2] The high-cost subcategories were: cardiovascular very-high; cardiovascular ischemic heart disease high; cardiovascular valvular, conductive and other heart disease medium; psychiatric, high and medium; nervous system high; nervous system multiple sclerosis, muscular dystrophy and others; nervous system Parkinson's disease; pulmonary high; pulmonary pneumonia high; gastrointestinal high, medium, and ostomy; diabetes Type 1 or 2 with rare complications; diabetes Type 1; skin, high and low; renal, extra high, very high, and medium; cancer, very high, high, and medium; metabolic high; cerebrovascular, high and medium; AIDS high; infectious disease, high and medium; HIV medium; hematological, very high, high, and medium.

[3] The frequency of the renal extra high subcategory is 0.0003.

SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Table S-3
Predictive Ratios for Six CDPS-Medicare Model Variants

Group	Base Model	Disability Interaction Model	Full Model	End-of-Life Model	Restricted Model	Inpatient Model
Diagnoses						
Any Year1 Chronic Condition	0.99	0.99	0.98	0.98	0.93	0.91
Depression	0.92	0.92	0.93	0.92	0.79	0.84
Alcohol or Drug Dependence	0.94	0.96	0.95	0.96	0.66	0.88
Hypertensive Heart or Renal Disease	0.94	0.94	0.94	0.92	0.86	0.84
Benign/Unspecified Hypertension	0.97	0.97	0.97	0.95	0.91	0.91
Diabetes With Complications	0.89	0.89	0.90	0.91	0.83	0.73
Diabetes Without Complications	0.99	0.99	0.99	1.00	0.89	0.82
Heart Failure or Cardiomyopathy	0.98	0.98	0.98	0.98	0.97	0.81
Acute Myocardial Infarction	0.97	0.97	0.98	0.99	0.79	0.90
Other Heart Disease	0.97	0.97	0.97	0.98	0.84	0.85
Chronic Obstructive Pulmonary Disease	0.97	0.97	0.97	0.97	0.79	0.84
Colorectal Cancer	0.97	0.97	0.97	1.00	0.85	0.84
Breast Cancer	1.00	1.00	1.00	1.01	0.95	0.86
Lung or Pancreas Cancer	0.91	0.91	0.91	1.00	0.86	0.68
Other Stroke	0.96	0.96	0.96	0.96	0.77	0.80
Intracerebral Hemorrhage	1.02	1.02	1.02	0.99	0.80	0.88
Hip Fracture	1.03	1.02	1.02	1.03	0.78	0.95
Arthritis	0.92	0.92	0.92	0.90	0.84	0.85
Diabetes, Coronary Artery Disease	0.93	0.93	0.95	0.95	0.80	0.79
Diabetes, Cerebrovascular Disease	0.93	0.93	0.97	0.97	0.77	0.78
Heart Failure, Copd	0.92	0.92	0.95	0.96	0.80	0.79
Coronary Artery Disease, Vascular Disease	0.93	0.93	0.93	0.94	0.74	0.77
Copd, Coronary Artery Disease	0.93	0.93	0.94	0.95	0.72	0.80
Heart Failure, Renal Failure	0.92	0.92	0.98	0.98	0.90	0.79
Diabetes, Heart Failure, Renal Failure	0.86	0.86	0.97	0.97	0.84	0.77
Copd, Cerebrovascular Disease, Coronary Artery Disease	0.91	0.91	0.93	0.93	0.67	0.79
Diabetes, Cerebrovascular Disease, Vascular Disease	0.92	0.92	0.97	0.97	0.74	0.77
Expenditures						
First (Lowest) Quintile, Year1 Expend	1.15	1.14	1.18	1.22	1.75	1.97
Second Quintile, Year1 Expend	1.22	1.22	1.23	1.21	1.46	1.45
Middle Quintile, Year1 Expend	1.16	1.16	1.16	1.14	1.20	1.05
Fourth Quintile, Year1 Expend	1.04	1.04	1.04	1.03	0.98	0.81
Fifth (Highest) Quintile, Year1 Expend	0.86	0.86	0.86	0.86	0.73	0.82
Top 5 Percent Year1	0.76	0.76	0.77	0.77	0.63	0.75
Top 1 Percent Year1	0.66	0.66	0.68	0.68	0.56	0.64
No Home Health Spending Year1	1.10	1.10	1.10	1.09	1.13	1.11
Some Home Health Spending > 0 Year1	0.74	0.74	0.74	0.76	0.65	0.70
Home Health Spending>0:First Quintile, Year1	0.99	0.99	0.98	0.99	0.85	0.94
Home Health Spending>0:Second Quintile, Year1	0.99	0.99	0.98	0.99	0.85	0.94
Home Health Spending>0:Middle Quintile, Year1	0.88	0.88	0.88	0.90	0.76	0.84
Home Health Spending>0:Fourth Quintile, Year1	0.75	0.75	0.75	0.78	0.65	0.71
Home Health Spending>0:Fifth Quintile, Year1	0.46	0.46	0.46	0.49	0.42	0.43
Home Health Spending>0: 10% Of Spending Year1	0.38	0.38	0.38	0.42	0.35	0.35
Home Health Spending>0: 5% Of Spending Year1	0.32	0.32	0.33	0.36	0.30	0.30
No DMESpending Year1	1.09	1.09	1.09	1.08	1.13	1.13
DME Spending > 0 Year1	0.82	0.82	0.82	0.84	0.74	0.73
DME Spending>0:First Quintile, Year1	0.96	0.96	0.96	0.96	0.87	0.87
DME Spending>0:Second Quintile, Year1	0.91	0.91	0.90	0.90	0.81	0.82
DME Spending>0:Middle Quintile, Year1	0.89	0.89	0.89	0.90	0.81	0.78
DME Spending>0:Fourth Quintile, Year1	0.82	0.82	0.82	0.84	0.74	0.71
DME Spending>0:Fifth Quintile, Year1	0.64	0.64	0.65	0.71	0.57	0.57
DME Spending>0: 10% Of Spending Year1	0.58	0.58	0.59	0.66	0.52	0.51
DME Spending>0: 5% Of Spending Year1	0.56	0.56	0.56	0.62	0.50	0.49

Dme						
Oxygen Supplies/Equipment (Dme)	0.64	0.64	0.64	0.73	0.55	0.58
Wheelchairs (Dme)	0.67	0.67	0.68	0.72	0.61	0.62
Walkers (Dme)	0.84	0.84	0.84	0.85	0.71	0.81
Hospital Admissions						
0 Year1 Hosp Admissions	1.03	1.03	1.03	1.03	1.13	1.01
1 Year1 Hosp Admissions	1.03	1.03	1.01	1.01	0.87	1.05
2 Year1 Hosp Admissions	0.98	0.98	0.97	0.97	0.80	1.01
3+ Year1 Hosp Admissions	0.80	0.80	0.82	0.82	0.65	0.84
End-Of-Life						
Dth97 = Died In 1997	0.31	0.31	0.31	1.00	0.29	0.28
Dth98 = Died In 1998	0.70	0.70	0.70	1.00	0.66	0.64
Dth99 = Died In 1999	0.93	0.93	0.93	1.00	0.88	0.86
Dth00 = Died In 2000	1.01	1.01	1.01	1.00	0.97	0.95
Alive As Of 01/01/01	1.21	1.21	1.21	1.00	1.23	1.24

Source: Table 4-1, authors' analysis of 1996 diagnoses and 1997 expenditures

Table S-4
Expenditures Predicted by CDPS-Medicare Model and by End-of-Life Model Compared with Actual Expenditures for Beneficiaries Grouped by Number of ADL Impairments

Number of ADL Impairments	Number of Beneficiaries	CDPS-predicted Expenditures	End-of-Life Model Predicted Expenditures	Actual Expenditures	CDPS Predictive Ratio	End-of-Life Model Predictive Ratio
0	5,217	$4,509	$4,199	$3,832	1.18	1.10
1	1,048	6,636	6,771	6,391	1.04	1.06
2	608	7,092	7,189	8,060	0.88	0.89
3	368	8,615	8,735	12,067	0.71	0.72
4	309	8,369	9,063	11,566	0.72	0.78
5	386	10,030	11,204	14,399	0.70	0.78
6	436	10,287	13,865	11,609	0.89	1.19
All beneficiaries	8,372	5,588	5,588	5,588	1.00	1.00

SOURCE: Medicare Current Beneficiary Survey, 1996. ADLs are from 1996, diagnoses are from 1996 and expenditures from 1997.

Table S-5
Predictive Ratios for CDPS Medicare and End-of-Life Models, by Institutional Status

	Number of Beneficiaries	CDPS-Medicare	End-of-Life	Actual Expenditures	CDPS-Medicare Predictive Ratio	End-of-Life Predictive Ratio
All beneficiaries	8,372	5,588	5,588	5,588	1.00	1.00
Community beneficiaries	7,661	5,368	5,229	5,132	1.05	1.02
Institutionalized beneficiaries	711	9,429	11,527	13,125	0.72	0.88

Source: Table 4-7, Medicare Current Beneficiary Survey, 1996. ADLs are from 1996, diagnoses are from 1996 and expenditures from 1997.

Table S-6
Relative Mortality Rates of HMO Beneficiaries, 1997–2000

Beneficiary Groups	HMO Beneficiaries	HMO Decedents	HMO Mortality	Expected FFS Mortality	Relative Mortality Rate
1997	1,242,844	39,716	0.032	0.038	0.848
1998	1,429,186	48,015	0.034	0.039	0.861
1999	1,503,347	53,814	0.036	0.041	0.874
2000	1,482,667	54,403	0.037	0.041	0.892
1997-2000 combined	5,658,044	195,948	0.035	0.040	0.870

SOURCE: Twenty-percent sample of the 1997–2000 denominator files.

Note: Expected FFS mortality is adjusted for age, gender, county of residence, and Medicaid buy-in status. It is not adjusted for institutional status or hospice enrollment.

Table S-7
Expenditures in the Last Four Years of Life and Predicted Expenditures Based on Demographic and Diagnostic Characteristics

Time Period	1997 Expenditures	Predicted Expenditures, Controlling for: Demographic Characteristics	Predicted Expenditures, Controlling for: Demographic and Diagnostic Characteristics	Additional Expenditures for End-of-Life Care, Controlling for: Demographic Characteristics	Additional Expenditures for End-of-Life Care, Controlling for: Demographic and Diagnostic Characteristics
Last 12 months of life	$25,235	$4,271	$7,080	$20,964	$18,155
Months 13-24 before death	10,030	4,250	6,355	5,780	3,675
Months 25-36 before death	8,027	4,264	5,999	3,763	2,028
Months 37 to 48 before death	7,065	4,220	5,641	2,845	1,424
Total for last 48 months of life				$33,352	$25,281

SOURCE: Authors' analysis of 1996 diagnostic and demographic data and 1997 expenditure data.

Table S-8
Effect of Differential Mortality for HMO Beneficiaries on Expected Resource Needs

Year	Overprediction of HMO Expenditures Due to Differential Mortality If Expected Expenditures Are Adjusted For: Demographic Characteristics	Demographic and Diagnostic Characteristics
1997	0.036	0.027
1998	0.034	0.026
1999	0.032	0.025
2000	0.028	0.021

SOURCE: Authors' analysis of five-percent sample of 1996 diagnostic and demographic data, 1997 expenditure data, and twenty-percent sample of the 1997–2000 denominator files.

Note: Expected FFS mortality is adjusted for age, gender, county of residence, and Medicaid buy-in status. It is not adjusted for institutional status or hospice enrollment.

CDPS-Medicare:
The Chronic Illness and Disability Payment System
Modified to Predict Expenditures
for Medicare Beneficiaries

final report to CMS
June 24, 2002

Introduction

This report describes our work to revise the Chronic Illness and Disability Payment System (CDPS) for use in adjusting capitated Medicare payments to health plans. We originally developed CDPS to allow states to use diagnoses to adjust payments for their Medicaid beneficiaries. CMS staff believed that CDPS could prove a useful tool for Medicare's risk adjustment needs, but that some revision of the original model would likely improve its performance for Medicare beneficiaries.

The first two chapters of our report describe the development of the original CDPS model and its modification to create the CDPS-Medicare model. The third and fourth chapters describe regression results for six variants of CDPS-Medicare and the prediction of expenditures for various biased groups. The fifth chapter compares CDPS-Medicare with the HCC model. The remaining two chapters examine the effects of mortality on HMO resource needs and the problem of changes in disease burden.

The work described in this report was supported by a CMS contract (number 500-00-0008) awarded to Richard Kronick at the University of California, San Diego. Sarah Thomas, Mel Ingber, Jesse Levy, Leslie Greenwald, and Gerald Riley at CMS helped guide our work, as did Christopher Hogan. Readers of this report who would like further information can contact Richard Kronick by phone (858) 534-4273 or e-mail:rkronick@ucsd.edu

Chapter 1
The Original CDPS Model and Its Application to Medicare Data

The Development of the Original CDPS

We developed our first health-based payment model, the Disability Payment System (DPS) in 1995 and the second, the Chronic Illness and Disability Payment System (CDPS) in 1998-99.[9] We created both models for use by state Medicaid programs. To date, eight states have begun using DPS or CDPS and others are evaluating its use. See Table 1-1 for a list of states that have implemented health-based payment using DPS, CDPS or other systems.

The revision of DPS into CDPS was intended to make the system more complete and more effective in its adjustment of payments for the TANF population. DPS was developed on a relatively small data base of 120,000 SSI Medicaid beneficiaries in two states for identification of diagnoses and 400,000 beneficiaries in five states for testing and determination of categories. For CDPS, we used a much larger database, with claims records for nearly four million Medicaid beneficiaries from seven states. Effects of diagnoses on future expenditures were analyzed for all the 15,000 diagnosis codes in the *International Classification of Diseases* (ICD), and physician specialists were consulted extensively to help determine the appropriateness and organization of diagnoses included in the new system.

The resulting CDPS includes 20 major categories of diagnoses, which correspond to body systems or type of diagnosis.[10] Most of the major categories are further divided into several subcategories according to the degree of the increased expenditures associated with the diagnoses. For example, diagnoses of the nervous system are divided into three subcategories for high cost, medium cost, and low cost conditions.

Method of analysis

The selection and grouping of diagnoses for CDPS depended on analysis of our expenditure data and on the advice of 15 clinician consultants. The basic method of analysis was to use the presence of diagnoses recorded in the first year of individuals' claims as regression variables to predict expenditures in individuals' subsequent year of claims. We empirically identified diagnoses that are significantly associated with increased future health care costs. These diagnoses can serve the aim of health-based payment to provide additional resources to plans that enroll people with greater ongoing needs.

An important challenge to any effort to construct a diagnosis-based payment system is the defining of diagnoses in terms of ICD codes. The 15,000 ICD codes are organized under nearly a thousand three-digit general codes, nearly all with further subcodes for more specific diagnoses. Creating the diagnostic classification system requires decisions about what level of detail should be used in defining the system's diagnoses. Defining a diagnosis more narrowly

[9] For detailed information on the models, see R. Kronick, T. Gilmer, T. Dreyfus and L. Lee, "Improving Health-Based Payment for Medicaid Beneficiaries: CDPS," *Health Care Financing Review*, vol. 21, no. 3, pp. 29-64, Spring 2000; and R. Kronick, T. Dreyfus, L. Lee and Z. Zhou, "Diagnostic Risk Adjustment for Medicaid: The Disability Payment System, *Health Care Financing Review*, vol 17, no. 3, pp. 7-33, Spring 1996;
[10] For prospective estimation of payment weights, we exclude the categories for infants, leaving the model with the 19 major categories shown in Tables 1-2 and 1-4.

appears to give greater accuracy in predicting expenditures, but too narrow a definition could make it difficult for clinicians to agree whether an individual's condition justifies a given diagnosis, and could lead to unstable expenditure estimates.

We call each of the diagnoses in CDPS a "stage one group," which is defined by a group of ICD codes. For example, the codes 359, 359.0-359.6, 359.8 and 359.9 define the stage one group 359 for muscular dystrophies. Many of the stage one groups consist simply of all the codes grouped in ICD under a single three-digit code. For another example, the ICD codes 482.0, 482.1 and 482.2 together constitute the stage one group 4820_2 for especially high cost bacterial pneumonias.

Excluding ill-defined diagnoses: a key issue for implementation

Much of our consultation with clinicians was intended to screen out diagnoses that are clinically not well defined. We made special efforts to exclude ill-defined diagnoses from CDPS in order to make the system more reliable and reduce the chances that health plans, clinicians and Medicaid programs will find themselves questioning diagnoses. Given that health-based payment will naturally cause plans to make greater efforts at reporting diagnoses, a focus on well-defined diagnoses seems advisable to prevent difficult disagreements between payers and plans. Ill-defined diagnoses would make it difficult for payers to audit plans and distinguish between accurate and inaccurate reporting. We considered a diagnosis well-defined if it has a clear, shared meaning among clinicians. The diagnosis should be distinctive enough that an auditing clinician could judge from a good medical record whether the diagnosis was made on an adequate clinical basis.

Many of the diagnoses that we excluded from the model came from sections in the *ICD* created for ill-defined descriptions of disease or for the recording of symptoms not yet tied to a specific disease. Some conditions that we excluded depend entirely on patient report, such as chest pain or dyspnea. We also excluded many common symptoms that we judged too easily elicited in patient histories: symptoms such as headache, backache or joint pain might be recalled by many adults at some time in the months previous to a physician visit.

The inclusion of ill-defined diagnoses may increase predictive accuracy but will likely reduce accuracy in implementation. In general, as more diagnoses are included in a payment system, a greater volume of diagnoses needs to be reported and audited, and a higher proportion of variation in level of need observed among plans would result from differences in plans' abilities to make and report diagnoses rather than from actual differences in their enrollees. It seems likely that the inclusion of ill-defined diagnoses would particularly make the payment system more vulnerable to aggressive plan efforts to increase reporting. The modest improvement in accuracy on a given data set that is gained through ill-defined diagnoses seems far less important than having a system that is more easily administered and probably more accurate in practice.

Counting diagnoses within categories

In the original DPS, we had counted multiple diagnoses within some of the major categories, but in revisiting this issue for CDPS, we placed a higher value on limiting incentives for proliferative coding and on consistency across major categories. We also found that subdivisions and counting rules added substantially to the complexity of the model but

relatively little improvement in its performance. As a result, every one of the major categories in CDPS is counted "hierarchically," that is with only the single most severe diagnosis within the major category counted. This approach simplifies the model, strengthens its resistance to additional coding and produces only small decreases in the accuracy of simulated payments.

Single counting within major categories is intended to avoid encouraging a proliferation of different diagnoses reported for a single disease process just in order to increase payment. For example if someone is diagnosed with hemiplegia resulting from stroke, an additional diagnosis of transient cerebral ischemia is probably not of much additional significance for cost. As a result of this approach, the expenditures associated with people with multiple diagnoses in a single major category are loaded onto the single highest subcategory.

Meanwhile, CDPS counts multiple diagnoses when they are from different major categories. This multiple counting across major categories substantially improves accuracy because average expenditures are much higher for people with diagnoses from greater numbers of categories.

The Application of the Original CDPS to Medicare Data

Data

We used the data files that Health Economics Research (HER) had constructed for the development of the HCC model created for CMS. In order to make our results as comparable as possible with those of HER, we followed the same methods as they did in their prospective analyses in selecting beneficiaries appropriate for the analysis, weighting partial-year observations, defining expenditures to be included in the analysis, and in the sources of diagnoses used. This section provides a brief summary of the data and our use of it. More details of the file construction are provided in Chapter 2 of HER's July 2000 report.[11]

The initial sample for the files was the 1996-1997 Medicare five percent sample Standard Analytic Files. Our use of this data focused on the prospective sample, which contains data on beneficiaries eligible for Medicare for all of 1996 and at least part of 1997. Beneficiaries retained in the sample had to meet the following conditions: be continuously enrolled in both Medicare Parts A and B starting on January 1, 1996; have no period enrolled in an HMO in 1996; have at least one month of eligibility in 1997 while not enrolled in hospice or an HMO; not have working-aged status in either 1996 or 1997. ESRD-eligible beneficiaries were excluded because they have not been allowed to enroll in Medicare HMOs.

These requirements for inclusion in the data set were designed to create a sample of beneficiaries with a complete set of claims and expenditures. The result of the requirements was to reduce the five percent sample from its original two million beneficiaries to a sample for model development of 1.4 million beneficiaries.

[11] G.C. Pope and others, "Diagnostic Cost Group Hierarchical Condition Category Models for Medicare Risk Adjustment," Draft Final Report, July 31, 2000.

Medicare expenditures included inpatient, hospital outpatient, Part B physician/supplier, home health and durable medical equipment. Not included in the expenditure amount were deductibles and co-payments paid by beneficiaries, hospice payments, or indirect medical education payments. For each beneficiary not eligible for all of 1997, the sum of expenditures was annualized by dividing by the proportion of the year the beneficiary was eligible; for regression analyses, the observations of the partial-year beneficiaries were weighted by the proportion of the year the beneficiary was eligible.

We used diagnoses from the same sources that HER had used, including the following sources that appear in Medicare claims: hospital inpatient principal and secondary diagnoses; hospital outpatient diagnoses; physicians, including radiologist, anesthesiologist and pathologists; and other clinicians including psychologists, therapists and podiatrists. Diagnoses from a number of sources were not used, including home health agencies, skilled nursing facilities, hospice, providers of durable medical equipment.

Comparison of disease frequency between Medicaid and Medicare populations

The frequencies of diagnoses among subgroups of the Medicaid and Medicare populations allow us to compare the health status of various populations. See Table 1-2 for a comparison of the frequencies in CDPS-Medicaid diagnostic categories for various Medicaid and Medicare beneficiary groups.

Comparing the data for Medicaid disabled adults and Medicare beneficiaries under age 65, we see that the frequencies for most diagnostic categories are quite similar but somewhat higher for the Medicare under-65 group. Most of the major categories have frequencies two to four percentage points higher for Medicare under-65 than for the Medicaid disabled adults. The cardiovascular and skeletal major categories have greater differences. Thirty-six percent of the Medicare under-65 beneficiaries have a CDPS cardiovascular diagnosis, versus only 27 percent among the Medicaid disabled adults, or nine percent less. For the skeletal diagnoses, the frequencies are 24 percent and 17 percent, for a difference of seven percent. One exception to the general pattern is the subcategory of high-cost psychiatric diagnoses, where the frequency for Medicaid disabled adults is greater by two percent.

Comparing the Medicaid disabled adults with the Medicare 65-and-over population, we find much greater differences in diagnostic frequencies, with the Medicare 65-and-over frequencies approximately twice as frequent in many of the major categories. One of the most impressive differences is in the frequency of cardiovascular diagnoses: 63 percent among the older Medicare beneficiaries, 2.3 times the frequency of 27 percent among the Medicaid disabled adults. Similar proportional differences are also found in the frequencies of skeletal, renal and hematological diagnoses, which are approximately twice as frequent among the older Medicare beneficiaries as the Medicaid disabled adults. Even larger proportional differences are found in some categories: eye diagnoses are twelve times more frequent among older Medicare beneficiaries than among Medicaid disabled adults; cancer, genital and cerebrovascular diagnoses are more than three times more frequent.

Some other major diagnostic categories, such as pulmonary, GI, diabetes, and skin exhibit more modest higher frequencies for the Medicare 65-and-over group. An exception is the category of nervous system diagnoses, which have a slightly higher frequency for the Medicaid disabled adults (17 percent) than for the older Medicare group (15 percent).

A more significant exception to the general pattern is found among psychiatric diagnoses, which are 2.8 times more common among the Medicaid disabled adults. In even greater contrast, high-cost psychiatric diagnoses, principally schizophrenia, are found among 12 percent of the Medicaid disabled adults but only one-half of one percent of the older Medicare group. A similar pattern is found for drug and alcohol abuse, which is indicated among five percent of the Medicaid disabled adults, but among less than one percent of the older Medicare group, which seems like a gross under-reporting of substance abuse problems (this issue is discussed further in Chapter 5).

In general, we can see that the TANF adults experience far less chronic illness than the other three groups. The only diagnostic category with a higher frequency for the TANF adults is the pregnancy category. The genital category also has a frequency higher than for the Medicaid disabled adults and the Medicare under-65 group, but less than for the older Medicare group. TANF children have even lower frequencies than the TANF adults for almost all major categories except pulmonary and infectious.

Summaries of disease burden are provided by the proportions of the different population groups that are indicated to have no CDPS diagnoses. Among Medicaid disabled adults, 29 percent have no CDPS diagnosis; among the Medicare under-65 group, 24 percent have no CDPS diagnosis; among the older Medicare group, only 13 percent have no CDPS diagnosis. In the average for all Medicare beneficiaries, the much larger 65-and-over group dominates, and we find a proportion of 15 percent with no CDPS diagnosis.

Analyzing the beneficiaries who have at least one CDPS diagnosis, we find that Medicare beneficiaries age 65 and over have more diagnoses per person than in the other groups. The average number of categories counted among Medicaid disabled adults with at least one diagnosis is 2.3; the same average among Medicare beneficiaries under age 65 is 2.9; and among older Medicare beneficiaries, 3.2.[12] These data confirm the picture provided so far: the Medicare beneficiaries age 65 and over are on average sicker than both the Medicaid disabled adults and the Medicare beneficiaries under age 65.

Predicting Medicare expenditures with the original CDPS subcategories

Before using CDPS-Medicaid to estimate regression coefficients from the Medicare data, we used an easier method to gauge the overall appropriateness of CDPS for modeling Medicare expenditures. We used CDPS-Medicaid to count the diagnoses of Medicare beneficiaries, and multiplied the counts by the CDPS-Medicaid coefficients previously calculated from our large disabled adult Medicaid sample.[13] In the Medicaid regression to compute these coefficients the dependent variable was the annualized expenditures for an individual divided by the average expenditures for all beneficiaries in the regression. Thus the mean of the dependent variable in the Medicaid regression was 1.0. We used the parameter estimates from the CDPS-Medicaid regression to compute a case-mix value for each Medicare

[12] Because of the hierarchical counting rules, only one diagnosis is counted for each major category. In the calculation of the averages, counts in the category of pregnancy were excluded.

[13] The original Medicaid regression did not have age categories for persons over 65. We assign a baseline value of approximately 0.3 to all Medicare beneficiaries, approximately equal to the intercept from the Medicaid regression plus a weighted average of the age and gender dummy variables, where the weights are proportional to the number of Medicaid beneficiaries in each age and gender category.

beneficiary in the analysis. We then used this case-mix score as an independent variable in a new regression along with demographic variables for age, sex and reason for entitlement. The average case-mix score for the Medicare beneficiaries is 1.20, indicating that Medicare beneficiaries have on average a 20 percent higher burden of diagnoses than disabled adult Medicaid beneficiaries.

The resulting R^2 of 0.095 suggests that the basic architecture of CDPS is appropriate for the Medicare population. Table 1-3 displays the regression variables and coefficients. The coefficient for the case-mix variable of $3,729 indicates that Medicare expenditures are expected to increase by $3,729 as the predicted case-mix score (where the prediction is based on our Medicaid regression) goes from 1.0 to 2.0.

To see how our original CDPS model would work for the Medicare population before any modification, we regressed the year two expenditures of Medicare beneficiaries against their year one diagnoses as summarized by the original CDPS subcategories. Most of the subcategories of the original CDPS model (referred to in this report as "CDPS-Medicaid") appear to be good predictors of increased future expenditures among Medicare beneficiaries. (See Table 1-4 for a comparison of the coefficients of CDPS-Medicaid diagnostic subcategories for disabled Medicaid beneficiaries and for Medicare beneficiaries.) Most of the categories that are predictive of high costs in the Medicaid population are also predictive of high costs in the Medicare population. Of the 56 CDPS-Medicaid diagnostic subcategories, 50 worked well as predictive variables, and the vast majority had estimated coefficients at least 20 times larger than their standard error. The R^2 for this regression of 0.105 is approximately ten percent higher than the 0.095 that resulted from predicting Medicare expenditures using CDPS Medi*caid* coefficients.

The similarity of expenditure patterns among Medicaid and Medicare beneficiaries is striking, especially given the differences in populations and the benefits covered. When we used CDPS-Medicaid to regress separately expenditures for the Medicaid disabled sample and the Medicare population on the respective diagnostic data, we found that the subcategory coefficients for the two populations are very similar. Diagnostic subcategories such as very high-cost pulmonary diagnoses, high-cost CNS conditions or high-cost diabetes have high coefficients for both groups; diagnostic subcategories such as low-cost cardiovascular, low-cost psychiatric and low-cost renal conditions have low coefficients for both groups. For some major categories such as skeletal, CNS or skin the sets of coefficients for the different subcategories are similar to each other.

A handful of subcategories from the CDPS-Medicaid model were unsuccessful as variables for the Medicare sample. The subcategories of medium-cost and low-cost developmental disability had very low frequencies (0.15 percent and 0.58 percent) among the Medicare sample and were predictive of significantly *reduced* expenditures in the following year (–$1,900 and –$1,200). Two CDPS-Medicaid subcategories, genital diagnoses and very low cost eye diagnoses, had large frequencies among Medicare beneficiaries (11 percent and 32 percent), but were also significant predictors of *reduced* expenditures (–$300 and –$150). Two subcategories for pregnancy, both with very low frequency (0.10 and 0.18), failed as variables (t-value of –0.24 for completed pregnancy and 0.87 for incomplete pregnancy). Finally, the subcategory of hypertension, coded for 21 percent of the Medicare sample, was predictive of only $90 in annual expenditure, and the t-statistic of 2.9 was far lower than for most of the other variables.

The results for the developmental disability (DD) variables deserve further attention. In the preparation of our data for the Medicaid analysis, we had attempted to remove state expenditures for "non-acute" home and community-based services in order to focus the analysis on acute care services that would normally be part of the managed care benefit package. We suspect that we may not have succeeded in removing these expenditures for all the states, thus producing the positive coefficients in the DD categories for the Medicaid analysis. The negative coefficients for DD in the Medicare analysis could be explained by barriers to care experienced by people with DD or might be due to better health status.[14]

One shortcoming evident in the original CDPS-Medicaid model used for Medicare data is the lack of separation between the coefficients of some subcategories. If the coefficients of adjacent subcategories are statistically indistinguishable, then maintaining separate subcategories brings no gain in payment accuracy or incentives for serving sicker people. For example, the coefficients of the metabolic high- and medium-cost subcategories were $3,200 and $3,000. In two cases, coefficients were "reversed," that is with the lower subcategory having the higher coefficient, for example with medium-cost cancers at $786 and low-cost cancers at $819. A more substantial reversal of expected coefficients is found with the very low-frequency subcategories of extra-high cost hematological diagnoses at $7,300 and very-high cost hematological diagnoses at $12,000. The extra-high cost subcategory comprises the diagnoses of congenital factor VIII and factor IX coagulation defects (hemophilia). Much of the high cost for these diagnoses among the Medicaid population is to pay for expensive clotting factors, which are not covered by Medicare.

Predicting Medicare expenditures with a modified CDPS-Medicaid model

Because of the half-dozen unsuccessful variables and the lack of separation between some subcategories in the original CDPS-Medicaid model, we eliminated some subcategories and combined others to create a model with greater validity for implementation. Negative coefficients are clearly inappropriate for payment purposes; it is unreasonable for Medicare to reduce payments to plans because additional diagnoses are reported. Similarly, "reversed" coefficients are particularly troublesome in a hierarchical model because additional reporting of diagnoses could result in a reduction in payments.

We call this model, which is the original CDPS-Medicaid model only lightly modified to work better with the Medicare data, the "modified CDPS-Medicaid model" (see Table 1-5). Its main purpose is to provide a baseline against which we can see the effects of more detailed modifications of CDPS for use with Medicare payments. The subcategories we eliminated were medium- and low-cost developmental disability, genital, very low-cost eye, complete and incomplete pregnancy, and extra low-cost cardiovascular. The subcategories we combined were medium- and low-cost cancer; high- and medium-cost metabolic; extra high- and very high-cost hematological. Table C shows the frequencies and predicted additional expenditures for Medicare beneficiaries with diagnoses in the subcategories of the modified CDPS-Medicaid model.

[14] For example, this regression does not control for mortality. It may be that people with DD have lower death rates than people without and that this leads to the negative coefficients.

Chapter 2

Reassigning Diagnoses, Creating New Subcategories and Changing Counting Rules to Create the CDPS-Medicare Model

The original CDPS model and its lightly modified version predict expenditures for Medicare beneficiaries fairly well, but a more thorough modification of CDPS produces a model, "CDPS-Medicare," which is still more appropriate for Medicare beneficiaries. To develop CDPS-Medicare, we re-examined the placement of diagnoses within the model and reconsidered whether diagnoses should be included in the model for payment purposes. We also made new subcategories and modified the rules for counting diagnoses among cardiovascular, pulmonary and nervous system conditions in order to allow better predictions for beneficiaries with diagnoses in these areas. Finally, we also made significant changes in the major category for diabetes.

Reassigning Diagnoses

Movement of diagnoses within the payment model

We re-examined the placement of diagnoses within the payment model to assure that diagnoses are in the subcategory with the right level of predicted expenditures for Medicare beneficiaries. We used both statistical and clinical information to decide whether a diagnosis should be moved from one subcategory to another.

We reassigned diagnoses for several reasons. In some cases, we may have originally misclassified a diagnosis based on a fairly small number of Medicaid beneficiaries recorded with the condition. Where we found larger numbers of Medicare beneficiaries with a diagnosis, we could classify the diagnosis with greater confidence. For other diagnoses, we suspect that the relative cost effects among diagnoses for Medicare beneficiaries differ from the relative cost effects for Medicaid beneficiaries, mostly because of the much greater average age of the Medicare beneficiaries.

We based our decisions to reassign diagnoses on statistical evidence and clinical advice. The statistical evidence came regressing year two expenditures against year one diagnoses – not as summarized by the 56 CDPS subcategories but as counted in the 787 diagnoses that we had defined in the creation of CDPS-Medicaid. Each of the 787 diagnoses was treated as an independent dummy variable, set to one if an individual had in his or her record one of the ICD codes with which we had defined the diagnosis. We refer to the each diagnosis defined in CDPS by a group of ICD codes as a "stage one group."

By breaking the stage one groups out of their subcategories and treating each as an independent variable, we were able to examine the cost effects of separate diagnoses for Medicare beneficiaries and consider whether the placement of a diagnosis into its subcategory might be changed. When the coefficient for an individual stage one group based on Medicare data was very different from the other stage one groups in the same subcategory, we considered moving it to a higher- or lower-cost subcategory with diagnoses of more similar coefficient.

We did not, however, move stage one groups simply on the basis of their coefficients. In general we did not move stage one groups that had small numbers of people or modest t-values. Each change was discussed with our consulting clinician to see if the new placement seemed clinically sensible. In an additional review of the model, we and our clinical consultant looked at the diagnoses in each subcategory to judge whether the changes led to the collocation of diagnoses within a subcategory that seemed too different in terms of expected cost effects to be classed together.

For an example of a stage one group promoted from a lower subcategory to a higher one, consider intestinal obstruction (ICD code 560). This diagnosis had been placed in the CDPS-Medicaid subcategory of low-cost gastrointestinal diagnoses based on the additional cost found among 6,700 adult Medicaid beneficiaries with disability. In the regression of Medicare expenditures against individual stage one groups, however, intestinal obstruction showed among 23,000 beneficiaries a cost effect of $1,100, much higher than most of the other diagnoses in the subcategory of low-cost GI diagnoses and similar to the costs of the diagnoses in the subcategory of medium-cost GI diagnoses such as regional enteritis or chronic liver disease. Our physician consultant observed that intestinal obstruction is associated with a variety of significant diseases, including colon cancer, and often requires hospitalization. Considering all this information, we decided to promote this diagnosis to the subcategory of medium-cost gastrointestinal diagnoses.

For an example of a demotion, consider malignant melanoma and other malignant cancers of the skin (ICD codes 172 and 173), which had been placed in the CDPS-Medicaid subcategory of low-cost cancer diagnoses based on the additional cost found among 3,700 adult Medicaid beneficiaries with disability. In the regression of Medicare expenditures against individual stage one groups, however, malignant skin cancer showed among 58,000 beneficiaries a cost effect of only $200. We decided to create a new subcategory for very low-cost cancers and to demote malignant skin cancer to it.

For an example of a promotion suggested by the data that we chose not to make, consider hepatomegaly (enlargement of the liver, code 789.1), which had originally been placed among gastrointestinal low-cost conditions. In the Medicare stage one group regression hepatomegaly showed a coefficient of $1,300, with a t-value of 5 and N of 2,600 – strong statistical grounds for promotion to the GI medium, where it would fit in with other diagnoses with similar coefficients. Our clinician pointed out, however, that hepatomegaly is quite variable in its severity, from mild to bad; it also has a variety of causes, ranging from fatty deposits as a result of too much alcohol intake, to early heart failure, to dangerous cancer; and it might often be followed by a more specific diagnosis in a different major category. With this clinical perspective and despite the data, we decided not to promote hepatomegaly.

For an example of a demotion that we considered because of the data but then chose not to make, consider malignant neoplasm of the small intestine (code 152), in the subcategory of medium-cost cancers. In the Medicare stage one group regression it showed a coefficient of only $240, with a t-value near zero. The number of people recorded with malignant neoplasm of the small intestine, however, was so small, only 360, that we decided we did not have an adequate statistical basis for demotion.

The movement of diagnoses within the model can be summarized through the number of stage one groups that were assigned to a different subcategory in the new model. Considering most of the major categories, 51 stage one groups were promoted from a lower to a higher subcategory, while 42 stage one groups were demoted from a higher subcategory to a lower one. Important changes in the organization of the pulmonary, cardiovascular and central nervous system diagnoses cannot be summarized into numbers of promotions and demotions and are discussed further below.

Movement of diagnoses into or out of the payment model

A second important element of our revision was the movement of diagnoses into or out of the payment model. We removed stage one groups from the payment model either because they showed no significant cost effects among Medicare beneficiaries or because of our heightened concern about excluding ill-defined diagnoses. In each major diagnostic area, diagnoses excluded for payment purposes were assigned to subcategories not used in the regressions for calculating payment weights. Stage one groups excluded because they show no significant association with increased future costs were moved to subcategories labeled as "super low-cost," for example super low-cost metabolic diagnoses. Stage one groups that our clinical consultants judged to be not well enough defined to be used for payment purposes were moved to subcategories labeled as "not well-defined," for example not well-defined gastrointestinal diagnoses.[15]

Finally, we also removed some entire subcategories from the payment model in the very last stages of model testing when all the demographic and interaction variables were finalized. These removed subcategories were the extra low-cost cardiovascular subcategory (hypertension), the pulmonary subcategory for asthma, the very low-cost hematological subcategory, and the eye subcategory. These subcategories were deemed to have too low an association with increased future cost to justify their inclusion. We excluded most subcategories with coefficients significantly less than $300.

We also moved some previously excluded diagnoses back into the model. A number of stage one groups that had been in the super-low subcategories showed significant cost effects among Medicare beneficiaries. Some also were judged to be well enough defined to be included. We also changed our evaluation of the well-definedness of a very few diagnoses that we had previously judged ill-defined and brought them into the model.

The number of diagnoses removed from the model was much greater than the number added. The net effect was to reduce the number of stage one groups from 451 to 389. This reduction in stage one groups makes the model more resistant to increased coding of diagnoses.

For an example of a diagnosis moving out of the payment model, consider migraine (ICD code 346), which had been placed in the CDPS-Medicaid subcategory of low-cost CNS diagnoses. With the Medicare data, migraine failed as a variable, showing no cost effect (–$13 and t-value of 0), even with a sample size of 12,700. Our clinician consultant argued

[15] We first excluded diagnoses that showed no cost effect, then excluded diagnoses judged to be not well-defined. As a result, the super low-cost subcategories include a mixture of diagnoses that would be judged as well-defined and not well- defined, while the not well-defined subcategories include primarily ill-defined diagnoses with significant cost effects.

that migraine is well-defined in the textbook but has many types that in practice can be hard to distinguish from tension headaches. Further, migraines are much less of a problem for the elderly than for younger people and they can often be helped by drugs that elderly people are taking for other purposes. With the data and this clinical perspective, we concluded that it was appropriate to demote migraine to the subcategory of CNS super-low cost, where it would not be used to adjust payments.

For an example of a diagnosis moving into the payment model, consider iron deficiency and unspecified anemia (ICD codes 280, 285). We had placed these diagnoses in a special CDPS-Medicaid subcategory for very-low cost hematological diagnoses and excluded them from use in payment because of very low additional costs for Medicaid adults with disability and no additional costs for AFDC adults. For Medicare, however, anemia appears a significant diagnosis, with $500 of increased expenditures for 117,000 beneficiaries. Although we were concerned about the very large number of beneficiaries who might be coded with anemia, our clinical consultant argued that anemia is well-defined even with the cause unspecified (ICD 285.9), can indicate significant disease or debility, and deserves medical attention. We placed iron deficiency and unspecified anemia, along with some other specified deficiency anemias (ICD 281), into a new CDPS hematological subcategory for deficiency anemias (Anemia).

New Subcategories and Changes in Counting Rules

Increased counting for cardiovascular, pulmonary, and nervous system

Multiple diagnoses within most major diagnostic categories in CDPS-Medicare continue to be counted as they were in CDPS-Medicaid: only the single highest-cost subcategory is counted within the major area regardless of diagnoses made in lower-cost subcategories. (See Figure 2-1 for a graphic representation of the cancer subcategories as an example of a full hierarchy.) We changed the rules, however, to allow multiple counting in the major categories of cardiovascular, pulmonary and nervous system diagnoses. Multiple counting should allow more accurate predictions for beneficiaries with more than one type of disease within a major category. Such multiple counting could be extended to other major areas, but would make the payment model more susceptible to proliferative coding. The three major areas in which we do allow multiple counting were chosen because of the importance of these areas for older beneficiaries and because of the distinctiveness of the diagnoses within the area.

For cardiovascular diagnoses, we created *three types* of subcategories: a first type for ischemic heart disease; a second for valvular, conductive and other heart disease; and a third for peripheral vascular disease. A beneficiary with diagnoses in two or three of the different types of cardiovascular disease will have multiple subcategories turned on as part of the overall counting of his or her diagnoses. Peripheral vascular disease has only one subcategory and hence can receive a maximum count of one. The valvular, conductive and other heart disease diagnoses are divided into three subcategories (medium cost, low cost, and very low cost), among which only the highest cost subcategory can be counted – hence an additional count of one. Within ischemic heart disease, however, two counts are allowed, one each in the two ischemic heart disease subcategories – high-cost ischemic disease (essentially congestive heart failure), and low-cost ischemic disease (mostly acute myocardial infarction and angina).

Hence a total of four cardiovascular counts is possible. (See Figure 2-2 for a representation of the cardiovascular hierarchy.)

At the same time, we limit counting for the very few beneficiaries, one quarter of one percent, with heart transplant or problems with vascular devices and grafts. For these beneficiaries we count only a very high-cost condition and count no other cardiovascular diagnoses.

The counting rules for pulmonary diagnoses are quite similar to those for cardiovascular diagnoses. For those with the most serious pulmonary diagnoses such as respiratory arrest or failure, tracheostomy, or respirator dependence, no other pulmonary diagnoses are counted and a single count is made for a high-cost pulmonary diagnosis. Other pulmonary diagnoses are divided into three types: pneumonia, chronic obstructive pulmonary disease, and other pulmonary disease. A person may have one count among the two pneumonia subcategories, one count from the single chronic obstructive pulmonary disease subcategory, and one count from the subcategory for medium-cost pulmonary disease. (See Figure 2-3 for a representation of the pulmonary hierarchy.) Finally, because of the substantial overlap between respiratory arrest and cardiac arrest, if both are coded we count only respiratory arrest.

The counting rules for CNS conditions are also similar, but with a greater number of types. A diagnosis in the subcategory of high-cost CNS diagnoses turns off all other subcategories. Otherwise, up to five counts are possible: one count from among two subcategories for peripheral nervous conditions; a second count from a subcategory for multiple sclerosis, muscular dystrophy and other significant nervous system diagnoses; a third count from a subcategory for Parkinson's disease; a fourth from a subcategory for convulsions and epilepsy; and a fifth from a subcategory for other low-cost CNS conditions. (See Figure 2-4 for a representation of the nervous system hierarchy.)

A new major category for delirium and dementia

We brought together diagnoses that had previously been in the nervous system and psychiatric categories into a new major category for delirium and dementia, with two subcategories, one for the higher-cost subcategory of delirium and a second for the lower-cost subcategory of dementia. A maximum of one count is allowed in the two subcategories, with a count in delirium turning off the dementia subcategory. In addition, because of the occasional association between psychiatric illness and delirium, we imposed an additional counting rule across major categories: if either the high-cost or the medium-cost psychiatric subcategory is counted, then delirium cannot be counted. There is no such restriction, however, on dementia, which can be counted even if a high-cost or medium-cost psychiatric diagnosis is counted.

New approach in diabetes

We made a significant change in the classification of diabetes and its complications. In CDPS-Medicaid, we had created four subcategories: one for Type 1 diabetes with renal manifestations (including nephropathy) or coma; a second for Type 1 diabetes without complications or with neurological or ophthalmic complications; a third for Type 2 diabetes with complications; and a fourth for uncomplicated Type 2 or unspecified diabetes. The data

on frequencies in Table 1-2 and on expenditures in Table 1-4 suggest that this approach developed for Medicaid disabled adults also predicts well for Medicare beneficiaries.

Yet when we reviewed the more detailed Medicare data with frequencies for each stage one group, we discovered a large discrepancy between the frequency of important complications as reported in the Medicare data and their frequency as known from clinical experience and literature. For example, 30 to 40 percent of individuals with Type 1 and Type 2 diabetes will show clinical evidence of early nephropathy (microalbuminuria). Half or more of those with early nephropathy will progress to more significant nephropathy, among whom half again will progress to end stage renal disease in ten years.[16] Among those with early nephropathy, most require only a small amount of additional medication.

In contrast to expectations, the Medicare data showed far lower frequencies of complications. Compared with 57,000 beneficiaries identified with Type 1 diabetes without complications, we found only 2,200 coded with Type 1 and renal manifestations, or less than four percent. And compared with 196,000 beneficiaries whom we found coded with Type 2 or unspecified diabetes with no complications, unspecified complications or circulatory manifestations, we found only 3,500 with Type 2 or unspecified diabetes with renal manifestations, or less than two percent. We believe that the fee-for-service data significantly under-count those with renal manifestations and are strongly biased toward the more costly individuals.

Because of this discrepancy, our CDPS-Medicaid classification for diabetes would be quite vulnerable to the increased coding expected under diagnosis-based payment. (The HCC model, for much the same reasons, is also very vulnerable to increased coding of diabetes complications, as discussed in Chapter 5.) Of course, when any comprehensive diagnosis-based payment model is implemented, the number of diagnoses reported is likely to climb from current levels of fee-for-service under-reporting up toward the true frequency. In general, this change will be good for patient care and quality monitoring; it will also require counter-balancing reductions by payers in overall diagnosis-based payment. But the estimation of additional costs for these common diabetes manifestations based on a very small and high-cost subset will create a point of extreme vulnerability to increased coding.

The CDPS model resolves this difficulty by creating one subcategory specifically for Type 1 diabetes with high-frequency complications and another for Type 2 diabetes with high-frequency complications. In our recommended payment model, we constrain the coefficients of these categories to be equal to those of the categories for uncomplicated Type 1 and Type 2. In future applications of CDPS, these constraints could be removed and the coefficient values adjusted to reflect better estimates of additional costs. For now, the constraints lower the predictive accuracy of the model, but we expect that the model should be more accurate in actual use, because it avoids the mis-estimation of the payment weights for high-frequency diabetic complications based on very small and probably unrepresentative subsamples.

An additional change in the classification of diabetes was to merge the most costly low-frequency complications of Type 1 and 2 into a single subcategory for Type 1 or 2 with rare complications, which are ketoacidosis, hyperosmolarity, coma and proliferative retinopathy.

[16] M.E. Molitch, "Management of early diabetic retinopathy," *American Journal of Medicine*, vol. 102, pp. 392-398. 1996.

Our clinical consultant argued that the costs for these conditions do not differ by type of diabetes; the combination allows a more stable estimate of the coefficient.

The counting rule for diabetes is fully hierarchical, so that for each beneficiary only the single highest subcategory is counted.

Retaining the subcategory for dialysis

Because of the exclusion of beneficiaries enrolled in the end-stage renal disease program, only 0.03 percent of our sample, or approximately 430 beneficiaries, were indicated in the diagnostic record as receiving dialysis and classified in the subcategory of extra high-cost renal. We would generally regard this size sample as too small for reliable estimation of a payment weight, but in this case decided to retain the separate subcategory. The extra high-cost renal subcategory should be useful for predicting expenditures of people on dialysis and its coefficient could easily be re-estimated when applied to populations that do not exclude people eligible for Medicare as a result of end-stage renal disease.

Effects of Moving Diagnoses and Changing Counting Rules

The changes to the model described above were intended not to make dramatic improvements in the predictive accuracy of the model but primarily to improve the validity of the model and its resistance to proliferative coding. Consider the range of possible improvement in predictive accuracy: The original CDPS-Medicaid model used to predict Medicare expenditures with coefficients estimated on Medicare expenditures had an R^2 of 0.105, which represents the starting point or minimum level of prediction we would hope to see in an improved model.

At the maximum, improvements in the predictive accuracy of the final model were constrained by the limited predictability of medical expenditures for the Medicare population. When we disaggregated the 787 original CDPS-Medicaid stage one groups from the subcategories, including the super low-cost and not well-defined subcategories, we achieved an R^2 of 0.125 percent. This R^2 would seem to represent the maximum predictive power possible with this population and current diagnostic data after the combining of ICD codes required to define the stage one groups. For purposes of implementation, however, some of this predictive power must be sacrificed; ill-defined diagnoses need to be excluded for payment purposes and the diagnoses need to be collapsed into a smaller number of variables to calculate stable payment amounts.

After all the changes in the placement of diagnoses in subcategories, in the inclusion of diagnoses, and in the increased counting allowed in certain areas, the R^2 of the CDPS-Medicare model is 0.110. CDPS-Medicare thus predicts Medicare expenditures better than CDPS-Medicaid, but the R^2 climbs less than half the way from 0.105 to the maximum possible R^2 with the disaggregated stage one groups of 0.125. This modest improvement reflects our strategy of both improving the classification of diagnoses to correspond better to Medicare expenditures and reducing the number of diagnoses to make the model more resistant to proliferative coding. The real improvement is to increase confidence that the model is rewarding diagnoses to the right degree.

(See Appendix 1 and Appendix 2 for the CDPS-Medicare assignment of ICD diagnosis codes to diagnostic subcategories. Appendix 1 shows the diagnostic codes grouped in the subcategories and ordered like the tables for Chapters 1 and 3, beginning with the cardiovascular subcategories. Appendix 2 shows the same information but ordered by ICD code, starting with code 001 for cholera.)

Chapter 3
Regression Results for Six CDPS-Medicare Models

In this chapter we describe six variants of the CDPS-Medicare model. The first section starts with the simplest base model and finishes with the full CDPS-Medicare model. The second section explores three additional models of policy interest: one based on inpatient data, a second based on a restricted set of CDPS subcategories, and a third that incorporates information on end-of-life.

From the Base Model to the Full CDPS-Medicare Model

The base model includes all the diagnostic subcategories and a set of demographic variables. The second, or "disabled interaction model," adds interactions between disability status and selected diagnostic categories. The third or "full" model adds interactions among selected disease categories and variables for beneficiaries with four or more high-cost subcategories.

The base CDPS-Medicare model

All the diagnostic subcategories of the base model appear to be good predictors of increased future expenditures among Medicare beneficiaries (see Table 3-1 for the base model). Of the 66 CDPS-Medicare diagnostic subcategories, all work well as predictive variables and the vast majority had estimated coefficients at least 20 times larger than their standard error. The R^2 of 0.110 is approximately five percent higher than the R^2 of 0.105 obtained on the same data set using our original CDPS-Medicaid model.

A small number of subcategories are predictive of very large increased expenditures in the following year. The subcategories of very high-cost cardiovascular diagnoses, high-cost nervous system diagnoses, high-cost pulmonary diagnoses, extra high-cost renal diagnoses, very high-cost cancer diagnoses, and high-cost and very high-cost hematological diagnoses all were predictive of more than $7,000 of increased expenditures in the following year. These expensive subcategories had very low frequencies, mostly under one-half of one percent of the Medicare population. The high-cost pulmonary subcategory, however, which was predictive of an additional $8,700, included 1.2 percent of the Medicare beneficiaries. The subcategory of very high-cost cancer, predictive of $7,900 in additional expenditures, included nearly one percent of the population.

An additional seven subcategories were predictive of more than $4,000 in additional expenditures: high-cost cerebrovascular diagnoses, with one percent of the population; high-cost skin diagnoses, also with one percent; diabetes with rare complications, with eight-tenths of one percent (0.008); very high-cost renal diagnoses (0.007); high-cost gastrointestinal diagnoses (0.005); high-cost infectious disease (0.002); and AIDS (0.001).

The remaining subcategories are associated with smaller increased expenditures but much larger numbers of beneficiaries. Fifteen of the subcategories have frequencies of five percent or more, including five of the seven cardiovascular subcategories, the three skeletal and connective subcategories, two of the pulmonary subcategories, the low-cost psychiatric category, the low-cost gastrointestinal subcategory, the Type 2 diabetes category, the very

low-cost cancer subcategory, and the anemia subcategory. For some of these subcategories the additional predicted expenditures were quite substantial: $2,800 for the ten percent of beneficiaries with high-cost ischemic heart disease (mostly congestive heart failure); $2,000 for the eleven percent of beneficiaries with high-cost chronic obstructive pulmonary disease. For others among these relatively high-frequency subcategories, expenditure effects were more moderate (for example, low-cost valvular, conductive and other heart disease with predicted additional expenditures of $1,300 for twelve percent of the population; or even quite low (for example, low-cost psychiatric diagnoses with a coefficient of $600 for five percent of the population).

In our final regressions, we constrained the coefficients of eight sets of subcategories to the same value. For example, we set the renal medium-cost and renal low-cost subcategories to have the same coefficient of approximately $2,700. These constraints were mostly imposed when a subcategory that we had placed in hierarchy above a second category was, contrary to expectation, estimated to have a lower coefficient. We prevented such "reversals" of coefficients because they would produce the undesirable effect that reporting of additional diagnoses could result in a reduction in payments. For example, we expected that the diagnoses of precerebral occlusion and cerebral artery occlusion, which constitute the majority of the low-cost cerebrovascular subcategory, would generally be more expensive than late effects of cerebrovascular disease in the very low-cost cerebrovascular subcategory. In unconstrained regressions the very low-cost subcategory had a higher coefficient than the low-cost subcategory, so we constrained them to be equal for the final regressions.

In some cases, the frequency of beneficiaries in one of the constrained subcategories was extremely small, for example AIDS, HIV, and hematological very high-cost each with frequencies of 0.001 or less. The case of diabetes, where we constrained the subcategories for Type 1 and for Type 1 with complications and constrained the subcategories for Type 2 and for type 2 with complications, was discussed above, under *New approach in diabetes*. And the constraint for the high-cost and medium-cost psychiatric subcategories is discussed below under *The disability interaction model*.

The intercept for the regression is the estimated expenditures for someone with no CDPS diagnosis who is male and aged 70 to 74 (the reference demographic category). For such a person, we predict expenditures of $1,760, which is 33 percent of the average expenditure for all beneficiaries of $5,314. Estimated expenditures for other beneficiaries can be calculated by adding to the intercept additional coefficients, one from the appropriate age-gender category and others from diagnostic subcategories in which the beneficiary has a diagnosis. The addition of diagnostic coefficients, however, is limited by the counting rules described earlier.

The base CDPS-Medicare model supplements the diagnostic subcategories with demographic variables that are defined independently of the subcategories. The demographic variables use combinations of gender and age to define different subsets of Medicare beneficiaries, for example male age 55 to 59 or female age 80 to 84. To maintain comparability with the HCCs, we generally followed the HCCs in our demographic variables.

The negative age-gender coefficients estimated for males under age 70 and females under age 65 can be understood as amounts that must be subtracted from the intercept to estimate

expenditures for younger beneficiaries with no CDPS diagnoses. For example, the expenditures for women without a CDPS diagnosis and aged 65 to 69, for whom the age-gender coefficient is –$800, would be estimated to have expenditures of $1,760 – $800, or $960. For women in this age group with CDPS diagnoses, expenditures would be estimated by adding appropriate diagnostic coefficients to the base amount of $960.

The coefficients for the age-gender variables show that beneficiaries' increasing age is associated with greater expenditures even when diagnoses are controlled for (with the exception of the very few beneficiaries age 95 and over). The pattern of steadily increasing age coefficients appears to be broken when we compare the coefficients for age 60 to 64 and for age 65 to 69: for men, -$302 and -$460, for women, -$186 and -$800. However, for a 64-year-old who turns 65, the originally disabled variable is turned on and an additional $1,387 is predicted, thus maintaining the age gradient.

The variable "originally disabled" is activated for beneficiaries age 65 or over who had originally become Medicare beneficiaries because of disability. This variable allows additional expenditures of $1,387 to be predicted for this group than for the majority of Medicare beneficiaries who entered the program at age 65.

The variable "Medicaid beneficiary" is activated for beneficiaries for whom a state Medicaid program buys the Part B premium, and also helps predict additional expenditures, with a coefficient of $943. Approximately 14 percent of Medicare beneficiaries are also on Medicaid. These dual eligibles may have greater health care needs even controlling for diagnoses because of low income. Another possible explanation is that these poorer beneficiaries are often treated in less efficient systems of care. A third factor may be that these beneficiaries are less constrained in seeking treatment since their copayments and deductibles are fully covered by Medicaid.[17]

In addition to "Medicaid beneficiary," the variable "Medicaid beneficiary, age < 45" is turned on for younger Medicaid beneficiaries. The coefficient of –$273 reduces the expenditures of $943 associated with all Medicaid beneficiaries down to a net of $670 for the younger Medicaid beneficiaries. We added this variable because we had found in previous regressions without it that the predicted expenditures for all beneficiaries under 45 with no diagnoses were implausibly close to zero.

The disability interaction model

The disability interaction model adds to the base model a set of interaction variables (see Table 3-2). Each of these interactions variables indicates whether a beneficiary began Medicare coverage because of disability *and* has a diagnosis recorded from a specific CDPS-Medicare subcategory. These interaction variables allow additional amounts of expenditure to be estimated for beneficiaries currently or originally disabled and with certain types of diagnosis. To determine the list of disability-diagnosis interaction variables, we entered all the subcategories interacted with disability into a test regression, then selected the eleven that had coefficients greater than $1,000 and t-values greater than 4.0 and for which our clinical

[17] Most Medicare beneficiaries also have some form of supplemental coverage so that the difference in demand is not so great as it would be if the Medicare-only beneficiaries had no other coverage.

consultant found it plausible that there could be different effects among disabled and aged populations.

The HCC model appears to handle disability-diagnosis interactions differently, applying them only to beneficiaries who are under age 65.[18] It seems somewhat improbable that the greater cost effects of a diagnosis for a disabled beneficiary would disappear when the person turns 65.

We also included two other disability-diagnosis interactions for the subcategories of high-cost psychiatric diagnoses and medium-cost psychiatric diagnoses. In the full Medicare sample, we had estimated a higher coefficient for the medium-cost psychiatric subcategory (mostly bipolar and manic depression) than for the high-cost psychiatric subcategory (mostly schizophrenia). In earlier work on the Medicaid disabled population with much larger numbers of people with psychiatric diagnoses, we had found that beneficiaries with schizophrenia had greater costs, so we introduced a constraint on the these subcategories and estimated a coefficient of $2,500 in the base model. By introducing interactions with disability, we allow separate estimates of these coefficients for the disabled beneficiaries among whom schizophrenia appears substantially more expensive.

Most of the subcategory coefficients are extremely similar between the base and disability interaction models, but the coefficients for those subcategories that are used in the interactions are appreciably different. For example, the coefficient for the high-cost skin subcategory (decubitus ulcer) fell from approximately $4,800 in the base model to $4,200 in the disability interaction model. (See Table 3-7 for a comparison of expenditure effects of all six model variants.)

The R^2 of the disability model is 0.111, barely higher than the R^2 of 0.110 for the base model. This is unsurprising, because most of the disability interaction variables are indicated for less than one-half of one percent of the total Medicare sample (except for the two psychiatric-disability interactions, each of which accounts for approximately one percent of the beneficiaries). Beneficiaries who are disabled or originally disabled are only 17.5 percent of the total sample, and most of the interacted diagnoses are of modest or low frequency, so that the effect on overall predictive accuracy is inevitably small.

The full model

The full model adds two sets of additional variables, one set for beneficiaries with diagnoses in four or more high-cost subcategories and a second for beneficiaries with specified combinations of diagnoses (see Table 3-3). The R^2 for the full model is also 0.111.

We added variables for beneficiaries with diagnoses in four or more high-cost subcategories, because we found significant underpredictions for individuals with high numbers of high-cost subcategories.[19] We added four variables: one to indicate beneficiaries with four or more

[18] Pope and others in the HCC Report, pages 4-3 to 4-4, seem to indicate that only the under-65 disabled are counted in their variables and not the 65-and-over "originally disabled."

[19] The high-cost subcategories were: cardiovascular very-high; cardiovascular ischemic heart disease high; cardiovascular valvular, conductive and other heart disease medium; psychiatric, high and medium; nervous system high; nervous system multiple sclerosis, muscular dystrophy and others; nervous system Parkinson's disease; pulmonary high; pulmonary pneumonia high; gastrointestinal high, medium, and ostomy; diabetes

high-cost subcategories, a second for five high-cost subcategories, a third for six high-cost subcategories, and a fourth for seven or more high-cost subcategories.

As expected, very few beneficiaries have diagnoses in so many multiple high-cost subcategories, but the additional costs associated with these beneficiaries is considerable. Only eight-tenths of one percent (0.008) of the Medicare sample have four such diagnoses, and only one-tenth of one percent (0.001) have seven or more. The expenditures associated with these variables are in addition to costs already associated with the high-cost subcategories. For beneficiaries with four high-cost subcategories, the additional amount is approximately $1,500; for those with six high-cost subcategories, $4,100; and for seven or more $6,300. Because of the small numbers of beneficiaries involved, the addition of these variables does little to improve predictive accuracy, but the variables help improve prediction for a subset of Medicare beneficiaries who are particularly expensive.

In addition we added some of the interaction variables that the HCC model included for beneficiaries with specified combinations of diagnoses. We decided to incorporate five of the six diagnostic interactions that the HCC model has used: diabetes and congestive heart failure; diabetes and cerebrovascular disease; congestive heart failure and chronic obstructive disease; congestive heart failure and renal failure; and a triple interaction for those with renal failure, congestive heart failure and diabetes. We defined these interactions somewhat differently than did the HCC model.[20] Compared to the coefficients for the multiple high-cost subcategory variables, the coefficients for these diagnostic interactions are lower, in the range of $600 to $1,300, but three of them pick up considerable numbers, two to three percent of the beneficiaries.

The addition of the interaction terms used in the full model reduces many of the subcategory coefficients, in some cases quite significantly. For example, the coefficient for the very high-cost renal subcategory (chronic renal failure) was $3,700 in the disability interaction model, but only $2,650 in the full model. The coefficient for the subcategory of high-cost ischemic heart disease (congestive heart failure) was $2,800 in the disability interaction model, but only $2,140 in the full model.

Models for Alternative Approaches to Payment

The inpatient model

Because CMS is already receiving inpatient diagnostic data, it is of potential policy interest to use CDPS-Medicare for a regression with inpatient data only (see Table 3-4).[21] We used the disability interaction model rather than the 'full' model, because the inpatient frequencies in most subcategories were quite small, making the frequencies in the variables for diagnostic

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Type 1 or 2 with rare complications; diabetes Type 1; skin, high and low; renal, extra high, very high, and medium; cancer, very high, high, and medium; metabolic high; cerebrovascular, high and medium; AIDS high; infectious disease, high and medium; HIV medium; hematological, very high, high, and medium.

[20] We defined diabetes as any diabetes subcategory; congestive heart failure as high-cost ischemic heart disease or very high-cost cardiovascular disease; cerebrovascular disease as any cerebrovascular subcategory; chronic obstructive pulmonary disease as high-cost chronic obstructive disease; and renal failure as the very high-cost and medium-cost renal subcategories.

[21] We used all diagnoses found on the inpatient record, not just the primary inpatient diagnosis, which is the basis for the PIP-DCG model.

interaction and multiple high-cost subcategories too small for reliable estimation. The majority of the coefficients are higher in the inpatient regression than in regressions using both ambulatory and inpatient data, many substantially higher, but some are lower. For example, the parameter estimate for the subcategory of gastrointestinal high-cost subcategory increased from $3,900 in the disability model to almost $5,000 in the inpatient model; high-cost cancer from $3,700 to $8,500. Inpatient hospitalization is an indicator of severity of illness: for most diagnoses, beneficiaries who are hospitalized with the diagnosis have higher expenditures in the subsequent year than beneficiaries who have the diagnosis but are not hospitalized. Compared with the R^2 of 0.111 for the regression on full data, the R^2 for the regression using only inpatient data is 0.085.

An important concern about the use of an inpatient model for payment purposes is its effect on patterns of care. In particular, policymakers should be wary of using only inpatient data for a long period of time because its use will create strong incentives to hospitalize beneficiaries, and will penalize the health plans that have reorganized care most effectively to reduce the rate of hospitalization. To shed light on this question, we show with the inpatient regression data for each subcategory on: the frequency of inpatient diagnoses; the overall frequency of diagnoses from both inpatient and ambulatory settings; and the ratio of inpatient diagnoses to all diagnoses. For the great majority of subcategories (55 of 66), fewer than 40 percent of the beneficiaries would be identified using only inpatient diagnoses. Many subcategories have very low proportions of inpatient diagnoses, in the range of 10 to 20 percent, for example medium-cost peripheral vascular disease (16 percent) and medium-cost pulmonary disease (17 percent). Examples among the subcategories with high proportions of inpatient diagnoses include high-cost pneumonia (75 percent) and high-cost metabolic conditions (51 percent).

Because of the high proportion of non-inpatient diagnoses in so many areas, an inpatient-only system will create strong incentives to hospitalize beneficiaries. One might imagine that the additional payments associated with diagnoses in an inpatient-only system are not large enough to encourage plans to hospitalize their enrollees. Many of the larger coefficients are in the range of $4,000 to $9,000. Because the cost of hospitalization will often be greater than this amount, and additional reimbursement will not be received for at least twelve months (and then only if the beneficiary remains with the health plan), it may appear that there is relatively little incentive to hospitalize patients who do not very clearly need to be admitted.

Yet the choice faced by plans is typically not between hospitalizing at a substantial cost or not hospitalizing and facing no costs. The real incentive problem comes from a choice between a substantial cost in the hospital and a substantial cost serving the beneficiary with home, community-based or outpatient services such as skilled nursing for skin ulcers, intravenous drug therapy for an infection, or mechanical respiratory assistance. If plans receive large additional payments only when diagnoses are made in inpatient stays, it seems very likely that they would be influenced by the payment system. We have explored this question in greater detail elsewhere.[22]

[22] T. Dreyfus and R. Kronick, "Paying Plans to Care for People with Chronic Illness," pp. 40-41, in R. Kronick and J. de Beyer, *Medicare HMOs; Making Them Work for the Chronically Ill*, Chicago: Health Administration Press, 1999.

The use of diagnoses only from an inpatient setting sharply reduces the number of beneficiaries for whom the model is adjusting payment based on diagnosis. Whereas the base, disability interaction and full models use diagnostic information for 70.2 percent of the beneficiaries, the inpatient model uses diagnoses for only 16.8 percent of the beneficiaries.

The restricted model

A possible alternative to the inpatient model is a "restricted" model, where diagnoses are used from both inpatient and ambulatory sources, but the subcategories for which payment is made are restricted to a subset with substantial coefficients and generally with smaller numbers of beneficiaries (see Table 3-5). An advantage of the restricted model is that it might lower the reporting burden on plans without offering inappropriate incentives to hospitalize beneficiaries or penalizing the plans that have reduced the rate of hospitalization.

To create the restricted model, we selected 29 of the 66 subcategories used in the CDPS full model. The selected subcategories were chosen based on their coefficient in the base model and their overall frequency among beneficiaries. Most of the selected subcategories have coefficients of $3,000 or more and overall frequencies of three percent or less. The restricted model presented here is intended to illustrate how such an approach might work; the creation of a restricted model for actual implementation in the Medicare program would require additional work to establish the appropriate criteria for selecting diagnoses for use in such a payment system.

One subcategory that we included despite a much larger frequency was high-cost ischemic heart disease (congestive heart failure), with a coefficient of $2,800 in the base model and diagnosed among 10 percent of beneficiaries. We decided to include high-cost ischemic heart disease because of its significance as a cause of morbidity among Medicare beneficiaries, the proliferation of disease management programs designed to improve the care of beneficiaries with CHF, and its prominence in discussions about supplementing the diagnostic reporting of the PIP-DCG system with non-inpatient diagnoses. A similar subcategory from a statistical point of view that we did not include in the restricted model is high-cost chronic obstructive disease (COPD), with a coefficient of $2,000 and an overall frequency of 11 percent.

In comparison with the full model parameter estimates, 28 of the 29 restricted model parameters are higher. In some case, for example for Type 1 diabetes, the coefficient is only moderately higher: $3,300 in the full model, $4,100 in the restricted model. In many cases, however, the restricted model coefficients are $2,000 to $3,000 higher. For example, the coefficient for high-cost ischemic heart disease is $2,100 in the full model and $5,000 in the restricted model. The high-cost skin subcategory has a coefficient of $3,800 in the full model, $6,500 in the restricted model. The predictive accuracy of the restricted model is fairly good, with an R^2 of 0.089.

Compared with the base and full models, the reduced number of subcategories in the restricted model sharply reduces the number of beneficiaries for whom payments are adjusted through diagnoses. Whereas the base and full models use diagnoses for 70 percent of the

beneficiaries, the restricted model uses diagnoses to predict expenditures for 27.4 percent of the beneficiaries.

The end-of-life model

The final model we present is the end-of-life model, which supplements the full model with variables indicating how close a beneficiary is to the end of life (see Table 3-6). Because a large proportion of health care expenditures is devoted to people in their final years of life, the incorporation of information on when people die improves predictive accuracy far beyond what can be obtained using diagnoses alone. We analyze the components of end-of-life care and look in greater detail at policy implications in Chapter 6. Here we present the results of adding end-of-life variables to the full model.

Our most important finding is that the period before death is expensive even when we control for the effects of diagnosis. We also found that the association between the end of life and increased expenditures, still controlling for diagnosis, extends back from the end of life for several years.

Our data indicate date of death if a beneficiary died in the four years 1997 to 2000. We constructed eight variables to indicate whether a beneficiary died in any of the eight half-year periods during this time. As expected, the first two variables, "died during the first six months of 1997" and "died during the last six months of 1997" are associated with very large increases in annualized expenditures in 1997, the year for which our models are predicting expenditures: $39,500 and $21,100.[23] On the assumption that people who died in the first six months of the year were alive for an average of three months, the additional expenditures in 1997 for people dying in the first half of 1997 are estimated to be $9,900 ($39,500 x 3/12 = $9,875). And on the assumption that people who died in the last six months of the year were alive for an average of nine months, the additional expenditures in 1997 for people dying in the last half of 1997 are estimated to be $15,800 ($21,100 x 9/12 = $15,825). Thus, even when we control for diagnoses, the end of life is associated with large increases in expenditures.

The variables indicating date of death in the years 1998 to 2000 are also strongly associated with substantial 1997 expenditures: for beneficiaries who died in the first half of 1998, $8,100; for those dying in the second half of 1998, $4,300; for the first half of 1999, $3,100; for the second half of 1999, $2,300; for the first half of 2000, $1,800; and for the second half of 2000, $1,600. While the coefficients for deaths in 1998 can be partly understood as reflecting increased expenditures in 1997 that are in the twelve months preceding a 1998 death, the coefficients for 1999 and 2000 indicate that the relationship between end-of-life health status decline and expenditures is significant over a several year period. Again, this relationship between final decline of health status and expenditures is found controlling for

[23] The regressions are weighted by the proportion of the year that the beneficiary had FFS eligibility; similarly, the frequencies are, in general, weighted. However, the frequencies reported in Table 3-6 for the proportion dying in eachsix-month period are unweighted; weighted frequencies would have made it appear that an anomalously small proportion died during the first six months of the year.

diagnosis and age. People who are going to die are much more costly than people with similar diagnoses who are not going to die.

The costs of end-of-life care are so significant that the inclusion of the end-of-life variables leads to a much higher predictive accuracy than we have seen before. Compared to the full model's R^2 of 0.111, the end-of-life model has an R^2 of 0.193, far above what we expect is possible using diagnoses alone, which might be 0.12 or 0.13. The end-of-life variables, of course, are not *predicting* expenditures in the same sense that our diagnostic variables are. The diagnostic variables are based on 1996 diagnoses and are being used to truly predict 1997 expenditures, while the first two end-of-life variables are 1997 information being associated with 1997 expenditures that have occurred before the date of death.

The inclusion of the end-of-life variables causes the coefficients of most of the diagnostic subcategories to fall, some considerably. For example, the coefficient for high-cost pneumonias falls from $2,900 in the full model to $1,800 in the end-of-life model. The coefficient for very high-cost cancer falls from $7,900 to $4,400, and high-cost cancer falls from $3,600 to $2,000. We can understand the decline of the diagnostic variables in the end-of-life model as resulting from the strong association between the diagnoses and death among Medicare beneficiaries.

The effect of the end-of-life variables on the age-gender variables is even more striking (Figures 3-1 and 3-2). For women age 65 and over, the steep age gradient of the full model is very much reduced. In the full model, the coefficients rise from –$820 for ages 65-69 to a maximum at $1,700 for ages 90-94; in the end-of-life model, the coefficients rise from –$310 for ages 65-69 to a maximum of only $980 for ages 85-89 and then fall to $780 for ages 90-94. (Recall that the reference group chosen to have a coefficient of zero is the group of males, age 70 to 74; negative coefficients indicate expenditures less than those for the reference group.)

For men, the inclusion of the end-of-life variables leads to even stronger changes in the age gradient. In the full model, the coefficients rise from –$470 for men age 65-69 to $600 for ages 75-79; in the end-of-life model, the coefficients rise from –$290 to $180. For still older men, we find a *reversal of the age gradient*. In the full model, the coefficients rise from $1,140 for men age 80-84 to a maximum of $2,570 for men aged 90-94. In the end-of-life model, each successive age group has a lower coefficient: from $180 for the age 75-79 group, the coefficients fall to $50 for ages 80-84, –$280 for age 85-89, and –$1,100 for age 90-94. Thus, for men age 75 and over, when we control for diagnoses and nearness to death, aging is associated with lower expenditures. The additional expenditures for older beneficiaries appear to be associated not with aging itself but to result from increasing incidence of illness and from reaching the final few years of life, which occurs for different individuals at very different ages.

Similarly, the parameter estimate for the "originally disabled" variable falls significantly in the end-of-life model: from $1,191 in the full model to $642 in the end-of-life model. Approximately one-half of the additional expenditures among the elderly associated with being originally disabled is accounted for by the fact that beneficiaries who were originally disabled have a significantly higher mortality rate than others of similar age, gender, and diagnostic characteristics.

Chapter 4
Predicting Expenditures for Various Biased Groups and for Functionally Impaired Beneficiaries

Predicting Expenditures for Various Biased Groups

To test our models' performance, we calculated the ratio of predicted to actual expenditures for various groups of beneficiaries. A ratio greater than one indicates overprediction of expenditures for the group, while a ratio less than one indicates underprediction (see Table 4-1). To facilitate comparisons with the HCC model and others, we used the same groups of beneficiaries as the HCC team used.

As expected, the predictive ratios for demographic groups are all equal to one, since the models contain variables that correspond to the demographic groups and therefore make unbiased predictions for the entire group of beneficiaries in any particular age-gender group. The average predictions for all aged beneficiaries taken together and for all disabled beneficiaries taken together are also unbiased, because these two groups can be defined by simply combining the appropriate age-gender variables for beneficiaries.

Examining the predictive ratios for diagnostically defined groups, we find that all the CDPS model variants perform far better than an age-sex model without diagnostic variables. For an age-sex model, 20 of 27 predictive ratios are below 0.60 and only two are higher than 0.80 (HCC Draft Report, Table 4-8). By contrast, the predictive ratios of the CDPS full model for diagnostically defined groups range from 0.90 to 1.02, and 19 of 27 are 0.95 or higher.

Diagnostic groups for which CDPS substantially underpredicts might be areas in which additional exploration of model alternatives might be useful. For example, the CDPS full model underpredicts for beneficiaries with depression (predictive ratio of 0.93); perhaps depression interacts with other conditions to produce costs higher than the sum of depression and other individual diagnoses estimated separately. The low ratio for diabetes with complications (0.90) results from our decision to constrain the coefficients for diabetes with common complications to be equal to the coefficient for uncomplicated diabetes (described in the section *New approach for diabetes*, on p. 5).

A comparison among the predictive ratios of diagnostically-defined groups for different model variants highlights the advantages and disadvantages of certain models. The ratios show the advantage of the full model over the base and disabled interactions models for the groups defined by diagnostic combinations, such as diabetes and cerebrovascular disease. Most of the diagnostic combinations are incorporated as variables into the full model. Most notably, the ratio for the group defined by the combination of diabetes, heart failure and renal failure increases from 0.86 in the base model to 0.97 in the full model. Another notable difference is between the full model and the end-of-life model for beneficiaries with lung or pancreas cancer, who have a predictive ratio of 0.91 in the full model and 1.00 in the end-of-life model.

The restricted and inpatient models perform much less well than the other models in making accurate predictions for most diagnostic groups. The predictive ratios for the restricted model are lower than for the full model for every diagnostic group. For most groups the ratio

is from five to 20 points lower in the restricted model. For example, the ratio for depression falls from 0.93 to 0.79; the ratio for colorectal cancer falls from 0.97 to 0.85; and for acute myocardial infarction from 0.98 to 0.79. All the diagnostic group predictive ratios for the inpatient model are also lower than for the full model. For example, the ratio for depression is 0.84; for colorectal cancer, 0.84; for acute myocardial infarction, 0.90. The ratio for heart failure/cardiomyopathy falls from 0.98 in the full model to only 0.81 in the inpatient model.

Lower predictive ratios for the inpatient model than for the full model are certainly to be expected. As we saw in Table 3-4, for every diagnosis, many beneficiaries are identified with the diagnosis over the course of a year using ambulatory data but do not have this diagnosis identified during an inpatient hospitalization. Those beneficiaries identified through ambulatory data are not, on average, as expensive in the subsequent year as those identified with inpatient data, but are significantly more expensive than beneficiaries without the diagnosis at all. As a result, the inpatient model underpredicts actual expenditures for these groups.

More difficult tests for a diagnostic model are posed by groups defined without reference to diagnosis. For groups of beneficiaries defined by their level of expenditure in the base year, the first four CDPS models underpredict by 14 percent for the most expensive fifth of beneficiaries and overpredict for the other four quintiles, by as little as three percent and by as much as 23 percent. (Under- and overpredictions are greater for the restricted and inpatient models.) The first four CDPS models predict approximately three-quarters of expenditures for the most expensive five percent of beneficiaries and two-thirds for the most expensive one percent of beneficiaries. No diagnosis-based model is likely to do much better in prediction for the most costly beneficiaries, nor are many actual health plans likely to seek enrollment especially among people who were extremely high cost in the preceding year.

More relevant tests are posed by groups defined by levels of spending on home health services or durable medical equipment. For all beneficiaries with home health costs in the base year taken as a single group, the CDPS models predict only three-quarters of their expenditures. Among these beneficiaries with some use, predictions for the first four CDPS models are good for those in the lower quintiles (with predictive ratios of nearly one for the first two quintiles and .88 for the third quintile), but poor for the fourth and fifth quintiles (0.75 and 0.46) and for the highest decile and highest five percent (0.38 and 0.33).

These data tell us that diagnostic models have difficulty in predicting expenditures for the subset of beneficiaries who receive large numbers of home health services, in part because use of home health services is an indicator of frailty or poor health status that is not captured by diagnoses. We look at this question further in the second part of this chapter by examining predictive accuracy for beneficiaries with varying levels of functional impairment. Predictive ratios for groups defined by the base year expenditures in durable medical equipment produce similar results, though the underpredictions for the groups with the greatest expenditures on equipment are less sizeable. Among users of DME, predictive ratios are .65 for the highest quintile of users, 0.59 for the highest decile and 0.56 for the highest five percent.

Predictive ratios for groups defined by the number of base year hospitalizations are good for those with no admissions, one admission and two admission (1.03, 1.01 and 0.97), less good for those with three or more admissions (0.82).

All the CDPS models perform poorly in "predicting" expenditures for beneficiaries in groups defined by resource use in the prediction year itself, whether by home health services, durable equipment, hospital admissions or expenditures. All of these tests are perhaps more appropriate for concurrent modeling.

The end-of-life model clearly does a better job than the other models in "predicting" expenditures for beneficiaries who die between 1997 and 2000. The full CDPS model overpredicts 1997 expenditures on persons still alive in January, 2001 by 21 percent, while underpredicting expenditures for 1997 decedents by 69 percent. It is clear that 1997 expenditures for persons who will die at some point between 1997 and 2000 are much greater than for long term survivors, even controlling for 1996 diagnoses.[24]

Predicting Expenditures for Functionally Impaired Beneficiaries

A significant concern about the use of payment methods based on diagnoses is that they may not predict expenditures well for functionally impaired beneficiaries. It seems reasonable to suspect that significant functional impairments might be associated with declines in health status and additional future expenditures that cannot be predicted by diagnoses alone. The unpredicted expenditures for functionally impaired beneficiaries would be of special concern to programs that are designed to attract beneficiaries with significant functional impairments, such as the Program of All-Inclusive Care for the Elderly (PACE).

Using data on functional status from the Medicare Current Beneficiary Survey

To examine this question, we used data from the Medicare Current Beneficiary Survey. This survey includes information on activities of daily living (ADLs) such as bathing, dressing, sitting in a chair, toileting and eating. The survey data are linked to claims data on diagnoses and expenditures, and allow analysis of the relationship between impairments in ADLs and expenditures predicted by diagnoses.

The data we used included information on 8,372 MCBS respondents who were enrolled in Part A and Part B Medicare Fee-for-Service for all twelve months of 1996; were not enrolled in hospice during 1996; were not ESRD in 1996; and were enrolled in Part A and Part B Medicare FFS for at least one month in 1997. Beneficiaries who became ESRD, entered a hospice, or died in 1997 are included in the analysis, but are only included for the

[24] The change in the predictive ratio for black beneficiaries in the end-of-life model deserves further exploration. Actual 1997 expenditures for black beneficiaries are four percent lower than predicted by the full model. That is, black beneficiaries use fewer services than would be expected given their diagnosis and age – either because unmeasured aspects (e.g., functional status) are better for blacks than for other beneficiaries, or, more likely, because access to care and patterns of care for black beneficiaries are different than for whites. In the end-of-life model, the predictive ratio for black beneficiaries is very close to 1.0, indicating that controlling for diagnoses and proximity to the end-of-life, black beneficiaries use services at the same rates as beneficiaries of other races. A potential explanation for this change is that mortality rates for blacks are lower than for other races, but life table data show the reverse: age-adjusted mortality rates for blacks are slightly higher than for whites, even among the elderly. A second potential explanation is that while blacks use less care than would be expected based on diagnoses, end-of-life care for blacks is more expensive than for whites. This explanation is supported by the data presented in Table 6-2 in C. Hogan, J. Lynn, J. Gabel and others, "Medicare Beneficiaries Cost and Use in the Last Year of Life," Final Report submitted to Medpac, May, 2000, No. 00-1.

number of months that they are enrolled in FFS. In the analyses reported below, beneficiaries are classified by their ADL status in 1996.

Because the predicted expenditures from the CDPS-Medicare model are annualized, we also annualized the MCBS expenditure data, multiplying the MCBS reported expenditures by 12 and dividing by the number of months in the year that the beneficiary was eligible for Medicare parts A and B. All analyses report weighted average expenditures, where the weights are equal to the calendar 1996 MCBS sampling weight multiplied by the fraction of 1997 that the beneficiary was eligible for Medicare. We normalized the CDPS-Medicare predicted expenditures to the annualized MCBS expenditures by multiplying the CDPS-Medicare prediction by the ratio of the weighted average CDPS-Medicare prediction to the weighted average MCBS expenditure.[25]

For beneficiaries with no ADL impairments, actual annualized expenditures were approximately $3,800 (Table 4-2 and Figure 4-1). Actual expenditures increase substantially, to $6,400 for beneficiaries with one ADL impairment, and continue to increase with the number of ADL impairments, except for a decline in actual expenditures for beneficiaries with six ADL impairments.[26]

CDPS-Medicare predicted expenditures also increase as the number of ADL impairments increase, but at a much more gradual rate. Predicted expenditures are 18 percent higher than actual expenditures for those with no ADL impairments, and are approximately 30 percent below actual for those with three to five ADL impairments. The high costs of frail beneficiaries are not fully accounted for by diagnostic and demographic adjustment.

CDPS-Medicare does a much better job of accounting for the costs of frail beneficiaries who also have Medicaid than among frail Medicare-only beneficiaries (see Figures 4-2 and 4-3). Actual expenditures among dual eligibles increase with the number of ADL impairments somewhat more slowly than among the Medicare-only beneficiaries; in contrast, predicted expenditures among dual eligibles increase somewhat more rapidly than among the Medicare-only beneficiaries as ADL impairments increase. As a result, predicted expenditures track actual expenditures much more closely among dual eligibles than among Medicare-only beneficiaries as ADL impairments increase.

If reliable information on functional status, such as ADL impairment, were available for all beneficiaries, policymakers might be glad to incorporate such data in HMO payment systems. As it stands, such information is available only for a very small number of beneficiaries, and it would be very costly to add such information to the diagnostic record, since physicians do not routinely gather such data. It is possible that at some point gathering of such information might become routine, especially for disabled beneficiaries or those aged 80 and above. Until then, widespread adjustment of payments with information on functional status seems impractical. Our analysis supports the view that payments

[25] The weighted average annualized MCBS expenditure was $5,588; the weighted average CDPS-Medicare predicted expenditure was $5,315. We normalized the CDPS-Medicare predictions to the MCBS amounts by multiplying the predicted amounts by 1.05.

[26] As we will see below, the relatively high actual expenditure of $12,067 for those with three ADL impairments is heavily influenced by a small number of high-cost deaths. We suspect that with a larger sample actual expenditures for this group would follow the fairly linear pattern of expenditure increases for beneficiaries with between one and five ADL impairments, and would be approximately $10,500.

adjusted only by diagnosis could be unfair to programs that specialize in serving beneficiaries with high levels of functional impairment.

Using end-of-life variables to account for expenditures of functionally impaired beneficiaries

We also investigate whether end-of-life variables can help account for the high costs of beneficiaries with functional impairments. We showed in Chapter 3 that diagnoses do not fully account for the high costs of end-of-life care. Further, mortality rates among beneficiaries with functional impairments are higher than mortality rates among beneficiaries with no impairments. As shown in Table 4-3, among MCBS respondents with no impairments in 1996, the 1997 mortality rate was 2.5 percent; among respondents with one ADL impairment in 1996, 1997 mortality was 6.8 percent, over 2.5 times as high.[27] Mortality rates increase steadily with the number of ADL impairments, jumping to 31 percent for those with six ADL impairments. Further, we find increases in mortality as the number of ADL impairments increases even when controlling for age, gender, Medicaid status, and CDPS-Medicare predicted score (data not shown). Since the frail have higher mortality rates than would be expected based on their demographic and diagnostic characteristics, we expect that adding end-of-life variables to our diagnostic model should improve our ability to account for the high costs of the functionally impaired.

To analyze the relationships among mortality, frailty, diagnoses, and expenditures, we linked the MCBS file to a file that has information on deaths through calendar year 1999. Because we do not have data on deaths in calendar year 2000 for the MCBS respondents, we re-estimated the end-of-life model presented in Chapter 3 on the five percent sample of 1996-1997 data, but omitting the two variables indicating death in the first six months and second six months of 2000. We then used the parameter estimates from this slightly modified end-of-life model to predict expenditures for MCBS respondents. We normalized the predicted expenditures from the modified end-of-life model to the annualized actual expenditures in the MCBS sample.[28]

As shown in Table 4-4, the modified end-of-life model accounts somewhat better than CDPS-Medicare for the high costs of the functionally impaired. For beneficiaries with no ADL impairments, the end-of-life model overpredicts expenditures by substantially less than CDPS-Medicare – a predictive ratio of 1.10 for the end-of-life model compared to 1.18 for CDPS-Medicare. Similarly, for beneficiaries with four or five ADL impairments, the end-of-life model undepredicts by less than the CDPS-Medicare model. However, even the end-of-life model underpredicts actual expenditures for these highly impaired beneficiaries.[29] The high costs of the functionally impaired are partially accounted for by their greater mortality, but even when we adjust for mortality and diagnoses, the functionally impaired have significantly higher expenditures than predicted.

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[27] The MCBS file we analyzed was restricted to respondents who were enrolled in FFS Medicare for twelve months in 1996 and for at least one month of 1997. As a result of this restriction, any beneficiary who died in January, 1997 would not be included in the file. This exclusion will cause us to underestimate the 1997 mortality rate of beneficiaries eligible for all of 1996.

[28] The weighted average prediction from the modified end-of-life model was $5,581, almost exactly equal to the MCBS annualized expenditure of $5,588, so that the normalization resulted in a negligible change in the predicted amounts.

[29] The pattern reverses for beneficiaries with six ADL impairments, related to the pattern we observed before of lower than expected expenditures for these beneficiaries.

Predicting Expenditures for the Institutionalized

This section investigates whether institutional status should be used as an adjuster as part of the payment system. The traditional demographically-based system does adjust for institutional status, while the PIP-DCG system implemented by CMS does not adjust for institutional status. Our work, however, supports the argument that adjustment for institutional status is desirable. We first review the adjustment for institutional status in the traditional demographic system and research conducted by Health Economics Research (HER) which suggested that adjustment for institutional status was not needed when also adjusting for diagnoses. We then assess what is known about the relationship between institutional status and mortality and between mortality and expenditures, and finally present new analysis using MCBS data on the relationship between institutional status, diagnoses, and expenditures.

Adjustment for institutional status in the traditional demographic and the PIP-DCG models

The traditional demographic method adjusts capitation payments for institutional status, paying M+C plans additional amounts for beneficiaries who are institutionalized – defined as residing in an institution on the last day of the month preceding the month of payment, and having been in an institution for at least the preceding 29 days. As described by Pope, Liu and others associated with HER, work by some researchers suggests that the adjustment is too large, so that overpayments are made for those in institutions and underpayments for those not in institutions.[30]

Most recent diagnostic modeling, however, does not adjust at all for institutional status. Research conducted by HER suggests that the PIP-DCG model adequately accounts for the high costs of the institutionalized. Using data from the 1991-1994 MCBS, HER analysts used the facility event records and institutional event records to identify those beneficiaries who would have qualified as institutionalized at some point during a calendar year. They compared actual expenditures with expenditures predicted by the PIP-DCG model for the institutionalized and the non-institutionalized. As seen in Table 4-5 (reproduced from Table 7-1 of the HER report[31]), actual annualized expenditures for the institutionalized were $8,570, or 67 percent higher than actual expenditures for the entire MCBS sample. Predicted expenditures for the institutionalized were almost exactly equal to actual, supporting the argument that the PIP-DCG model adequately accounts for the high costs of the institutionalized and that a separate payment adjustment is not needed.[32]

[30] See Chapter 7 in Gregory C. Pope, Chuan-Fen Liu and others, *Principal Inpatient Diagnostic Cost Group Models for Medicare Risk Adjustment*, final report, February 24, 1999.
[31] Pope, Liu and others, 1999.
[32] HER noted that while correct predictions were made for the institutionalized as a group, the apparent success of the PIP-DCG model masked balancing errors. The PIP-DCG model overpredicts expenditures for the institutionalized who also had Medicaid (who had relatively low actual expenditures but relatively high PIP-DCG scores), and underpredicts for the institutionalized without Medicaid (who had relatively high expenditures but relatively low PIP-DCG scores). The two groups were almost exactly equal in size, and the errors in the two groups almost exactly cancelled out.

Given the high mortality rate for the institutionalized and the high cost of end-of-life care, it is surprising to us that the high costs of the institutionalized can be fully accounted for by diagnoses. Hogan and colleagues report that among the approximately seven percent of beneficiaries residing in a facility for all or part of a year, mortality rates are 21 percent, compared to approximately three percent for beneficiaries residing in the community throughout the year.[33] We showed in Chapter 3 that actual expenditures for decedents are much higher than the expenditures predicted by a diagnostic model, and we will see in Chapter 6 that expenditures in the last 12 months of life are approximately $18,000 higher for decedents than would be predicted using CDPS-Medicare. From the higher mortality rate of the institutionalized and the higher than predicted expenditures for decedents, we would expect that diagnostic adjustment would underpredict expenditures in the last twelve months of life for the institutionalized by approximately $3,200.[34]

We consider several possible explanations of why HER's analysis finds that the PIP-DCG model correctly predicts expenditures for the institutionalized despite our expectation of underprediction. However, none of the potential explanations appears adequate to account for the surprising HER finding.

PIP-DCGs, based on inpatient diagnoses only, might do a better job of accounting for the high costs of mortality than does the all-diagnosis CDPS-Medicare model. This seems unlikely, however, because the CDPS inpatient model doesn't predict expenditures for decedents any more accurately than CDPS-Medicare, as indicated by the predictive ratios in Table 4-1.

A second possibility is that expenditures for institutionalized decedents are lower than expenditures for community decedents, and expenditures for institutionalized survivors are lower than expenditures for community survivors. If this were the case, then the institutionalized might have higher death rates than community-based beneficiaries, but not have higher expenditures than predicted by their diagnoses. However, as we see below, while expenditures for institutionalized decedents are slightly lower than expenditures for community decedents, expenditures for survivors who are institutionalized are much higher than expenditures for community survivors.

Hogan's result on the high mortality rate of the institutionalized does not control for other factors, such as age, gender and Medicaid status, that are included in PIP-DCGs. Perhaps when these factors, particularly age, are controlled for, the mortality rate of the institutionalized is not much higher than for community beneficiaries. But unpublished analysis by Hogan has found that even when these factors are controlled for, those residing in facilities have much higher mortality than community beneficiaries.

Differences in definitions of institutionalization could contribute to the difference between the HER analysis and Hogan's work. The HER analysis follows the

[33] C. Hogan and others, *Medicare Beneficiaries Cost and Use in the Last Year of Life*, Final Report to the Medicare Payment Advisory Commission, May, 2000, No. 00-1.

[34] This simple calculation assumes that annual expenditures for survivors are $4,000 and expenditures in the last twelve months of life for decedents are $23,000 in both community and facility settings, and that 21 percent of institutionalized beneficiaries die each year compared to three percent of community-based beneficiaries.

operational policy definition (residing in an institution at the end of a month and for at least the preceding 29 days). Hogan uses two definitions: full-year residence in a facility, and part of the year in a facility and part in the community. In Hogan's work, five percent of beneficiaries were institutionalized all year, and these beneficiaries have a mortality rate of 22 percent. Virtually all of these beneficiaries would have satisfied HER's definition of institutionalization.[35] An additional two percent were in a facility for part of the year and in the community for part of the year. HER reports that a total of 8.4 percent of the MCBS respondents were "institutionalized" for some part of the year.

These potential explanations do not resolve the puzzle: HER's analysis suggests that diagnostic adjustment accounts adequately for expenditures made for institutionalized beneficiaries, while our understanding of the relationships between institutionalization and mortality and between mortality and expenditures suggests that diagnostic and demographic adjustment should not account for the high costs of the institutionalized that are associated with end-of-life care.

Analysis of expenditures for community and institutionalized beneficiaries

We now use the 1996-1997 MCBS file to investigate directly the relationships among mortality, Medicaid status, diagnoses, institutional status, and expenditures.

We define the institutionalized as beneficiaries who report being in a "facility" or a "skilled nursing facility" for a total of at least 60 days during 1997.[36] This does not exactly match the CMS Operational Policy Definition or the HER analysis, which defines as institutionalized those beneficiaries who were in a facility on the last day of the preceding month and for at least 29 prior consecutive days, but our data did not contain the institutional event records needed to more precisely model the Operational Policy Definition. As a result, the group of beneficiaries identified as institutionalized in our analysis may be slightly different from the group identified as institutionalized in the HER analysis. However, most of the beneficiaries in our group of institutionalized were in a facility for the entire year, and this group must be similar to, if not exactly the same as, the group of institutionalized beneficiaries analyzed by HER.

As shown in Table 4-6 (row 3), approximately 8.5 percent of the MCBS sample is designated as institutionalized in our analysis, almost exactly equal to the percentage institutionalized in the HER analysis. However, in our analysis, annualized expenditures on the institutionalized are $13,125, over 2.3 times the expenditures for the average beneficiary (compare rows 3 and 1), while in the HER analysis, expenditures on the institutionalized are only 1.67 times the average expenditures. Further, our results confirm the earlier work of Hogan and colleagues that the institutionalized have much higher mortality rates than

[35] It is not clear from HER's description whether the event records that they analyzed were available for the prior year. It is possible that a beneficiary who died in January after being in an institution for all of January would have met Hogan's definition but not HER's.

[36] We counted beneficiaries who died between January 15 and March 1 as institutionalized if they were in a skilled nursing facility or other facility for each day they were alive. Because we could not distinguish long-term from short-term stays for beneficiaries who died before January 15, we did not assign an institutional status for any of these decedents. As a result, we will slightly underestimate the mortality rate among the institutionalized.

community beneficiaries; the 1997 mortality rate among the institutionalized is 23 percent, compared to 4.3 percent among community beneficiaries.

As HER analysts report, we too find that the institutionalized who also have Medicaid have substantially lower Medicare expenditures than the institutionalized without Medicaid. However, while HER found that the institutionalized without Medicaid had expenditures that were 1.85 times the average for all beneficiaries, we find that the institutionalized without Medicaid have expenditures that are 2.79 times the average for all beneficiaries (rows 10 and 1). We also show, similar to HER's results, that community beneficiaries with Medicaid are much more expensive than community beneficiaries without Medicaid (rows 9 and 8).

As Hogan also shows, we find that end-of-life care is more expensive for community decedents than for facility decedents, but the proportional difference is not large (rows 13 and 15). By contrast, expenditures for facility survivors are close to 2.5 times larger than expenditures for community survivors (rows 14 and 12).

We also find that non-Medicaid institutionalized beneficiaries have substantially higher costs than Medicaid institutionalized beneficiaries (rows 10 and 11). This is primarily a result of much higher expenditures among non-Medicaid institutionalized survivors than among Medicaid institutionalized survivors (rows 20 and 22)

Using CDPS models to predict expenditures for the institutionalized

We turn now to examine the extent to which CDPS-Medicare and the modified end-of-life model accurately predict the expenditures of the institutionalized.

As shown in Table 4-7, the CDPS-Medicare model substantially underpredicts expenditures for the institutionalized, with a predictive ratio of 0.72. As expected, the end-of-life model does much better, but the predictive ratio of 0.88 shows that it still somewhat underpredicts the expenditures of the institutionalized.

The end-of-life model predicts expenditures reasonably accurately for community survivors and decedents (rows 27 and 28), for institutionalized decedents (row 31), and for institutionalized Medicaid survivors (row 45). What it does not do well is predict the elevated expenditures of the non-Medicaid institutionalized survivors (row 42). The underprediction for this group is related, we think, to the fact that the institutionalized are defined, in part, by their use of Medicare-covered services. That is, a portion of those defined as institutionalized in 1997 meet that definition because they used Medicare-reimbursed institutional services in 1997. A prospective diagnostic model has difficulty accurately predicting expenditures for groups partially defined by receipt of costly services in the prediction year.

In contrast to the relatively good predictions made by the end-of-life model, the CDPS-Medicare model, as expected, greatly underpredicts expenditures on decedents. Further, while it slightly overpredicts expenditures among survivors in general, it underpredicts expenditures among institutional survivors, while overpredicting expenditures among community survivors. Given these patterns and the much higher frequency of decedents

among the institutionalized, the Medicare-CDPS model substantially underpredicts expenditures for the institutionalized.

We conclude that a prospective diagnostic model without adjustment for mortality will result in payments for the institutionalized that are substantially below expected expenditures. A prospective model that does adjust for mortality will come much closer to accounting for expenditures made on the institutionalized, but may still result in payments that are lower than expenditures for non-Medicaid institutionalized survivors.

The difference between our results and HER's earlier results lies primarily in our estimates of the actual expenditures for the institutionalized. HER estimates that actual expenditures for the institutionalized are 1.67 times expenditures for all beneficiaries, and finds that the PIP-DCG model predicts that expenditures for this group should be 1.67 times average. The CDPS-Medicare model similarly predicts expenditures for the institutionalized at 1.70 times the average for all beneficiaries. But we estimate the actual expenditures for the institutionalized at 2.3 times the average for all beneficiaries, and find that diagnostic adjustment does not account for this elevated expenditure level. We cannot be sure whether our results or HER's are closer to the truth. However, given the very high mortality among the institutionalized and the inability of diagnostic adjustment to account for the high costs of end-of-life care, our results showing that diagnostic adjustment cannot fully account for the high costs of the institutionalized make intuitive sense.

Chapter 5
Comparison of CDPS-Medicare with HCCs

A comparison of CDPS-Medicare with the HCCs reveals important similarities in basic approach and important differences in the final models.

Similarities of Approach

Compared with other approaches to risk adjustment, e.g. the ACG models, the HCC and CDPS models are very similar. The HCC and CDPS models use similar approaches to define individual diagnoses, to assign individual diagnoses to categories of diagnoses, and to group these diagnostic categories into larger areas according to body system or type of disease. Differences in both nomenclature and content disguise some of these similarities in approach.

The models group ICD codes, such as heart failure, schizophrenia or hemoglobin-S disease, in much the same way. The HCC model organizes ICD codes into 804 groups, called dxgroups, while CDPS uses 787 groups, called stage one groups. In both models, many groups are defined simply by a three-digit ICD code and all its subcodes, while other groups are defined using multiple three-digit codes, and still others by individual four-digit codes or combinations of three-, four- and five-digit codes. Despite many differences in detail, the HCC and CDPS ICD groups are parallel concepts.

For the purposes of estimating cost effects, each model aggregates its groups of diagnoses into diagnostic categories: the condition categories of the HCCs and the diagnostic subcategories of CDPS. For example, the HCC model has a category for schizophrenia (HCC54, Psychiatric 1), which is very similar to the CDPS subcategory for high-cost psychiatric diagnoses.

The two models' methods of counting diagnoses are very similar. The CDPS and the HCC categories each function as dummy or zero-one variables. If an individual's record contains a diagnosis code in one of the defined diagnoses in the category, the model initially sets the category to one for that individual; otherwise the category is set to zero. Both models count multiple diagnoses across categories that are very different from each other, for example a cardiovascular diagnosis and a psychiatric diagnosis. Thus both models share the assumption that the cost effects of multiple different types of diagnoses should be added together in order to produce an accurate prediction of total expenditures.

Finally, both models organize diagnoses into larger diagnostic areas partly by body system, partly by type of disease. Thus the HCCs have their categories grouped in "hierarchies" such as heart, lung, eye, and skin; or such as neoplasm, diabetes and metabolic. Closely corresponding major categories in CDPS are cardiovascular, pulmonary, eye, and skin; or cancer, diabetes and metabolic. Both models specify rules to determine how multiple diagnoses from different diagnostic categories within a larger areas are counted. As we see below, although each model uses such counting rules, the rules are substantially different for the two models.

Differences

We see two types of important differences between HCCs and CDPS: differences in the overall approach to counting diagnoses and specific differences in the classification of certain diagnoses.

Differences in counting diagnoses

Perhaps the most important difference between the HCC and CDPS models is that the CDPS model is much more conservative in the number of diagnoses it will count for a given population. One reason for this difference is that HCCs have been expanded to include 101 separate diagnostic categories in their recommended payment model.[37] By contrast, CDPS-Medicare has only 66 diagnostic categories. In even greater contrast is the maximum number of categories that can be counted according to the counting rules for each model: for the HCCs, 63; for CDPS, 25.[38]

Some of the increased possibility of counting in the HCC model comes from a larger number of different major areas. The HCC model, for example, has major areas for both liver categories and gastrointestinal categories, while CDPS has only a single group of GI subcategories. Similarly, the HCCs have four separate groupings for diagnoses in heart, vascular, lung and cardio-respiratory arrest categories, which are almost all covered in two CDPS major categories for cardiovascular and pulmonary diagnoses. The HCCs also use a number of additional categories – injury, complications, transplants, openings, amputations, respiratory therapy and mobility – for diagnoses that CDPS incorporates into categories defined by body system. Overall, the HCCs have 32 groups of categories while CDPS has only 16.

Much of the difference in the maximum number of countable categories results from the much more liberal counting rules used by the HCCs. For both models, the most conservative type of counting is "full hierarchy," where only a single category within the major area can be counted. In the HCCs, only 13 of 32 major areas use full hierarchy.[39] By contrast, in CDPS, 13 of 16 major areas use full hierarchy. In three HCC major areas – infection, musculoskeletal, and neurological – the counting rules allow all of the categories within the area to be counted separately, for a total of 14 counts in these three areas alone. Two of three categories can be counted within each of the HCC major areas for liver, blood, eye, and skin; three of four within gastrointestinal.

By contrast, CDPS allows counting of multiple categories within only three areas: cardiovascular, pulmonary and nervous system. We allowed more counting in these three in part because of the large numbers of individuals with these diagnoses, in part because of the

[37] Pope and others, HCC Report, page ES-4.

[38] The maximum number of counts in CDPS-Medicare is the sum of one count for each of the 13 fully hierarchical categories and a possible total of 12 from the three multiply counted areas (four from cardiovascular, five from nervous system and three from pulmonary). For the HCCs, the maximum count was calculated from the hierarchy rules given in the HCC report, appendix Table A-1, which indicate for each category in the payment model what other categories it turns off. Depending on which categories one selects moving down the list, slightly different numbers of total categories can be counted; we found 63 as the maximum.

[39] Three additional HCC areas have only a single category, so that only one count is possible within them: complications, opening and amputation.

distinctiveness of diagnoses within the areas. (The counting rules for these CDPS areas are explained in detail in Chapter 2.)

In looking at the counting rules of the two models, we find that the differences reflect differences in judgment. A third group of analysts might have taken either approach or some other. For example, the HCC model allows separate counting of all five of the infectious disease categories used in the payment model (HIV disease, septicemia and shock, CNS infection, tuberculosis, and opportunistic infections). One could certainly argue that each of these different kinds of infectious diseases would be associated with additional cost. On the other hand, one could also observe that these categories are highly inter-related: various kinds of infection can lead to septicemia or shock while HIV disease can be manifested in the other forms of infectious disease, not only opportunistic infections. One could reasonably conclude, as we did, that it would be better to impose hierarchical counting on these related diagnostic categories.

For another difference, consider how the HCC and CDPS-Medicare models deal with psychiatric and related diagnoses. Both models have two major areas, one for psychiatric diagnoses and a second for delirium and dementia, termed cognitive diagnoses in the HCC model (HCCs 48 and 49). In both models the psychiatric categories are fully hierarchic, with only one count allowed. For the HCC model, both delirium and dementia can be separately counted, and both are allowed even in the presence of a psychiatric diagnosis. In CDPS-Medicare, a count in the high-cost or medium-cost psychiatric subcategories turns off delirium, and a count for delirium turns off dementia.

Although each model's counting rules appear reasonable, the two models tended in rather different directions, and we believe that the CDPS rules are more appropriate for use in making payment. The HCCs favored much more open counting and CDPS favored much more restrictive counting. The HCCs may show some advantage in modeling exercises, because its greater number of categories and more liberal counting rules allow variation in expenditures to be distributed over more variables, producing higher R^2 statistics.

In use for payment, however, the much larger number of HCC diagnostic categories may not help achieve the goal of making equitable payments, because it offers so many more rewards to proliferative coding. Using either CDPS or HCCs, the plan that codes more completely will receive be paid more. We suspect that using CDPS rather than HCCs a greater portion of the variation across plans in case mix scores will be due to true variation in acuity and a smaller proportion due to variation in coding practices.

Differences in classification

We turn now to look at specific differences in the classification of certain diagnoses. In some cases, the models differ in how they group diagnoses. In other cases, the models differ in whether or not they include certain diagnoses in the payment model. Overall, we think that the HCC model draws too many distinctions that may not hold up well in implementation.

We see problems with the HCC classification of diabetes diagnoses, in which large additional payments are proposed for diabetic complications that are very common and variable in cost-effect. HCC 15, for diabetes with renal manifestations, brings an additional payment of $4,098 (Table 6-6, base model), while HCC 16, for diabetes with neurological or peripheral

circulatory manifestations, brings $2,650; these amounts are in addition to $1,982 for Type 1 diabetes. This classification is understandable in light of the data for the sample of Medicare beneficiaries, among whom we found only a small proportion coded with renal or neurological manifestations of diabetes. The drawback with the HCC classification in diabetes is that it is unusually vulnerable to increased coding expected under diagnosis-based payment. As explained in detail in the section in Chapter 2, *New approach in diabetes*, at least 20 times more Medicare beneficiaries could be legitimately coded with complications than are indicated in fee-for-service data, and these large additional payments are probably not the right amounts for those who will be coded with complications in the future.

We see similar problems with the HCC classification of diagnoses for drug and alcohol problems. The HCCs do not distinguish between drug and alcohol use, but instead place these diagnoses into three categories according to whether the diagnosis is psychosis, dependence, or abuse without dependence (including tobacco use disorder). In the HCC payment model, the two categories for drug and alcohol psychosis and dependence are constrained to a single coefficient and the abuse without dependence category is excluded. We think that the distinction between dependence and abuse without dependence may not be relevant for clinicians and is not clear enough in practice to be maintained for payment purposes.[40]

CDPS instead separates diagnoses in this area into categories for drug use and alcohol use. Although our coefficients for the Medicare sample were not significantly different ($1190 and $1054), we think that this distinction is much more practical for physicians to make and may prove useful in the future as the true costs of fuller treatment of substance abuse problems come to light.

The numbers of Medicare beneficiaries who could be appropriately described as having drug or alcohol problems are far greater than those currently coded. We found a total of only 16,000 people, or 1.2 percent, coded with such substance abuse problems. The actual number of Medicare beneficiaries with drug or alcohol problems is likely an order of magnitude greater,[41] and medical underattention to these problems is probably very widespread among the elderly.

Thus, as with complications of diabetes, it seems quite possible that risk adjustment will bring very large increases in the number of Medicare beneficiaries coded with drug and alcohol problems. If Medicare can establish incentives or quality measures that will encourage physicians to go beyond diagnosis to counseling of patients or other treatment to help reduce drug and alcohol use, then increased coding of drug and alcohol problems and payment for it will be well worthwhile. Heavy alcohol use is associated with substantial increased risk of heart disease, cancer, accidents and many other diseases.[42]

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[40] M.A. Schuckit, "Alcohol and Alcoholism," p. 2149, in Jean D. Wilson and others, eds., *Harrison's Principles of Internal Medicine*, 12th edition, New York: McGraw-Hill, 1991, argues that for alcohol abuse and dependence "this distinction may not be clinically relevant." Abuse means psychological dependence and continuation despite social or occupational problems while dependence encompasses such impairment along with signs of increased tolerance or withdrawal symptoms.

[41] Schuckit, p. 2146, estimates that ten percent of men and three to five percent of women develop alcoholism. Our clinical consultant reports that rates of alcoholism among people over age 65 are thought to be similar to those of the population as a whole.

[42] Schuckit, pp. 2147-2148.

Neither the HCC payment model nor our model makes additional payment for the diagnosis of tobacco use. As with drug and alcohol problems, Medicare might consider the inclusion of tobacco use as a risk adjuster linked to incentives or quality measures that encourage physicians to work harder at counseling patients to reduce or stop smoking.

In classifying diagnoses of cerebrovascular diseases, both models must contend with the problem that some of the important diagnoses in this area are not very well-defined. Notably, a cerebrovascular accident or stroke whose source cannot be specified can be recorded as "acute, but ill-defined cerebrovascular disease," code 436. Better defined diagnoses include subarachnoid hemorrhage (code 430) or subdural hemorrhage (432.1). But the ill-defined cerebrovascular accident is the most common way to record cerebrovascular disease and is a far better predictor of expenditures than the more specific codes that describe the condition more precisely. Both models include code 436.

We think, however, that the HCC model goes too far in including cerebral atherosclerosis (in HCC 98) and unspecified cerebrovascular disease (in HCC 99). We grouped codes for these conditions (437.0 and 437.9) with other generalized ischemic cerebrovascular disease (437.1) and other cerebrovascular disease (437.8), and placed them in our category of not well-defined cerebrovascular diagnoses. Our clinical consultant described cerebral atherosclerosis as extremely common among people over age 65, far more frequent than the 25,000 our data show for all these selected 437 codes, highly variable, and mostly without effect on patients. In addition, given the prevalence of cerebral atherosclerosis, physicians could legitimately diagnose it without angiogram, thus reducing the reliability of the diagnosis.

Many more differences in classification of individual diagnoses exist between the two models, some of minor importance, some perhaps more significant. For example, the HCC category for severe hematological disorders (HCC 44) combines in one group the costliest conditions such as hemophilia (congenital factor VIII and IX coagulation defects) and sickle-cell Hb-S disease with much lower cost diagnoses such as other/unspecified sickle cell anemia and acquired hemolytic anemia. In the CDPS-Medicare model, these hematological diagnoses are distributed into four different subcategories with different cost levels. More accurate predictions for beneficiaries with hematological diagnoses are likely with the greater number of diagnostic subcategories.

For another difference, consider how the two models handle pancreatic disease. In the HCC model, acute and chronic pancreatitis, other pancreatic diseases and intestinal malabsorption are placed together in a single category (HCC 32). In the CDPS-Medicare model, included diagnoses are split into medium-cost and low-cost subcategories and intestinal malabsorption is excluded from the model as not well-defined.

Even with all these differences between the HCCs and CDPS-Medicare, both models work well and could be used CMS to implement comprehensive risk adjustment. The CDPS-Medicare model, however, should give more stable results and be less affected by the increased coding that risk adjusted payment will encourage.

Chapter 6
Estimating Effects of Mortality on HMO Resource Needs

It is well known that expenditures for Medicare beneficiaries rise substantially in their last year of life.[43] Medicare payments to HMOs assume, implicitly, that the mortality of HMO enrollees is similar to that of fee-for-service beneficiaries. But if mortality among HMO enrollees is different from that of fee-for-service beneficiaries, payments to HMOs will not reflect the expected health care costs of the enrolled population. The end-of-life model in Chapter 3 and the predictive ratios in Chapter 4 for decedents in 1997-2000 suggest the importance of end-of-life expenditures. In this chapter we estimate the effect of differential mortality among HMO beneficiaries on the expected resource needs of HMO enrollees, and discuss implications for payment policy.

Previous Work

Riley, Lubitz and Rabey provide a comprehensive analysis of the mortality rates of non-institutionalized beneficiaries enrolled in HMOs in 1987 compared with the mortality rates of "similar" beneficiaries in FFS.[44] Their analysis controls for age, gender, county, Medicaid buy-in status and institutional status. The authors conclude that HMO enrollees died at 80 percent of the rate of similar beneficiaries in FFS. This analysis also showed that among beneficiaries who first enrolled in an HMO in 1987, the relative mortality rate (RMR) was even lower, 0.69; among beneficiaries who had enrolled in an HMO in 1980, the RMR was higher, 0.92. The explanation of the lower rate among those who first enrolled in 1987 is probably straightforward: fee-for-service beneficiaries who are close to death are less likely to switch from FFS into an HMO than FFS beneficiaries who are not close to death. The relative rate of 0.92 for those who first enrolled in 1980 shows that even after seven years of enrollment, HMO beneficiaries still had substantially lower death rates that demographically similar beneficiaries in FFS.

Two more recent studies suggest that the mortality rate of HMO enrollees in January, 1998 was 85% of the mortality rate of FFS beneficiaries of the same age, gender, and Medicaid status. Riley and Herboldsheimer analyze the mortality of beneficiaries enrolled in an HMO in January, 1998, and conclude that "After adjusting for age, sex, race, State buy-in status, ESRD status, and State of residence, the relative risk of death for HMO enrollees was 0.85 (95 percent confidence interval = (0.81, 0.90)), indicating lower mortality among HMO members than among persons in FFS beneficiaries."[45] Similarly, in a November, 2000 report to Congress, the Medicare Payment Advisory Commission reports that beneficiaries enrolled in an HMO on January 1, 1998 died at 85% of the rate of FFS beneficiaries, controlling for age, gender, and Medicaid status.[46] At first glance, the estimated relative mortality rate of

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[43] J.D. Lubitz and G.F. Riley, "Trends in Medicare payments in the last year of life," *New England Journal of Medicine*, vol. 328, no.15, pp.1092-1096, April 15, 1993. B.C. Spillman and J.D. Lubitz, "The effect of longevity on spending for acute and long-term care," *New England Journal of Medicine*, vol. 342 no. 19, pp. 1409-15, May 11, 2000.

[44] G. Riley, J.D. Lubitz, and E. Rabey, "Enrollee health status under Medicare risk contracts: an analysis of mortality rates," *Health Services Research*, vol. 26 no. 2, pp. 137-63, June 1991.

[45] G. Riley and C. Herboldsheimer, "Including hospice care in capitation payments to risk-based HMOs - would it save money for Medicare?," *Health Care Financing Review*, Fall, 2001.

[46] Medicare Payment Advisory Commission, *Improving Risk Adjustment in Medicare*, Report to the Congress, November, 2000, Washington DC. This report also shows that beneficiaries enrolled in an HMO one year of

0.85 for 1998 HMO enrollees appears similar to Riley's estimate of 0.80 for a relative mortality rate based on 1987 data , but there is a very important difference. The earlier result controlled for institutional status, while the more recent results do not. Since HMO beneficiaries are much less likely than FFS beneficiaries to be institutionalized, and since institutionalized beneficiaries are much more likely to die than persons living in the community, an analysis that does not control for institutional status will estimate a much lower RMR than an analysis that does control for institutional status. If the Medicare Payment Advisory Commission and Riley and Herboldsheimer analyses had controlled for institutional status, we expect that the RMR for HMO beneficiaries would have been much closer to 1.0.

We build on existing analyses, updating estimates of relative mortality rates with data through the year 2000.

Methods

In order to estimate the effects of differential HMO mortality on expected resource needs, we multiply the difference in HMO and FFS mortality rates by estimates of the additional costs of care in the last four years of life. The following model details our method, which we use twice, once controlling for demographic characteristics, and once controlling for both demographic and diagnostic characteristics. Let

Exp_{all} = annual expenditures for a group of beneficiaries
$Exp_{survivor}$ = annual expenditures for beneficiaries who are more than 48 months from death
Δ_{d1} = additional annual expenditures for beneficiaries in their last 12 months of life
Δ_{d2} = additional annual expenditures for beneficiaries in months 13 to 24 before death
Δ_{d3} = additional annual expenditures for beneficiaries in months 25 to 36 before death
Δ_{d4} = additional annual expenditures for beneficiaries in months 37 to 48 before death

$P_{survivor}$ = proportion of beneficiaries who are more than 4 years from death
P_{d1} = proportion of beneficiaries in their last twelve months of life
P_{d2} = proportion of beneficiaries in months 13 to 24 before death
P_{d3} = proportion of beneficiaries in months 25 to 36 before death
P_{d4} = proportion of beneficiaries in months 37 to 48 before death

Where, $P_{survivor} + P_{d1} + P_{d2} + P_{d3} + P_{d4} = 1$

Then

$$Exp_{all} = P_{survivor} * Exp_{survivor} + P_{d1} * (Exp_{survivor} + \Delta_{d1}) + P_{d2} * (Exp_{survivor} + \Delta_{d2}) + \quad (1)$$

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less had a mortality rate 21% lower than FFS beneficiaries; members enrolled 5 or more years had a mortality rate 11% lower than in FFS.

$$P_{d3} * (Exp_{survivor} + \delta_{d3}) +$$
$$P_{d4} * (Exp_{survivor} + \delta_{d4})$$

Because the mortality rate does not change much from year to year, we make the simplifying assumption that the proportion in the last twelve months of life is equal to the proportion in months 13 to 24, etc. That is, to simplify the analysis, we assume that $P_{d1} = P_{d2} = P_{d3} = P_{d4}$.

Then (1) simplifies to

$$Exp_{all} = P_{survivor} * Exp_{survivor} + 4\ P_{d1} * Exp_{survivor} + P_{d1} * (\delta_{d1} + \delta_{d2} + \delta_{d3} + \delta_{d4}) \qquad (2)$$

If mortality rates among HMO enrollees are different from mortality rates for FFS enrollees, P_{d1} will be different for HMO enrollees than for FFS beneficiaries. The effect of differential HMO mortality on expenditures will be

$$\Delta Exp_{HMO} = \Delta P_{d1,HMO} * (\delta_{d1} + \delta_{d2} + \delta_{d3} + \delta_{d4})$$

where ΔExp_{HMO} = the effect of differential HMO mortality on expenditures, and
$\Delta P_{d1,HMO}$ = the difference between P_{d1} for HMO enrollees and P_{d1} for FFS beneficiaries

For example, suppose that four percent of FFS beneficiaries die annually, and that 3.5 percent of HMO beneficiaries die each year. Suppose further that the additional expenditures in the last 12 months of life are $20,000, additional expenditures in months 13 to 24 are $8,000; in months 25 to 36, $4,000, and in months 37 to 48, $2,000. Then we would estimate that lower HMO mortality would result in $170 lower expenditures per year than in FFS: 0.005*(20000 + 8000 + 4000 + 2000).

If HMOs were paid the same amount for all beneficiaries who enrolled, then we would simply estimate $\Delta P_{d1,HMO}$ and δ_{d1}, etc., without controlling for any other variables. That is, the effect of differential HMO mortality on expenditures would be the raw difference between HMO and FFS mortality rates multiplied by the additional costs of death, where the additional costs of death were simply a comparison of expenditures made on survivors to expenditures made on decedents.

However, HMO payments under the AAPCC system are adjusted for age, gender, county of residence, Medicaid buy-in status, and institutional status. We are interested in estimating the effects of not accounting for differential HMO mortality in the payment system on the adequacy of payment. Therefore, we want to estimate $\Delta P_{d1,HMO}$ and δ_{d1} controlling for the variables that are used in the payment system. We are also interested in learning whether the effect of differential HMO mortality on the adequacy of payment would be materially affected if the payment system were to adjust for prior year diagnoses. As a result, we estimate δ_{d1} controlling for demographic variables as well as prior year diagnostic information.

To estimate differential HMO mortality, we use a 20 percent sample of the denominator file for each year from 1997 to 2000. For each year, we have information in each month on eligibility for Part A and B, ESRD status, Medicaid buy-in status, and HMO enrollment.

Beneficiaries in the 20 percent sample in one year remain in the sample in subsequent years. We excluded beneficiaries with ESRD from the analysis.

Our methods for estimating relative death rates of HMO and FFS beneficiaries are similar to those used by Riley, Lubitz, and Rabey.[47] We start by computing the FFS death rate for each combination of age, gender, county, and Medicaid buy-in status. Age is categorized into six groups – under 65, 65-69, 70-74, 75-79, 80-84, and 85 and over. The FFS death rate is calculated (for a particular combination of age, gender, county, and buy-in status) as the number of beneficiaries who died while they were in FFS divided by the "adjusted" number of people who were in FFS. The adjusted number of FFS beneficiaries is the sum of the number of months of FFS eligibility divided by 12, with beneficiaries who died counted as having 12 months of FFS eligibility. The FFS death rate for each age, gender, county, and buy-in status is calculated separately for each year.

We assign to each HMO beneficiary in each year the expected FFS death rate for beneficiaries with the same age, gender, county, and buy-in status. For HMO beneficiaries who were in FFS for part of the year and in an HMO for part of the year, we multiply the annual FFS death rate by the portion of the year enrolled in the HMO to calculate the expected probability of dying while in the HMO.

We then sum the expected FFS probability of death over all HMO enrollees to calculate the expected number of deaths of HMO enrollees if their mortality rate were the same as comparable beneficiaries in FFS. We divide the actual number of beneficiaries who died while enrolled in an HMO by the expected number of FFS deaths to calculate the relative mortality rate (RMR) of HMO beneficiaries. RMRs below 1.0 indicate that HMO enrollees are less likely to die than a FFS beneficiary in the same county, age, gender, and buy-in status; RMRs above 1.0 indicate that HMO enrollees are more likely to die than similar FFS beneficiaries. The relative mortality rate analysis does not adjust for the institutional status of the beneficiaries, because our data do not contain information on institutional status. Beneficiaries enrolled in a hospice at the time of death are included in the analysis. We consider the implications of not adjusting for institutional status or for hospice enrollment in the Limitations section below.

To estimate the additional expenditures in the four 12-month periods before death, we use expenditure data from 1997 (as described in Chapter 2), and the data from the 1997-2000 denominator files to identify date of death. The analysis is restricted to beneficiaries who were in FFS for all 12 months of 1996, had at least one month of non-hospice FFS eligibility in 1997, and who were not ESRD beneficiaries. For beneficiaries who were enrolled in a hospice for part of 1997, the months and expenditures of hospice enrollment are excluded from the analysis (we discuss the implications of this exclusion further below).

Ideally, we would have a sample of beneficiaries from a given year, e.g., 2000, along with information on monthly expenditures for five preceding years. Then we could straightforwardly calculate expenditures in the last twelvemonths of life, months 13 to 24 before death, etc. However, since the only expenditure data we have are annualized expenditures for 1997, the only decedents for whom we can directly measure expenditures in

[47] G. Riley, J.D. Lubitz, and E. Rabey. "Enrollee health status under Medicare risk contracts: an analysis of mortality rates," *Health Services Research*, vol. 26 no. 2, pp. 137-63, June 1991.

the last 12 months of life are those who died in December, 1997. For beneficiaries who died earlier in 1997, we observe expenditures for only part of the last 12 months of life; for beneficiaries who died in 1998 or after, we don't observe expenditures in the last few months of life at all. Similarly, the only decedents for whom we can directly measure expenditures in months 13 to 24 before death are those who died in December, 1998. For those who died earlier in 1998, 1997 expenditures include some expenditures in months 1-12 before death, and some expenditures in months 13 to 24 before death.

We use the 1997 expenditure data to estimate total expenditures in annual periods before death as follows. First, we tabulate total 1997 expenditures by the month in which the beneficiary died. We use these data to estimate expenditures in each month before death. We assume that monthly expenditures decline as beneficiaries are further from death, and that the rate of decline slows as the time from death increases. We sum the estimated expenditures in the 12 months before death, in months 13 through 24, months 25 to 36, and months 37 to 48.

In order to estimate the effects of mortality on expenditures (that is, the Δ terms), we need to subtract from the estimated total expenditure in each 12 month period the expenditures we would expect for beneficiaries in each 12 month period if they were not near death. To control for demographic characteristics, we estimate a regression similar to the CDPS end-of-life model presented in Chapter 2, but omitting the CDPS diagnostic categories. We then predict 1997 expenditures for each beneficiary in the sample, except that we set all of the "death" indicator variables equal to zero, in order to exclude the expenditures associated with the end of life. The predicted value from the regression is an estimate of 1997 expenditures for a beneficiary with a given set of demographic characteristics. Following a method similar to that described in the preceding paragraph we use these predictions to estimate expenditures that would be made on decedents in the last 12 months of life, months 13 to 24 before death, etc., given the beneficiaries demographic characteristics.

We then subtract estimated predicted expenditures from estimated actual expenditures to estimate the additional expenditures made on beneficiaries in the 12 months before death, in months 13 to 24 before death, etc. These estimated additional expenditures control for age, gender, Medicaid buy-in status, and whether the beneficiary was originally disabled.

To control also for 1996 diagnostic characteristics, we perform a similar exercise, except that we include the CDPS categories in the regression as well. In this exercise, the estimates of additional expenditures in each 12 month period controls for both demographic and diagnostic characteristics. These results provide an estimate of the additional expenditures made at the end-of-life when controlling for both demographic and diagnostic characteristics of decedents.

Finally, we combine our estimate of the difference in mortality rates between HMO and FFS beneficiaries (that is, our estimate of $\Delta P_{d1,HMO}$) with our estimates of the additional costs of care in the last 4 years before death (that is, our estimates of $\Delta_{d1}, \Delta_{d2}, \Delta_{d3}$, and Δ_{d4}) to estimate the effects of differential HMO mortality on expected resource needs for HMO enrollees.

Results

Among the 1.24 million HMO enrollees in the 20 percent sample of the 1997 denominator file, 39,716 died while they were enrolled in an HMO, for a mortality rate of 3.2 percent (Table 6-1). If the HMO enrollees had died at the same rate as "similar" fee-for-service beneficiaries, we would have expected the death rate of the HMO enrollees to be 3.8 percent.[48] The relative mortality rate (RMR) of HMO beneficiaries in 1997 is 0.85 – that is, HMO enrollees died at 85 percent of the rate of similar beneficiaries in fee-for-service. (As discussed above, and in the Limitations section below, this analysis is not adjusted for institutional status or for hospice enrollment.) The difference between the actual mortality rate for HMO beneficiaries and the expected FFS mortality rate ($\Delta P_{d1,HMO}$) is –0.006.

The relative mortality rate is substantially higher for the small number of HMO enrollees who are also on Medicaid than for those without Medicaid coverage. The RMR for HMO enrollees also on Medicaid is 0.94, compared to 0.84 for HMO beneficiaries not on Medicaid. It appears that HMOs receive a more favorable selection among non-Medicaid beneficiaries than among those on Medicaid.

Among beneficiaries not on Medicaid, the relative mortality rate declines with age, a pattern that persists when data from 1997 to 2000 are combined (Table 6-2). Among beneficiaries in 1997 who also have Medicaid coverage, the relative mortality rate appears to increase slightly with age, but in the 1997 to 2000 data combined, there is no significant trend of RMRs with age.

Variation in RMRs based on length of enrollment in an HMO

Among beneficiaries whose first HMO enrollment was in 2000, the RMR was 0.79, substantially lower than the RMR of 0.91 for HMO enrollees in 2000 whose first HMO enrollment was in January of 1997 or before (Table 6-3). This gradient in RMRs by length of enrollment is almost exactly the same as the gradient estimated by the Medicare Payment Advisory Commission for beneficiaries enrolled in an HMO in January, 1998.[49]

The pattern of change in RMRs by length of enrollment suggests that most of the reduced mortality in the early years of enrollment is due to selection effects rather than the effects of high quality care on the probability of survival. If the reduction in mortality were primarily the result of HMO care management, the difference in mortality rates between HMO enrollees and FFS beneficiaries should increase with length of enrollment. Instead, the difference in mortality decreases with length of enrollment, suggesting that much of the mortality reduction is due to favorable selection at the time of enrollment.

[48] As discussed in the methods section, this analysis controls for county of residence, Medicaid buy-in status, five-year age group, and gender. The results are also adjusted for the length of time a beneficiary was enrolled in an HMO, that is, a beneficiary whose expected fee-for-service death rate was six percent but who was enrolled in an HMO for six months was assigned a probability of 0.03 of dying while in the HMO.

[49] Medicare Payment Advisory Commission, *Improving Risk Adjustment in Medicare*, Report to the Congress, November, 2000, Washington DC.

Change in RMRs over time

While HMO members in 1997 were much less likely to die than their FFS counterparts, the mortality experience of HMO members in 2000 was more similar to that of fee-for-service beneficiaries. The RMR for HMO enrollees increased steadily from 0.85 in 1997 to 0.89 in 2000 (Table 6-4). We expect that this trend is primarily a result of slower growth (and even some decline) in HMO enrollment from 1998 to 2000, compared to the rapid growth from 1995 to 1997. In periods of rapid enrollment growth a larger share of enrollees will be new enrollees with relatively low RMRs, while in periods of slower growth, longer-term HMO enrollees, with relatively higher RMRs, will constitute a larger share of the enrollment, and the overall RMR will increase.

Even in a period of stable enrollment, however, it appears that the RMR for HMO enrollees will remain substantially below 1.0. Long-term enrollees (those with four or more years of enrollment) have an RMR below 1.0, so that, even if these enrollees constituted the entirety of HMO enrollment, the RMR would likely remain below 1.0.

Effects of mortality on expenditures

As shown in Table 6-5, expenditures (in 1997 dollars) in the last 12 months of life are estimated to be $25,235. Expenditures on survivors with similar age, gender and Medicaid status as decedents are estimated to have Medicare expenditures of $4,271. Thus, expenditures on decedents during the last 12 months of life are approximately $21,000 greater than expenditures on survivors with similar demographic characteristics. Expenditures on decedents during months 13 to 24 before death are $5,780 greater than expenditures on survivors with similar demographic characteristics. Summed over the last 48 months of life, expenditures on decedents are $33,400 higher than we would expect based on demographic characteristics alone.

When we include diagnostic as well as demographic characteristics of decedents in the regression, predicted expenditures in the four years before death increase, reflecting the greater frequency of serious diagnoses among decedents than among survivors. Yet even using the diagnostic characteristics of decedents, we predict expenditures in the last 12 months before death of only approximately $7,000, or $18,000 less than the actual expenditures during the last 12 months of life. Summed over the last 48 months of life, expenditures on decedents are $25,300 higher than we would predict based on both demographic and diagnostic characteristics.

The effects of lower HMO mortality on expected expenditures

To estimate the total effects of lower HMO mortality on expected expenditures, we combine the estimate that HMO beneficiaries are 0.6 percent less likely to die than comparable FFS beneficiaries in 1997 with the estimate that decedents have extra expenditures of $25,300 to $33,400 in their last 48 months of life. Our resulting estimate is that the lower mortality rate in HMOs leads to a lower expected expenditure of $144 to $190 per year for an average beneficiary, or 2.1 percent to 2.8 percent of expected expenditures on HMO beneficiaries (Table 6-6).

That is, given our finding that HMO beneficiaries in 1997 died less often than FFS enrollees, we would expect HMO beneficiaries to use 2.7 percent fewer resources than FFS beneficiaries with the same demographic characteristics and prior year diagnostic history, or 3.6 percent fewer resources than FFS beneficiaries with the same demographic characteristics.[50] The relative mortality rate for HMO beneficiaries in 2000 was closer to 1.0 than it was for 1997 beneficiaries (see table 6-4); given the RMR in 2000, we would expect that HMO beneficiaries would use 2.1 percent fewer resources than FFS beneficiaries with the same demographic and diagnostic characteristics, and 2.8 percent fewer resources than beneficiaries with the same demographic characteristics.

Limitations and Implications of the Analysis

The analysis of relative mortality rates did not adjust for institutional status. HMO beneficiaries are much less likely than FFS beneficiaries to be institutionalized – approximately five percent of FFS beneficiaries are institutionalized, compared to approximately one percent of HMO beneficiaries.[51]

The substantially lower rate of institutionalization for HMO beneficiaries could affect our analysis of relative resource use in two ways. First, Medicare expenditures for institutionalized decedents are much lower than for community beneficiaries. Analysis conducted by Christopher Hogan and his colleagues of data from the 1992 to 1996 Medicare Current Beneficiary Cost and Use files shows that Medicare expenditures during the calendar year of death were $9,000 for decedents living in a facility throughout the calendar year of their death, compared to $15,000 for all decedents.[52] Since HMO decedents are predominantly community residents, while FFS decedents include many facility residents, we would expect expenditures per decedent to be higher for HMO decedents than for FFS decedents.

Second, our relative mortality rate results would certainly be different if we were able to compute an RMR separately for community-based HMO beneficiaries, comparing the mortality rate for HMO beneficiaries in the community to the mortality rate for FFS beneficiaries in the community. Hogan and colleagues, again using data from the 1992 to 1996 MCBS files, report that the mortality rate for all Medicare beneficiaries was five percent, while the mortality rate for beneficiaries living in a facility was 21 percent and the mortality rate for beneficiaries living in the community was three percent. These data indicate that if we were able to directly estimate the mortality rate for FFS community-based beneficiaries, it would be substantially lower than the mortality rate we have estimated for all beneficiaries.

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[50] We remind the reader that the analysis does not control for differences between HMO and FFS beneficiaries in institutional status, nor does it adjust for hospice enrollment.

[51] The estimate for HMO enrollees is provided in a report from the Department of Health and Human Services, Office of the Inspector General, Review of Medicare Managed Care Payments for Beneficiaries With Institutional Status," (A-05-98-00046) , April 19, 1999, available at http://oig.hhs.gov/oas/reports/region5/59800046.htm.

[52] C. Hogan, J. Lynn, and J. Gabel, "Medicare Beneficiaries Cost and Use in the Last Year of Life, Final Report," submitted to the Medicare Payment Advisory Commission, May, 2000, No. 00-1.

In contrast, since a much smaller proportion of HMO beneficiaries live in a nursing home, adjusting the overall HMO mortality rate to reflect the experience of only community-based residents would not have a large effect on the HMO mortality rate. Our analysis of RMRs did control for age and Medicaid buy-in status, and part of the difference between the mortality rates of facility and community residents is accounted for by these factors – facility residents are older and much more likely to be on Medicaid. As a result, it would be wrong to simply conclude from the comparison of three percent mortality for community residents and five percent mortality for all Medicare beneficiaries that we should multiply our estimate of the FFS mortality rate by 0.6 in order to estimate the FFS mortality rate for community-based residents. Unfortunately, we do not have the data needed to directly estimate the correct adjustment factors.

The question of whether our results should adjust the RMRs for residential status depends on how the results are to be used. One purpose of the analysis is to gain further understanding of the process of selection of beneficiaries into HMOs, and of the effect of proximity to death on the likelihood that a beneficiary will join a health plan. For this purpose, comparison of the mortality of community-based HMO enrollees with community-based FFS beneficiaries is of interest. In their thorough and careful analysis, Riley and colleagues showed that community-based HMO beneficiaries in 1987 did die substantially less often (an RMR of 0.8) than community-based FFS beneficiaries.[53]

Our results – a relatively mortality rate for HMO beneficiaries of 0.85 in 1997, increasing to 0.89 in 2000 – are similar to those produced by the Medicare Payment Advisory Commission, and by Riley and Herboldsheimer.[54] Our results, like theirs, include both community-based and facility residents when computing FFS mortality rates. We suspect that if we compared mortality rates of community-based HMO and FFS beneficiaries, the relative mortality rates would be close to 1.0. If this suspicion is confirmed on further analysis, it should provide a different perspective on the conventional wisdom that HMO beneficiaries are healthier than FFS beneficiaries. It may be that disease burden of HMO beneficiaries is lighter than disease burden of FFS beneficiaries, but proximity to death for community-based HMO enrollees – an important driver of expenditures – may not be much different than proximity to death for FFS beneficiaries, controlling for age, gender, county, and Medicaid buy-in status.

A second potential use for our results is in determining whether HMOs are being paid equitably for the health care needs of enrollees. For this use, the question of whether the analysis of RMRs should adjust for institutional status depends on whether the payment system adjusts for institutional status. The "traditional" method of HMO payment, still used for 90 percent of the payment, does adjust for institutional status. If this method is continued, then our results should adjust as well. In contrast, the PIP-DCG payments, currently used for 10 percent of payments, do not adjust payments for institutional status, and the developmental work on payment systems using both inpatient and ambulatory diagnostic data also does not envision an adjustment for institutional status. If a payment system is adopted that does not adjust for institutional status, then the results we have

[53] G. Riley, J.D. Lubitz, and E. Rabey. "Enrollee health status under Medicare risk contracts: an analysis of mortality rates," *Health Services Research*, vol. 26 no. 2, pp. 137-63, June 1991.
[54] Medicare Payment Advisory Commission, *Improving Risk Adjustment in Medicare*, Report to the Congress, November, 2000, Washington DC, and G. Riley and C. Herboldsheimer, "Including hospice care in capitation payments to risk-based HMOs - would it save money for Medicare?" *Health Care Financing Review*, Fall, 2001.

presented here, combining community-based and facility residents, are appropriate without further adjustment for institutional status.

Hospice services merit special consideration. Riley and Herboldsheimer report that 19.4 percent of FFS decedents in 1998 and 27.0 percent of HMO decedents in that year were enrolled in a hospice in their last month of life.[55] HMOs are not responsible for the bulk of end-of-life expenditures for enrollees electing to use the Medicare hospice benefit: when an HMO beneficiary elects to use hospice benefits, the HMO receives a small monthly capitation to cover the additional services offered beyond the basic Medicare benefit package, but Medicare covered services are reimbursed on a fee-for-service basis using Medicare's standard payment mechanisms (hospice services are paid on a per diem basis).

Somewhat similarly, most of the end-of-life expenditures for FFS beneficiaries using hospice services are not included in the FFS base rate, since expenditures on hospice services are excluded when calculating the USPCC. The FFS base payment rate can be thought of as a weighted average of expenditures on survivors, end-of-life expenditures on non-hospice decedents, and non-hospice end-of-life expenditures on hospice decedents, where the weights are proportional to the number of beneficiaries in each of the three groups.

Because most end-of-life costs for hospice enrollees are excluded both from the FFS payment rate and from HMO liability, our analysis of relative mortality rates should have compared the mortality rate of non-hospice HMO decedents to the mortality rate of non-hospice FFS decedents.[56] Subtracting hospice deaths from the numerator of the mortality rate calculation, we would expect the FFS mortality rate for non-hospice beneficiaries to be 19.4 percent lower than the FFS mortality rate for all beneficiaries, and the HMO mortality rate for non-hospice beneficiaries to be 27 percent lower that the rate for all HMO beneficiaries. Then the relative mortality rate for non-hospice beneficiaries would be 9.4 percent lower than the RMR estimated for all beneficiaries.[57]

In summary, our analysis of the effects of differential mortality on expected resource needs of HMO enrollees is incomplete, because it does not adjust directly for institutional status or for hospice enrollment. If we were able to compute the RMR for community-based beneficiaries, it would certainly be larger than our estimated RMR of 0.85 for HMO enrollees in 1997. However, if we were able to compute the RMR for non-hospice beneficiaries, it would certainly be lower than the estimated value of 0.85. We suspect that

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[55] G. Riley and C. Herboldsheimer, "Including hospice care in capitation payments to risk-based HMOs - would it save money for Medicare?," *Health Care Financing Review*, Fall, 2001. Using data on decedents from 1994 through 1998, Hogan, Lynn, Gabel, et al report that 25 percent of HMO decedents used hospice services, compared to 15 percent of FFS decedents. See also, B.A. Virnig, N.A. Persily, R.O. Morgan, CF.A. DeVito, "Do Medicare HMOs and Medicare FFS differ in their use of the Medicare hospice benefit?," *The Hospice Journal*, vol. 14, no. 1, pp. 1-12, 1999.

[56] In our data, when an HMO beneficiary elected to use hospice services, the beneficiary was considered to remain an enrollee of the HMO, and was counted as an HMO decedent.

[57] That is, (1- .73)/.806 = 0.094. This back-of-the-envelope calculation does not adjust for other demographic characteristics such as age, gender, or buy-in status. Riley and Herboldsheimer find that, controlling for a variety of demographic characteristics, HMO decedents are 30 percent more likely than FFS decedents to use hospice services. On an unadjusted basis, HMO decedents are 39 percent more likely than FFS decedents to use hospice (27/19.4=1.39). This suggests that adjusting for demographic characteristics would reduce the 9.4 percent adjustment factor, perhaps by 30/39=0.77; that is, the RMR for non-hospice HMO beneficiaries should be 7.2 percent lower (0.77*0.094) than our estimates in Table 6-1.

adjustments for institutional status and hospice enrollment would largely cancel each other out, but we do not have the data needed to confirm this suspicion.

Paying HMOs for High Quality End-of-Life Care

The issues of end-of-life care highlight the positive potentials and the dangers of managed care. On one hand, end-of-life care under fee-for-service arrangements leaves much room for improvement and a more coordinated approach through managed care could help. On the other hand, capitated plans might stint on end-of-life care and current payment methods penalize plans that develop attractive programs of end-of-life care. Adjusting payments for mortality and applying standards for end-of-life care could constitute valuable steps toward improved end-of-life care for Medicare beneficiaries.

The deficiencies of end-of-life care in fee-for-service have received much attention.[58] Poor communication among physicians, patients, and families sometimes results in the provision of aggressive care that is costly and unwanted. Since fee-for-service does not pay for care management, the uncoordinated activity of specialists can result in increased payment to providers, but not an improvement in the quality of care for the terminally ill.

In theory, an HMO receiving a capitated payment might do a better job of creating an integrated system of care in which patient preferences were well understood and respected. But concern about the incentives of HMOs to stint on care is understandably heightened for end-of-life care. Health plans have powerful financial incentives to withhold care that might be desired by patients and their families to prolong life.[59]

End-of-life care also accents the perverse incentives of our HMO payment systems: health plans are financially rewarded for avoiding the enrollment of beneficiaries near the end of their lives and for the disenrollment of members near the end of life. Conversely, if a health plan were to develop a reputation as providing a compassionate and responsive system of care for persons near the end of life and were to attract a disproportionate share of people who die, it would be financially punished – quite severely.

It would not be difficult to construct a payment system that would equitably adjust plan payments based on the mortality of enrollees. Plans that attracted more beneficiaries near the end of life would receive higher payments; plans that attracted disproportionately few beneficiaries near the end of life would receive lower payments. There are some technical challenges in implementing a payment system that adjusts payments based on mortality rates, but, as we discuss in the next section, they are manageable. Compared with diagnostic data, the collection of which has been seen as potentially burdensome, information on mortality is easy to obtain and not subject to dispute.

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[58] J. Lynn, J.M. Teno, and R.S. Phillips, et al for the SUPPORT Investigators, "Perceptions by family members of the dying experience of older and seriously ill patients," *Annals of Internal Medicine*, vol. 126, pp. 126-97, 1997.

[59] J. Lynn, A. Wilkinson, F. Cohn, and S. B. Jones, "Capitated Risk-Bearing Managed Care Systems Could Improve End-of-Life Care," Ethics in Managed Care Series, *Journal of the American Geriatrics Society,* vol. 46, no. 3, pp. 322-330, March 1998.

The biggest problems with adjusting for mortality are not technical but political. CMS is right to be concerned about the appearance of "paying for death." Adjusting payments for mortality rates only makes sense if CMS can assure itself, politicians and the public that M+C plans are providing high-quality end-of-life care.

CMS should supplement paying for end-of-life care with the development of standards for quality far stronger than those that currently exist in this area. But strengthening of standards for end-of-life care should be undertaken even if CMS decides not to make payment adjustments for end-of-life care. Regardless of whether payments are adjusted for mortality, CMS should take a number of steps to improve end-of-life care.

CMS should adopt standards for end-of-life care, including standards about communication between physicians, patients and families, and about the respect that should be accorded to patient and family wishes. CMS should review medical records for a sample of decedents to determine whether medical errors or stinting contributed to death. The review should also study whether the death could have been prevented by medical care in cases where the record clearly indicates that the patient or family would have wanted a longer life and where it did not appear that additional care would have been futile. Surveys of family members of decedents should be used to determine whether patient and family preferences were solicited and honored. If medical record review and interviews with surviving family members lead CMS to determine that a health plan is not providing high quality end-of-life care, then corrective action would be required.[60] Further, if plan payments are adjusted based on the number of enrollees who die, the size of the mortality adjustment should be reduced for plans that do not provide high quality end-of-life care.

Technical Concerns in Implementing an End-of-Life Care Payment Adjustment

There are a number of possibilities for adjusting payments to plans based on mortality. One possibility would be to calculate rates for "survivors," e.g., for beneficiaries who are two or more years from death, and then calculate a set of supplemental payments for beneficiaries who are in their last 24 months of life. These payments could vary by month – a very high supplement for the last month of life, a somewhat smaller supplement for the second to last month of life, graduating down to a much smaller supplement for the twenty-fourth month before death.

The size of the supplements should vary by age, since the additional cost of death is much greater for younger decedents than for older decedents. Supplements should also vary by Medicaid buy-in status, since among decedents under-65 end-of-life care is more expensive for those on Medicaid, while the opposite is true for decedents 70 and over. Further, the supplements might vary by diagnostic group. Decedents identified with certain CDPS subcategories, such as cancer, might have higher end-of-life care costs than average decedents. Payment might also vary by institutional status (see discussion below).

One possibility is to use the most recent mortality rates among enrollees in an M+C plan to determine prospectively the size of the supplemental payment. For a plan with mortality

[60] Similarly, CMS should monitor the quality of end-of-life care in fee-for-service and require corrective action if care does not meet standards.

rates close to average, we would expect the supplemental payment to be approximately 20 percent of the base payment – that is, the additional costs of end-of-life care for persons in their last two years of life are approximately 20 percent of the average costs for survivors. This supplemental percentage might be computed separately for types of beneficiaries (e.g., by age or Medicaid buy-in status). Then for a payment year the supplemental percentage would be added on to the base payments for all enrollees.

If retroactive payment adjustments were acceptable, plans could be paid a lump sum estimated end-of-life supplement amount based on data from previous years, with the estimated amount reconciled to actual liability after the fact. If the plans or CMS wanted to avoid retroactive adjustments, the prospective approach could be used. In the prospective approach, if the mortality rate within a health plan changes substantially from the base period to the rate period, there will be a lag before payment is adjusted. This may be viewed as unfair, but will do a better job than the current system of getting resources to plans that make special efforts to provide good end-of-life care.[61]

Conclusion

We have shown that Medicare beneficiaries enrolled in HMOs in 1997 died at 85 percent of the rate of FFS beneficiaries of the same age, gender, county of residence, and Medicaid buy-in status. In 2000, when HMO enrollment was stable or declining in many areas, HMO beneficiaries died at 89 percent of the rate of "similar" FFS beneficiaries.

These relative mortality rates are not adjusted for institutional status, and include both hospice and non-hospice decedents. If we were able to directly compare the mortality rates of community-based HMO and FFS beneficiaries, the relative mortality rates would certainly be much closer to 1.0. Conversely, if we compared the relative mortality rate of decedents who do not use hospice services at the end of life, the relative mortality rate would be even lower than the estimates presented here. We do not have the data needed to precisely estimate the size of the institutional and hospice adjustments, but suspect that the two adjustments would likely cancel each other out.

We have also shown that decedents have expenditures in their four years before death that are $35,000 greater than expenditures of survivors who are similar in age, gender, and Medicaid buy-in status. Even controlling for diagnoses, we find that the decedents have additional expenditures of $28,000 in the last four years of life. Given the estimate that HMO beneficiaries die at 85 percent of the rate of FFS beneficiaries, and the estimate that decedents have an extra $28,000 to $35,000 of costs in their last four years of life, differential mortality of HMO beneficiaries results in HMO resource needs that are approximately 2.5 percent to 3.0 percent lower than they would be if HMO mortality rates were equal to FFS mortality rates.

[61] A yet more sophisticated version of a prospective payment system would adjust the supplemental percentage for enrollment trends in an M+C plan. For example, if plan enrollment is increasing rapidly, then CMS might adjust the base period mortality downwards; alternatively, if enrollment is stable or declining, then an upwards adjustment in base-period mortality might be warranted. If this idea were pursued, further analysis of these relationships would be needed prior to implementation.

Regardless of the relative mortality rates of HMO and FFS beneficiaries, it is certain that HMOs experience significant losses from serving enrollees who die and can make large gains from *avoiding* the enrollment of beneficiaries with greater-than-average mortality. If CMS wants health plans to do a good job of providing end-of-life care and to market themselves on the quality of their end-of-life care, then a payment system that rewards end-of-life care is important. We make suggestions for how such a system could be implemented. Regardless of whether CMS changes the HMO payment system to pay for end-of-life care, it should work towards establishing clear expectations for how end-of-life care should be delivered, for both HMO and FFS providers.

Chapter 7
Estimating Normal Disease Progression

The Need for a Baseline Estimate of Disease Progression

The challenge of increased diagnostic reporting

If diagnosis-based risk adjustment is implemented widely, we expect diagnostic reporting will become much more complete. As reported by the Medicare Payment Advisory Commission and previously by us, many chronic diagnoses do not "persist" in claims data from one year to the next.[62]

For example, among Medicaid beneficiaries coded with quadriplegia on at least one claim during one year, approximately 40 percent do not have quadriplegia coded on any claim during the subsequent year.[63] Almost all the beneficiaries with quadriplegia in the first year saw a physician in the second year, but their claims contained codes for urinary tract infections, pneumonia or respiratory infections, or other reasons for treatment, and not codes for quadriplegia. Although quadriplegia could in many cases have been legitimately coded as a co-existing condition that affected patient care, for many beneficiaries it was not coded. Similarly, among Medicare beneficiaries diagnosed with chronic obstructive pulmonary disease in 1994, 38 percent did not have that diagnosis appear on any claim in 1995.[64]

If health plans are paid based on the diagnostic profile of their members, we expect the reported persistence of diagnoses to increase. Plans might increase the persistence of coding in several ways. For example, a plan might routinely provide primary care physicians with a list of their patients' previous-year diagnoses, and encourage physicians to note any previous diagnosis that could be construed as affecting current patient care. A plan that raises the reported persistence of chronic diagnoses to near 100 percent could increase the measured case mix of its members by 25 percent or more.

Increased intensity of diagnostic reporting will create challenges for the equitable implementation of health-based payment. Many Medicaid programs have implemented health-based payment in a budget-neutral environment, where all beneficiaries are in capitated plans. The payer is using health-based payment to "divide the pie" rather than "size the pie," i.e., to determine the shares of a fixed budget going to different plans, not the total level of payments to all plans. In this setting, increased intensity of diagnostic reporting will have no effect on payment if all plans increase reporting at equal rates, but it would favor plans that increase the intensity of reporting more quickly than others.

The issue of increased diagnostic reporting is more serious for CMS, because increases in the intensity of diagnostic reporting by M+C health plans could cause overall increases in federal expenditures. In the implementation planned by CMS, health-based payment is being used

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[62] Medicare Payment Advisory Commission, *Report to the Congress, Medicare Payment Policy, Volume II,* Washington D.C., March 1998; Kronick and others, "Improving Health-Based Payment for Medicaid Beneficiaries: CDPS," *Health Care Financing Review*, vol. 21, no. 3, Spring 2000.

[63] Kronick and others, 2000. This analysis was performed on beneficiaries who were continuously eligible for 24 months.

[64] Medicare Payment Advisory Commission, March, 1998.

to measure the disease burden of HMO enrollees relative to fee-for-service beneficiaries. As a result, diagnoses reported by health plans will affect not only the distribution of the total payment among the plans but also the total payments to plans. When health-based payment is used both to divide and to size the pie, increased intensity of reporting could increase the total amount of money paid to health plans.

Possible responses to increased diagnostic reporting

Several responses to this problem are possible. One approach is to follow the lead of most Medicaid programs: make health-based payment budget neutral, audit diagnostic information to detect clearly fraudulent behavior, and trust that relatively equal rates of increase in the intensity of diagnostic reporting will create an equitable payment system. This approach would be compatible with Berenson's recent suggestion that M+C payment rates should receive an annual update based on input price growth.[65] The annual update could also be based on evidence (supplied by CMS or MedPAC) about changes in the relative risk of HMO enrollees and fee-for-service beneficiaries for the industry as a whole.

A second response, which could be used along with or independent of the first approach, is to lengthen the reporting window for diagnoses from 12 months to 24 months or more, at least for diagnoses that are typically longlasting or permanent. This approach deserves further consideration, but a full discussion is beyond the scope of this chapter.

A third response, which we suspect may play a key role in assuring the equity of health-based payment, is to measure change in the intensity of plans' diagnostic reporting. CMS can easily use its diagnosis-based payment system to measure annual changes in the disease burden reported for the subset of a plan's members that were enrolled for two consecutive years. If the group's reported disease burden grows unusually fast, then CMS would have a strong indication that the intensity of diagnostic reporting had changed. CMS could respond to increased intensity of diagnostic reporting by implementing a "data reporting adjustment" – that is, by adjusting case-mix factors downwards to compensate for increased intensity of reporting.

The remainder of this chapter examines a technical question that would have to be resolved in order for CMS to implement a data reporting adjustment: what is the normal annual increase in diagnostic burden? In order to determine whether disease burden is growing faster than expected, CMS needs to know the expected rate of growth in disease burden as a group of beneficiaries ages. We use CDPS-Medicare and diagnostic data of fee-for-service beneficiaries to assess how much sicker fee-for-service Medicare beneficiaries get as they age and examine how the rate of increase varies with age. Our analysis of this apparently straightforward question uncovers some unexpected complexity, suggesting that some additional analysis by other researchers is needed.

Defining Disease Burden and Estimating Its Annual Change

[65] See Robert A. Berenson, "Medicare+Choice: Doubling Or Disappearing?" *Health Affairs*, Web exclusive, November 28, 200l available at http://www.healthaffairs.org/WebExclusives/Berenson_Web_Excl_112801.htm.

We quantify disease burden by re-estimating the full Medicare model presented in Chapter 2, but omitting the indicator variables for age and gender. We define a beneficiary's "disease burden" for a given year as his or her predicted expenditures in the following year based on the diagnoses reported during the given year. Thus, the 1996 disease burden for a beneficiary is the level of expenditures that would be expected in 1997 based on the beneficiary's 1996 diagnoses. Disease burden is essentially a weighted counting of diagnoses, with more serious diagnoses given large weights and less serious diagnoses given small weights.

We compute the disease burden for each beneficiary in the sample using 1996 diagnoses and similarly compute the disease burden for each beneficiary using 1997 diagnoses. The average difference in disease burden from 1996 to 1997 is our estimate of how much sicker fee-for-service Medicare beneficiaries get as they age. We compute the average change separately by five-year age and gender cohorts, to allow for the possibility that disease burden increases differently by gender or age.

As shown in Table 7-1, for the 1.39 million beneficiaries in the five-percent sample, the average disease burden computed using 1996 diagnoses is $5,325, while the average disease burden using 1997 diagnoses for this same group of people is $6,024, or an increase of 13 percent. Disease burden increases substantially more quickly for men than for women, and more quickly for older beneficiaries than for younger beneficiaries. For all age groups 65 and over, average disease burden increases between 1996 and 1997 by at least 10 percent.

These results could be used by CMS to establish the baseline rate of change that would be expected when comparing disease burden for a group of HMO enrollees in successive years. That is, CMS could use encounter data to compute disease burden for a group of enrollees in one year, and subtract this amount from the disease burden computed for the same group of enrollees using diagnostic information in the subsequent year. The difference could be computed separately for five-year age and gender cohorts. If disease burden increases more rapidly than the baseline fee-for-service rates of increase shown in Table 7-1, then CMS would have a strong indication that the intensity of diagnostic reporting was changing.

Further Analysis of Disease Progression

Inconsistency between individual and cohort estimates of disease progression

Our result showing that disease burden for individuals increases by 13 percent from 1996 to 1997 seems large and difficult to reconcile with comparisons of disease burden calculated for successive five-year age cohorts. Table 7-1 shows that the average disease burden using 1997 diagnoses for beneficiaries age 75 to 79 (women and men combined) was $6,126, while the average disease burden in 1997 for beneficiaries age 70 to 74 was $5,397. Since individuals age 75 to 79 are on average approximately five years older than those age 70 to 74 and since they have an average disease burden that is 13.5 percent greater than the younger group, the average increase in disease burden across these two age cohorts is 2.6 percent per year.[66]

As shown in Table 7-2, the rate of increase in disease burden across age cohorts varies somewhat with age and gender, but the average rate of increase in disease burden when

[66] Dividing 6,126 by 5,397 yields 1.135. The fifth root of 1.135 is 1.026.

comparing successive five-year age cohorts among beneficiaries age 65 to 89 is between 1.6 percent and 2.9 percent per year. It appears inconsistent that the disease burden increase measured for individuals from 1996 to 1997 is 13 percent per year, while annual increases judged by comparing successive five-year age cohorts are for most beneficiaries in the range of 1.6 to 2.9 percent per year.

Accounting for different estimates of disease progression

The inconsistency of the estimates results partly from the significant mortality rate of older beneficiaries and the quickly rising disease burden among beneficiaries at the end of life. When we compare disease burden for the same individuals in successive years, all beneficiaries in the comparison are, by definition, one year closer to their death in the second year of measurement and hence have greater disease burden. For example, examining individuals at age 75 and 76, all individuals in the comparison must, by definition, have survived their seventy-fifth year. But some of these individuals die during their seventy-sixth year, and they have a much higher disease burden in their final year of life than they did in their penultimate year of life. The increase in disease burden is less for individuals who are further from the last year of life, but it is significant, as we see below, for many years before death.

In contrast, life table data tell us that a cohort of 80-year-olds is approximately 2.5 years closer to death than a cohort of 75-year-olds,[67] or only *one-half* year closer to death for each year of age difference. Since each individual 76-year-old is one year closer to death than he or she was at age 75, while the cohort of 80-year-olds is only 2.5 years closer to death than a cohort of 75-year-olds, we would expect the increase in disease burden for an individual aging from 75 to 76 to be greater than the average annual difference in disease burden between a cohort of 80-year-olds and a cohort of 75-year-olds.

We provide two methods of examining the inconsistency between the year-to-year estimate of annual change in disease burden and the cohort estimate of annual change in disease burden can be accounted for by the fact that in the year-to-year estimate all beneficiaries in the second year are one year closer to death than they were in the first year.

The first method simply compares the 1996 to 1997 change in disease burden for individuals who survive at least until January 2001 with the change in disease burden for those who die in the years before January 2001. As shown in Table 7-3, disease burden increases by 68 percent from the calendar year before the year of death to the year of death, by 31 percent from the second year before death to the year before death, by 15 percent from the third year before death to the second year before death, and by 12 percent from the fourth year before death to the third year before death. Notably, even for beneficiaries still alive in January, 2001 – that is, for beneficiaries who are at least five years prior to death in December, 1996 – disease burden increases by "only" 8.3 percent from 1996 to 1997.

This analysis shows that increases in disease burden towards the end of life and the greater proximity to death in the second year of analysis account for part of the very large 13 percent increase in disease burden from 1996 to 1997 for beneficiaries who were alive in both years. However, the increase in disease burden of 8.3 percent from 1996 to 1997 even for beneficiaries who are at least five years from death still seems surprisingly large.

The second method uses age- and gender-specific estimates of disease burden in each year before death to estimate how much we should expect disease burden in 1997 to be greater

[67] Life table information from: National Center for Health Care Statistics. Life Expectancy, LEWK3 United States Life Tables, 1999. Available at <http://www.cdc.gov/nchs/data/lt99internet.pdf>

than disease burden in 1996 as a result of being one year closer to death (the method is described in Appendix 7-A). As shown in Table 7-4, beneficiaries being one year closer to death in 1997 than in 1996 should cause disease burden, on average, to be 5.5 percent greater in 1997 than in 1996. Like mortality rates, which rise with age and more so for men, proximity to death has a larger effect on the 1996-1997 change in disease burden for men than for women, and a larger effect for older beneficiaries than for younger beneficiaries.

In each age and gender group, however, the effect of greater proximity to death on disease burden is no more than 50 percent of the actual amount of change. On average, only 40 percent of the rapid increase in the burden of illness from 1996 to 1997 can be accounted for by the changing proximity to death. Understanding why individual beneficiaries appear to get so much sicker from one year to the next while cohorts of beneficiaries five years apart appear to get sicker at a much more moderate rate remains a partially unresolved puzzle.

In summary, our comparison of successive years of diagnostic information for individual Medicare beneficiaries yields an increase in disease burden of 13 percent per year. This rate of change in disease burden would appear to be the baseline rate using fee-for-service data. If the rate of change using data from HMOs is significantly different, we would suspect that the intensity of diagnostic reporting is changing differently in the HMO data than in fee-for-service data. But we cannot fully explain the difference between this individual-based estimate of baseline change and a cohort-based estimate, and we expect that the expected "normal" rate of change for an enrolled group is related to its mortality rate. As a result, we recommend additional analysis to estimate the baseline rate of change needed to implement a data reporting adjustment. Being unable to fully resolve the puzzle, we encourage other researchers to venture into this thicket.

Appendix to Chapter 7
Estimating the Effects of a One-Year Increase in Proximity to Death on Disease Burden

This appendix describes the second method of estimating how much we should expect disease burden to increase from one year to the next as a result of individuals being one year closer to death. The first method (results in Table 7-3), compares the 1996-1997 disease burden change for individuals surviving at least until 2001 with the disease burden change for those who die in earlier years. The second method estimates the effects of being one year closer to death on disease burden in a more detailed way.

We define D_0 as the disease burden in the year of death, D_1 as the disease burden in the year before death, D_2 as the disease burden in the second year before death,…, and D_i as the disease burden in the *i*th year before death.[68] We define P_0 as the probability of dying this year, P_1 as the probability of dying next year,…, and P_i as the probability of dying in the *i*th year. The probabilities of dying in years P_0. to P_i sum to one.

The disease burden for a beneficiary alive in 1997 can then be estimated as

$$(\text{disease burden})_{1997} = P_0D_0 + P_1D_1 + \ldots + P_iD_i.$$

In estimating the disease burden for the same beneficiary in 1996, we know that the beneficiary did not die in 1996, so that the probability of death in 1996 was zero, and the probabilities of death in the following years are equal to the same series of P_i shifted forward one year. As a result, the disease burden is

$$(\text{disease burden})_{1996} = 0 \bullet D_0 + P_0D_1 + P_1D_2 + P_2D_3 + \ldots + P_iD_{i+1}.$$

Finally, we can estimate the change in disease burden from 1996 to 1997 due to changing proximity of death as the difference between the two equations:

$$(\text{disease burden})_{1997\text{-}1996} = P_0D_0 + P_1D_1 - P_1D_2 + P_2D_2 - P_2D_3 \ldots P_iD_i - P_iD_{i+1}.$$

This equation can also be expressed equivalently as:

$$(\text{disease burden})_{1997\text{-}1996} = P_0D_0 + P_1(D_1 - D_2) + P_2(D_2 - D_3) + \ldots + P_i(D_i - D_{i+1}).$$

The values for both the probabilities of death in future years and the associated disease burdens in those years vary with age. For a group of young beneficiaries, say those at 30 years of age, most deaths will be far in the future and the effect of moving one year closer, for example from 45 years before death to 44 years before death, will be very small. By contrast, for beneficiaries age 75, deaths are likely to be far nearer and the effect on disease burden of increasing proximity of death is more significant. For an 85-year-old, the effect will be still more substantial. As a result, we estimated separate values of the P and D terms for different age and gender groups (not indicated in the equation above to keep the notation simpler).

[68] Recall from the main text that disease burden is calculated by re-estimating the full Medicare model presented in Chapter 2, but omitting the indicator variables for age and gender. We define a beneficiary's "disease burden" for a given time period as the predicted expenditures for that beneficiary given the diagnoses reported during that time period.

The values for the probabilities of death in future years for different ages are known from life tables.

The values for D_0-D_4 can be straightforwardly estimated from our data. Table 7-3 indicates, for example, that the 1997 disease burden for beneficiaries dying in 1997 was $16,936; for beneficiaries dying in 1998, $11,356; for beneficiaries dying in 1999, $8,939; and for beneficiaries dying in 2000, $8,035. The same data are also shown in Table 7A-1 broken out by age group. The first five columns of Table 7A1 provide estimates of D_0-D_4 for five-year age-gender cohorts.

However, because we can only observe death through January 1, 2001, we had to create estimates for disease burden in each of the years six to 35 years before death.

We make these estimates using two assumptions: disease burden declines or exhibits no change with each year further from death; and the rate of decline is either constant or decreasing.[69] We also constrain the weighted sum of the estimated disease burdens in the sixth to thirty-fifth years before death to be equal to the average disease burden for all persons in their sixth or greater last year of life. The weights are equal to the proportion of beneficiaries expected to die in each year according to life tables.[70] Estimated disease burden in each year before death is shown in Table 7A-2. (The data in the first five columns repeat the calculated data shown in the first five columns of Table 7A-1, and the remaining 30 columns show the estimates for the sixth- through thirty-fifth year before death.)

A rough check of the estimates in Table 7A-2 is presented in Table 7A-3. We combined the estimates in Table 7A-2 with age- and gender-specific probabilities of death from life tables and summed them across the age-gender cohorts to estimate disease burden for beneficiaries in the age-gender cohorts who are in the sixth-to-last through thirty-fifth-to-last years of life. Table 7A-3 shows these estimated values alongside the original actual disease burdens on which our calculations depended and suggests that our estimated disease burdens are decent estimates.

The final step needed to reach the estimates in Table 7-4 was to combine the estimates of disease burden in each year before death for a beneficiary of a given age and gender (Table 7A-2) with life table information on the probability of death in each subsequent year. That is, we compute the $(\text{disease burden})_{1997} = P_0D_0 + P_1D_1 + \ldots + P_iD_i$. We also compute $(\text{disease burden})_{1996} = 0 \bullet D_0 + P_0D_1 + P_1D_2 + P_2D_3 + \ldots + P_iD_{i+1}$. Rather than perform this exercise for each single age and gender combination, we simplify the analysis by performing the exercise for 67-year-olds, 72-year-olds, 77-year-olds etcetera, separately for males and females. In the last step, we construct a weighted average of the results, where the weights are proportional to the number of beneficiaries in each five-year age-gender cohort in 1996. Results are shown in Table 7-4 and discussed in the main text.

[69] There are many different sets of numbers that could fit these assumptions and still fit the data. We created paths of decreasing effect of death upon disease burden that seemed plausible.

[70] Life table information is from the National Center for Health Care Statistics, "Life Expectancy, LEWK3," *United States Life Tables, 1999*. Available at <http://www.cdc.gov/nchs/data/lt99internet.pdf>

Table 1-1
Medicaid Health-Based Payment Activities

State	Population Covered	Date Implemented	Classification System	Data Source
Implemented				
Maryland	SSI + TANF	05-97	ACGs	prior FFS claims
Colorado	SSI + TANF	07-97	DPS	HMO encounter data
Oregon	SSI	06-98	CDPS	HMO encounter data
Utah	SSI	06-98	Marker Diagnosis	inpatient claims
Michigan	SSI	06-00	CDPS	HMO encounter data
Minnesota	TANF	01-00	ACGs	HMO encounter data
Delaware	SSI + TANF	07-00	CDPS	HMO encounter data
Tennessee	SSI + TANF	07-00	CDPS	HMO encounter data
New Jersey	SSI	10-00	CDPS	prior FFS + HMO encounter data
Utah	SSI + TANF	2000	CDPS	HMO encounter data
Washington	TANF	2001	CDPS	HMO encounter data
Planned				
Pennsylvania	SSI + TANF	2003	CDPS	HMO encounter data
Oklahoma	SSI + TANF	2003	CDPS	HMO encounter data

SOURCE: Authors' discussions with state officials and actuaries.

Table 1-2
Frequencies of CDPS-Medicaid Diagnostic Categories
by Selected Medicaid and Medicare Beneficiary Groups

Major Category Subcategory	Medicaid Disabled Adults	Medicare Under 65	Medicare 65 and Over	Medicare All	Medicaid TANF Adults	Medicaid TANF Children
Cardiovascular	27.06 %	36.15 %	62.44 %	59.37 %	9.38 %	1.19 %
Very High	0.23	0.53	0.22	0.26	0.02	0.01
Medium	3.52	5.95	12.16	11.43	0.46	0.00
Low	11.13	15.10	27.68	26.21	3.80	1.00
Extra Low	12.18	14.57	22.38	21.47	5.10	0.18
Psychiatric	22.67	25.19	8.08	10.08	6.83	3.32
High	11.65	9.95	0.52	1.62	0.34	0.04
Medium	1.63	2.31	0.29	0.53	0.27	0.06
Low	9.39	12.93	7.27	7.93	6.22	3.22
Skeletal	16.81	23.97	33.18	32.10	8.23	3.08
Medium	0.26	0.45	0.22	0.25	0.03	0.01
Low	4.17	5.90	5.75	5.76	1.43	0.60
Very Low	4.29	6.07	8.61	8.31	3.09	1.90
Extra Low	8.09	11.55	18.60	17.78	3.68	0.57
CNS	16.65	20.97	14.48	15.23	5.87	2.78
High	0.34	0.73	0.08	0.15	0.01	0.00
Medium	1.86	3.33	0.92	1.20	0.27	0.10
Low	14.45	16.91	13.48	13.88	5.59	2.67
Pulmonary	16.10	19.19	21.11	20.89	8.66	9.91
Very High	0.21	0.29	0.12	0.14	*	*
High	0.94	1.52	1.79	1.76	0.21	0.22
Medium	0.87	1.66	1.81	1.79	0.27	0.24
Low	14.08	15.72	17.39	17.20	8.18	9.45
Gastrointestinal	12.59	16.39	19.68	19.30	6.96	3.98
High	0.29	0.49	0.27	0.30	0.09	0.02
Medium	2.11	3.18	2.27	2.38	0.68	0.15
Low	10.19	12.72	17.14	16.62	6.19	3.81
Diabetes	11.25	13.72	15.27	15.09	4.23	0.45
Type 1 High	0.11	0.41	0.16	0.19	0.01	*
Type 1 Medium	2.61	5.02	4.25	4.34	0.45	*
Type 2 Medium	0.63	0.93	1.17	1.14	0.10	*
Type 2 Low	7.90	7.36	9.69	9.42	3.67	0.45
Skin	7.88	9.60	9.66	9.65	4.37	3.49
High	0.48	1.03	1.02	1.02	0.02	0.01
Low	0.97	1.65	2.04	1.99	0.21	0.04
Very Low	6.43	6.92	6.60	6.64	4.14	3.44
Renal	5.67	8.47	10.29	10.07	3.33	1.32
Very High	0.63	1.30	0.80	0.86	0.05	0.02
Medium	1.70	2.69	4.10	3.93	0.42	0.06
Low	3.34	4.48	5.39	5.28	2.86	1.24
Substance Abuse	4.92	5.03	0.71	1.21	2.27	0.18
Low	1.75	2.22	0.19	0.43	1.25	0.07
Very Low	3.17	2.81	0.52	0.78	1.02	0.11
Cancer	4.55	4.68	14.41	13.28	2.79	0.33
High	1.15	1.26	2.78	2.60	0.26	0.06
Medium	2.20	2.45	7.62	7.02	0.78	0.17
Low	1.20	0.97	4.01	3.66	1.75	0.10
Developmental Disability	3.90	5.24	0.14	0.74	0.09	0.10
Medium	0.76	1.11	0.02	0.15	*	0.01
Low	3.14	4.13	0.12	0.59	0.09	0.09
Genital, Extra Low	3.59	4.87	11.76	10.96	10.39	0.66
Metabolic	3.37	5.65	6.36	6.29	1.11	1.09
High	0.79	1.50	1.26	1.29	0.21	0.11
Medium	0.77	1.13	1.12	1.13	0.35	0.14
Very Low	1.81	3.02	3.98	3.87	0.55	0.84
Pregnancy	3.53	0.72	0.21	0.28	24.12	0.87
Incomplete	2.21	0.35	0.06	0.10	17.19	0.48

Major Category Subcategory	Medicaid Disabled Adults	Medicare Under 65	Medicare 65 and Over	Medicare All	Medicaid TANF Adults	Medicaid TANF Children
Complete	1.32	0.37	0.15	0.18	6.93	0.39
Eye	3.20	7.85	37.36	33.91	0.53	0.21
Low	0.46	0.94	1.78	1.68	0.13	*
Very Low	2.74	6.91	35.58	32.23	0.40	0.21
Cerebrovascular, Low	2.39	4.31	8.18	7.73	0.43	0.15
Infectious	1.18	3.26	2.95	2.99	0.41	1.64
AIDS, High	0.40	0.85	0.04	0.13	0.09	0.03
Infectious, High	0.11	0.24	0.16	0.17	0.03	0.02
HIV, Medium	0.12	0.06	0.00	0.01	0.06	0.01
Infectious, Medium	0.55	0.95	1.05	1.04	0.23	0.24
Infectious, Low	0.89	1.16	1.70	1.64	0.66	1.34
Hematological	1.74	2.81	3.17	3.12	0.65	0.43
Extra High	0.06	0.05	0.02	0.02	0.01	0.01
Very High	0.29	0.11	0.00	0.01	0.02	0.07
Medium	0.53	0.93	0.84	0.85	0.26	0.20
Low	0.86	1.72	2.31	2.24	0.36	0.15
With no CDPS diags	28.6	23.8	13.3	14.5	53.3	72.4
Average number of categories per-person with at least one	2.3	2.9	3.2	3.2	1.7	1.3
Sample size	960,760	155,774	1,238,927	1,394,701	1,548,488	3,640,871

* Subcategories were combined with the subcategory or subcategories below for the purposes of the regression, because the numbers of beneficiaries in the category were too small to allow a reliable estimate of the expenditure effect. For example, the pulmonary very-high-cost subcategory was combined into the pulmonary high-cost category for AFDC adults and AFDC children. For both disabled children and AFDC children, all subcategories of diabetes were collapsed into a single category.

SOURCE: For Medicare beneficiaries, authors' analysis of 1996 diagnoses. For Medicaid beneficiaries, authors' analysis of diagnostic data from Michigan, Ohio and Tennessee, 1991-1992; from California and Georgia, 1990-91; Missouri, 1991-1993; Colorado, 1992-1995.

Table 1-3
Subsequent-Year Annual Expenditure Effects of CDPS-Medicaid
Case-Mix Score for Medicare Beneficiaries

	Expenditure Effect	Standard Error	T -Statistic	P-Value
CDPS-Medicaid case-mix score[1]	$3,729	11	347.7	0.0001
Originally disabled	1,687	47	35.5	0.0001
Medicaid beneficiary	1,127	35	32.6	0.0001
Male, age 0 to 34	-1,717	133	-12.9	0.0001
Male, age 35 to 44	-1,521	99	-15.4	0.0001
Male, age 45 to 54	-1,046	91	-11.5	0.0001
Male, age 55 to 59	-522	120	-4.4	0.0001
Male, age 60 to 64	-15	109	-0.1	0.8904
Male, age 65 to 69	-442	57	-7.8	0.0001
Male, age 70 to 74 *	0	-	-	-
Male, age 75 to 79	612	56	10.9	0.0001
Male, age 80 to 84	1,197	64	18.6	0.0001
Male, age 85 to 89	2,006	86	23.5	0.0001
Male, age 90 to 94	2,639	140	18.8	0.0001
Male, age 95 and older	1,988	280	7.1	0.0001
Female, age 0 to 34	-1,660	164	-10.1	0.0001
Female, age 34 to 44	-1,428	121	-11.8	0.0001
Female, age 45 to 54	-1,083	107	-10.1	0.0001
Female, age 55 to 59	-737	133	-5.5	0.0001
Female, age 60 to 64	-49	121	-0.4	0.6884
Female, age 65 to 69	-907	52	-17.3	0.0001
Female, age 70 to 74	-568	48	-11.8	0.0001
Female, age 75 to 79	-15	50	-0.3	0.7627
Female, age 80 to 84	581	54	10.8	0.0001
Female, age 85 to 89	1,255	62	20.1	0.0001
Female, age 90 to 94	1,662	84	19.9	0.0001
Female, age 95 and older	1,004	132	7.6	0.0001
Intercept	536	38	13.9	0.0001
R^2	0.095			

* The age-gender group "Male, age 70 to 74" is the reference category.

[1] This regression was created by first using CDPS-Medicaid to count the diagnoses of Medicare beneficiaries, and then multiplying the counts by the CDPS-Medicaid coefficients previously calculated from our large disabled adult Medicaid sample (shown in the first column of Table 1-4). The resulting case-mix score for each beneficiary was then used as an independent variable along with the demographic variables shown to produce the regression shown here. In the original Medicaid regression to compute these coefficients the dependent variable was the annualized expenditures for an individual divided by the average expenditures for all beneficiaries in the regression. Thus the mean of the dependent variable in the Medicaid regression was 1.0.

SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Table 1-4
Subsequent-Year Annual Expenditure Effects of CDPS-Medicaid Subcategories
by Medicaid and Medicare Beneficiary Groups

Major category Subcategory	Medicaid Disabled	Medicare All	Medicaid TANF Adults	Medicaid TANF Children
Cardiovascular				
Very High	$14,939	$9,117	$7,343	$9,459
Medium	4,444	4,029	2,345	2,947
Low	1,799	1,231	943	890
Extra Low	708	91	701	489
Psychiatric				
High	4,841	2,865	2,477	6,037
Medium	3,770	2,439	2,477	3,322
Low	1,671	1,225	1,076	1,550
Skeletal				
Medium	5,313	4,208	3,822	1,365
Low	1,886	1,802	1,027	587
Very Low	1,233	996	809	369
Extra Low	545	511	809	225
Central Nervous System				
High	9,726	8,669	2,699	10,518
Medium	3,314	3,641	1,737	3,343
Low	1,582	1,348	954	654
Pulmonary				
Very High	13,586	9,191	*	*
High	7,548	7,196	1,991	2,422
Medium	5,163	4,081	2,268	1,385
Low	1,852	1,641	891	496
Gastrointestinal				
High	8,677	4,083	2021	3,231
Medium	3,353	2,542	2021	1,451
Low	1,506	647	798	304
Diabetes				
Type 1 High	9,911	8,165	10,312	*
Type 1 Medium	3,787	4,006	2,863	*
Type 2 Medium	3,111	2,548	2,514	*
Type 2 Low	1,452	1,245	664	729
Skin				
High	7,049	5,539	2,523	1,698
Low	2,594	3,390	1,122	787
Very Low	867	1,089	407	175

Major category Subcategory	Medicaid Disabled	Medicare All	Medicaid TANF Adults	Medicaid TANF Children
Renal				
Very High	14,741	4,731	8,387	2,270
Medium	2,536	2,011	1,465	646
Low	1,183	674	650	472
Substance Abuse				
Low	2,253	4,001	1,506	2,393
Very Low	1,115	1,804	821	967
Cancer				
High	5,114	4,986	3,080	4,661
Medium	1,727	786	1,153	1,199
Low	431	819	204	766
Developmental Disability				
Medium	5,314	-1,897	*	5,328
Low	1,642	-1,173	412	2,118
Genital, Extra Low	175	-329	464	559
Metabolic				
High	4,946	3,153	1,670	3,550
Medium	3,156	2,961	1,079	1,019
Very Low	1,089	828	883	582
Pregnancy				
Incomplete	560	-87	492	951
Complete	1,114	233	1,903	2,231
Eye				
Low	2,199	320	1,174	*
Very Low	1,018	-150	707	686
Cerebrovascular, Low	1,109	2,004	1,066	688
Infectious				
AIDS, High	11,477	5,513	3,125	1,282
Infectious, High	11,477	5,513	3,125	1,282
HIV, Medium	4,200	3,770	1,159	834
Infectious, Medium	4,200	3,770	1,159	834
Infectious, Low	1,369	623	285	145
Hematological				
Extra High	62,576	7,261	7,821	12,137
Very High	13,874	11,872	6,634	3,350
Medium	3,972	4,923	1,047	854
Low	1,967	1,392	982	500

Major category Subcategory	Medicaid Disabled	Medicare All	Medicaid TANF Adults	Medicaid TANF Children
Baseline[1]	1,382	2,150	944	429
Average annual expenditures	4,980	5,314	1,884	684
R-squared[2]	0.183	0.105	0.083	0.041
Sample size	960,760	1,394,701	1,548,488	3,640,871

Table 1-4
Subsequent-Year Annual Expenditure Effects of CDPS-Medicaid Subcategories by Medicaid and Medicare Beneficiary Groups

* Subcategories were combined with the subcategory or subcategories below for the purposes of the regression, because the numbers of beneficiaries in the category were too small to allow a reliable estimate of the expenditure effect. For example, the pulmonary very high-cost subcategory was combined into the pulmonary high-cost category for AFDC adults and AFDC children. For both disabled children and AFDC children, all subcategories of diabetes were collapsed into a single category.

[1] The baseline amount is the sum of the intercept plus the weighted average of the age-gender variables.

For the Medicaid disabled, the age-gender variables are: under one year of age, age 1-4, male age 5-14, female age 5-14, male age 15-24, female age 15-24, male age 25-4, female age 25-44, male age 45-64, female age 45-64. For TANF adults the age-gender variables are: male age 18-24; female age 18-24; male age 25-44; female age 25-44; male age 45-64; female age 45-64. For TANF children, the age-gender variables are: under one year of age; age 1-4; male age 5-14; male age 15-17; female age 15-17. The regression for the Medicaid disabled includes interaction terms for beneficiaries under age 19 and with the following diagnostic subcategories: very high-cost cardiovascular, medium-cost central nervous system, very high-cost pulmonary, high-, medium- and low-cost gastrointestinal, diabetes, high- and medium-cost metabolic, medium-cost infectious disease, and very high-cost hematological.

For the Medicare beneficiaries, 12 age-gender variables were used for males and 12 for females, both genders with the following age groups: age 0-34, 35-44, 45-54, 55-59, 60-64 65-69, 70-74, 75-79, 80-84, 85-89, 90-94, and 95 and older. Two other demographic variables were included, one for beneficiaries 65 or over who had originally been disabled, and one for Medicare beneficiaries who also have Medicaid coverage.

[2] The R-squared statistics for the Medicaid groups are from a validation sample.

SOURCE: For Medicare beneficiaries, authors' analysis of 1996 diagnoses and 1997 expenditures. For Medicaid beneficiaries, authors' analysis of diagnostic and expenditure data from Michigan, Ohio and Tennessee, 1991-1993; from California and Georgia, 1990; Missouri 1991-1994, Colorado 1992-1996.

Table 1-5
Frequency and Subsequent-Year Annual Expenditure
Effects of Modified CDPS-Medicaid Subcategories
and Other Variables for Medicare Population

CDPS Category	Expenditure Effect	Frequency
Cardiovascular		
Very High	$9,098	26.00 %
Medium	3,989	11.43
Low	1,178	26.21
Psychiatric		
High	2,859	1.62
Medium	2,427	0.53
Low	1,223	7.93
Skeletal		
Medium	4,239	0.25
Low	1,797	5.76
Very Low	980	8.31
Extra Low	503	17.78
CNS		
High	8,625	0.15
Medium	3,625	1.20
Low	1,328	13.88
Pulmonary		
Very High	9,189	0.14
High	7,199	1.76
Medium	4,079	1.79
Low	1,640	17.20
Gastrointestinal		
High	4,072	0.30
Medium	2,536	2.38
Low	631	16.62
Diabetes		
Type 1 High	8,202	0.19
Type 1 Medium	4,019	4.34
Type 2 Medium	2,546	1.14
Type 2 Low	1,254	9.42

CDPS Category	Expenditure Effect	Frequency
Skin		
High	5,541	1.02
Low	3,388	1.99
Very Low	1,075	6.64
Renal		
Very High	4,736	0.86
Medium	1,943	3.93
Low	622	5.28
Substance Abuse		
Low	4,062	0.43
Very Low	1,851	0.78
Cancer		
High	4,973	2.60
Medium	782	7.02
Low	782	3.66
Metabolic		6.29
High	3,073	1.29
Medium	3,073	1.13
Very Low	835	3.87
Eye		
Low	372	1.68
Cerebrovascular, Low	2,014	7.73
Infectious		
AIDS, High	5,537	0.13
Infectious, High	5,537	0.17
HIV, Medium	3,772	0.01
Infectious, Medium	3,772	1.04
Infectious, Low	612	1.64
Hematological		
Extra High	9,003	0.02
Very High	9,003	0.01
Medium	4,914	0.85
Low	1,389	2.24
Originally disabled	1,470	6.3
Medicaid beneficiary	970	14.4

CDPS Category	Expenditure Effect	Frequency
Male, age 0 to 34	-1,592	0.8
Male, age 35 to 44	-1,443	1.6
Male, age 45 to 54	-1,082	1.9
Male, age 55 to 59	-679	1.0
Male, age 60 to 64	-207	1.3
Male, age 65 to 69	-452	7.6
Male, age 70 to 74 *	0	14.0
Male, age 75 to 79	608	7.7
Male, age 80 to 84	1,149	4.8
Male, age 85 to 89	1,897	2.2
Male, age 90 to 94	2,468	0.7
Male, age 95 and older	1,743	0.2
Female, age 0 to 34	-1,493	0.5
Female, age 35 to 44	-1,345	1.0
Female, age 45 to 54	-1,090	1.3
Female, age 55 to 59	-852	0.8
Female, age 60 to 64	-207	1.0
Female, age 65 to 69	-854	9.4
Female, age 70 to 74	-476	13.4
Female, age 75 to 79	63	11.6
Female, age 80 to 84	594	8.7
Female, age 85 to 89	1,157	5.3
Female, age 90 to 94	1,450	2.4
Female, age 95 and older	681	0.8
Intercept	1,551	
R^2	0.104	

* The age-gender group "Male, age 70 to 74" is the reference category.

SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Figure 2-1
Cancer as example of full hierarchy

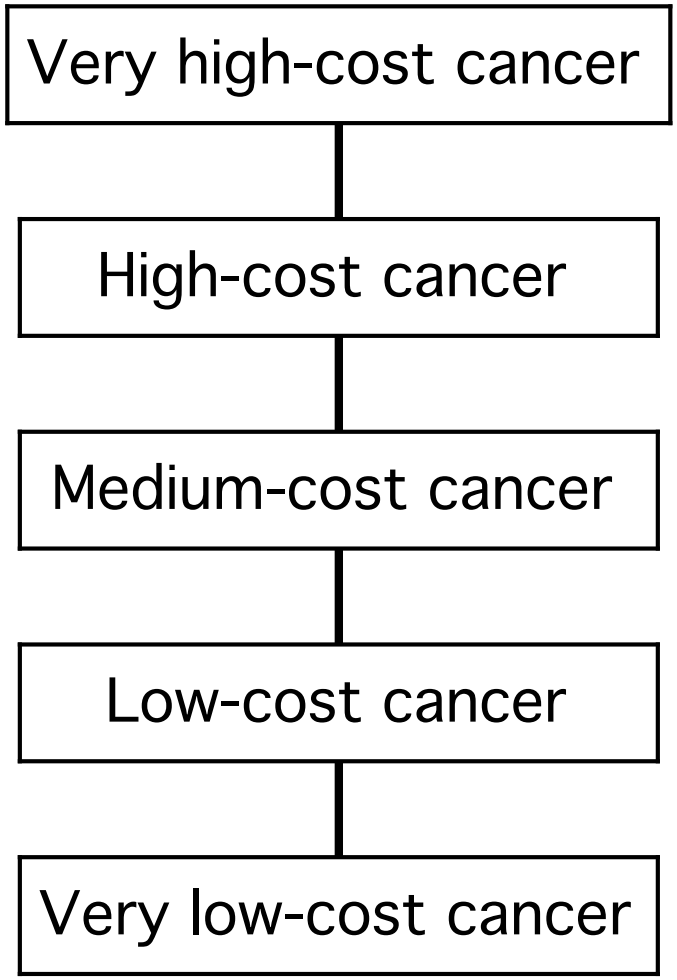


Figure 2-2
Cardiovascular hierarchy

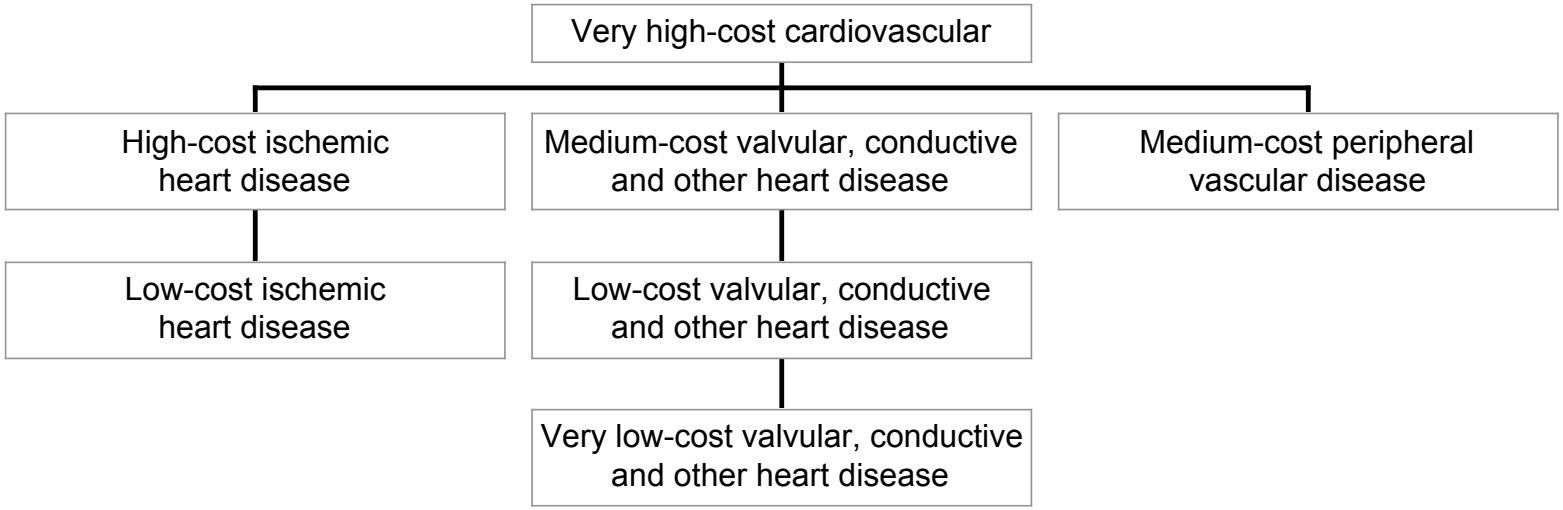


Figure 2-3
Pulmonary hierarchy

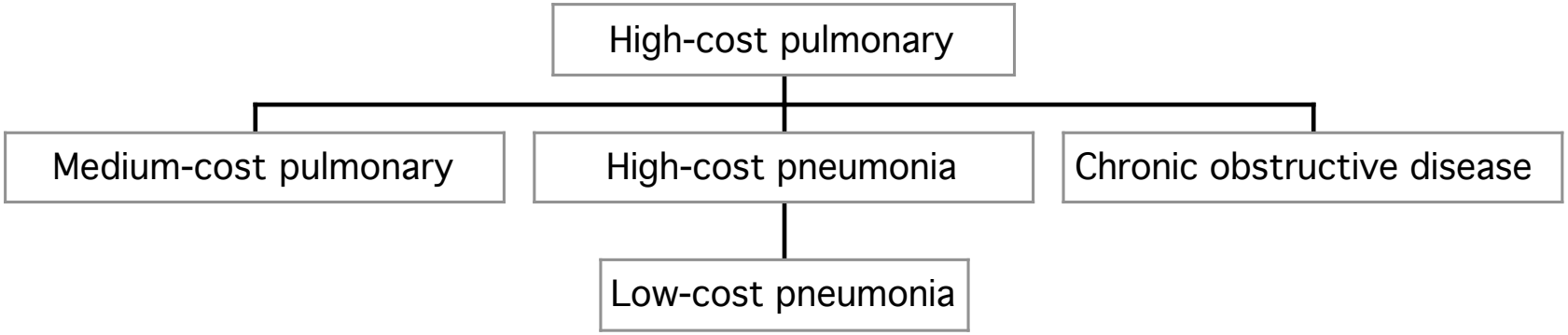


Figure 2-4
Nervous system hierarchy

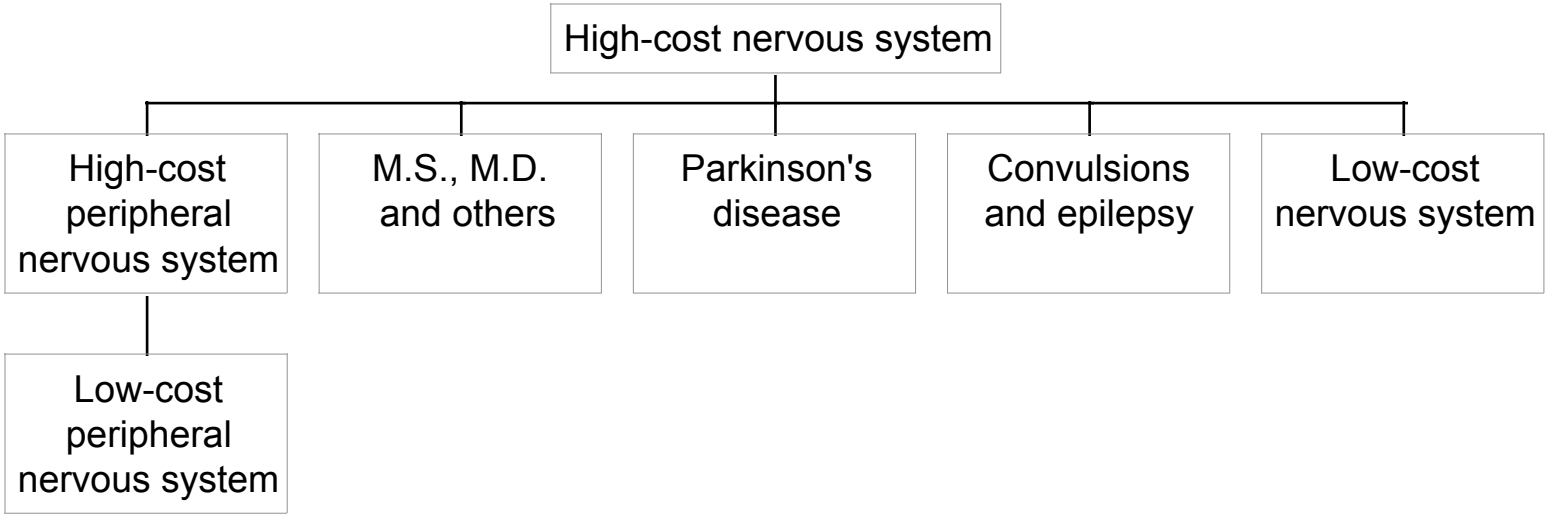


Table 3-1
Frequency and Subsequent-Year Annual Expenditure Effects
of CDPS-Medicare Subcategories and Other Variables
for Medicare Population: Base Model

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Cardiovascular					
Very high	$8,795	226	39.0	0.0001	0.002
Ischemic heart disease, high	2,788	42	66.5	0.0001	0.101
Ischemic heart disease, low	1,202	43	28.0	0.0001	0.082
Valvular, conductive and other heart disease, medium	2,453	201	12.2	0.0001	0.003
Valvular, conductive and other heart disease, low	1,288	38	34.0	0.0001	0.121
Valvular, conductive and other heart disease, very low	611	47	13.0	0.0001	0.062
Peripheral vascular, medium	1,591	40	39.5	0.0001	0.094
Psychiatric					
High	2,508	59	42.4	0.0001	0.016
Medium	2,508	59	42.4	0.0001	0.026
Low	628	52	12.1	0.0001	0.052
Skeletal and connective					
Medium	1,962	49	40.4	0.0001	0.060
Very Low	858	43	19.8	0.0001	0.075
Extra Low	568	39	14.4	0.0001	0.090
Nervous system					
High	7,861	217	36.2	0.0001	0.003
Peripheral, high	2,103	86	24.6	0.0001	0.018
Peripheral, low	714	95	7.5	0.0001	0.014
Multiple sclerosis, muscular dystrophy and others	2,685	124	21.6	0.0001	0.008
Parkinson's disease	2,152	100	21.5	0.0001	0.013
Convulsions and epilepsy	1,352	75	18.1	0.0001	0.024
Low	1,160	77	15.1	0.0001	0.022
Delirum and dementia					
Delirium	1,339	149	9.0	0.0001	0.006
Dementia	639	61	10.6	0.0001	0.040
Pulmonary					
High	8,655	104	83.2	0.0001	0.012
Medium	1,582	60	26.4	0.0001	0.039
Pneumonia, high	3,341	146	22.8	0.0001	0.006
Pneumonia, low	1,154	53	21.8	0.0001	0.052
Chronic obstructive disease, high	1,967	37	52.5	0.0001	0.109
Gastrointestinal					
High	4,503	161	28.0	0.0001	0.005
Ostomy	3,146	187	16.8	0.0001	0.004
Medium	1,779	69	25.6	0.0001	0.027
Low	848	47	18.0	0.0001	0.062
Diabetes					
Type 1 or 2 with rare complications	5,050	125	40.4	0.0001	0.008
Type 1 with common complications	3,829	60	63.8	0.0001	0.006
Type1	3,829	60	63.8	0.0001	0.031
Type 2 with common complications	1,353	38	36.0	0.0001	0.009
Type 2	1,353	38	36.0	0.0001	0.090

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Skin					
High	4,786	116	41.3	0.0001	0.010
Low	2,669	75	35.4	0.0001	0.023
Renal					
Extra high	13,002	635	20.5	0.0001	0.000[1]
Very high	4,332	131	33.0	0.0001	0.007
Medium	2,734	101	27.2	0.0001	0.008
Low	2,734	101	27.2	0.0001	0.005
Very low	756	51	15.0	0.0001	0.053
Substance abuse					
Low	3,788	176	21.5	0.0001	0.004
Very low	1,529	130	11.8	0.0001	0.008
Cancer					
Very high	7,900	119	66.5	0.0001	0.009
High	3,661	107	34.4	0.0001	0.011
Medium	2,066	77	26.7	0.0001	0.021
Low	1,012	64	15.8	0.0001	0.032
Very low	297	51	5.8	0.0001	0.050
Metabolic					
High	3,051	87	35.1	0.0001	0.018
Low	562	74	7.6	0.0001	0.023
Cerebrovascular					
High	4,065	113	36.1	0.0001	0.010
Medium	1,926	64	30.2	0.0001	0.033
Low	1,123	56	20.0	0.0001	0.037
Very low	1,123	56	20.0	0.0001	0.005
Extra low	801	99	8.1	0.0001	0.013
Infectious disease					
AIDS	4,839	210	23.1	0.0001	0.001
High	4,839	210	23.1	0.0001	0.002
HIV	2,824	100	28.2	0.0001	0.000
Medium	2,824	100	28.2	0.0001	0.013
Hematological					
Very high	7,404	209	35.4	0.0001	0.000
High	7,404	209	35.4	0.0001	0.002
Medium	4,074	164	24.8	0.0001	0.005
Low	1,704	104	16.4	0.0001	0.012
Anemia	891	42	21.0	0.0001	0.083
Originally disabled	1,387	47	29.3	0.0001	0.063
Medicaid beneficiary	943	36	26.0	0.0001	0.144
Medicaid beneficiary, age < 45	-273	119	-2.3	0.0222	0.024

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Male, age 0 to 34	-1,398	154	-9.1	0.0001	0.008
Male, age 35 to 44	-1,287	117	-11.0	0.0001	0.016
Male, age 45 to 54	-1,111	91	-12.2	0.0001	0.019
Male, age 55 to 59	-760	119	-6.4	0.0001	0.010
Male, age 60 to 64	-302	108	-2.8	0.0053	0.013
Male, age 65 to 69	-460	56	-8.2	0.0001	0.076
Male, age 70 to 74 *	-	-	-	-	0.140
Male, age 75 to 79	582	56	10.4	0.0001	0.077
Male, age 80 to 84	1,110	64	17.4	0.0001	0.048
Male, age 85 to 89	1,857	85	21.8	0.0001	0.022
Male, age 90 to 94	2,474	140	17.7	0.0001	0.007
Male, age 95 and older	1,801	278	6.5	0.0001	0.002
Female, age 0 to 34	-1,247	182	-6.9	0.0001	0.005
Female, age 35 to 44	-1,100	138	-8.0	0.0001	0.010
Female, age 45 to 54	-1,033	107	-9.6	0.0001	0.013
Female, age 55 to 59	-807	133	-6.1	0.0001	0.008
Female, age 60 to 64	-186	121	-1.5	0.1233	0.010
Female, age 65 to 69	-800	52	-15.3	0.0001	0.094
Female, age 70 to 74	-406	48	-8.4	0.0001	0.134
Female, age 75 to 79	150	50	3.0	0.0026	0.116
Female, age 80 to 84	681	54	12.6	0.0001	0.087
Female, age 85 to 89	1,249	63	19.9	0.0001	0.053
Female, age 90 to 94	1,594	84	19.0	0.0001	0.024
Female, age 95 and older	867	132	6.6	0.0001	0.008
Intercept	1,760	38	46.1	0.0001	
R^2	0.110				

* The age-gender group "Male, age 70 to 74" is the reference category.

[1] The frequency of the renal extra high subcategory is 0.0003.

SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Table 3-2
Frequency and Subsequent-Year Annual Expenditure Effects
of CDPS-Medicare Subcategories and Other Variables
for Medicare Population: Disability Interaction Model

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Cardiovascular					
Very high	$8,662	226	38.4	0.0001	0.002
Ischemic heart disease, high	2,804	42	66.9	0.0001	0.101
Ischemic heart disease, low	1,210	43	28.2	0.0001	0.082
Valvular, conductive and other heart disease, medium	2,450	201	12.2	0.0001	0.003
Valvular, conductive and other heart disease, low	1,297	38	34.3	0.0001	0.121
Valvular, conductive and other heart disease, very low	606	47	12.9	0.0001	0.062
Peripheral vascular, medium	1,598	40	39.7	0.0001	0.094
Psychiatric					
High	2,497	86	29.2	0.0001	0.016
Medium	2,497	86	29.2	0.0001	0.026
Low	645	52	12.5	0.0001	0.052
Skeletal and connective					
Medium	1,966	49	40.5	0.0001	0.060
Very Low	863	43	20.0	0.0001	0.075
Extra Low	575	39	14.6	0.0001	0.090
Nervous system					
High	7,434	219	33.9	0.0001	0.003
Peripheral, high	2,101	86	24.6	0.0001	0.018
Peripheral, low	715	95	7.5	0.0001	0.014
Multiple sclerosis, muscular dystrophy and others	2,212	165	13.4	0.0001	0.008
Parkinson's disease	2,176	100	21.7	0.0001	0.013
Convulsions and epilepsy	1,328	74	17.8	0.0001	0.024
Low	1,141	77	14.8	0.0001	0.022
Delirum and dementia					
Delirium	1,419	149	9.5	0.0001	0.006
Dementia	681	61	11.2	0.0001	0.040
Pulmonary					
High	7,938	119	66.8	0.0001	0.012
Medium	1,584	60	26.5	0.0001	0.039
Pneumonia, high	3,350	146	22.9	0.0001	0.006
Pneumonia, low	1,152	53	21.8	0.0001	0.052
Chronic obstructive disease, high	1,973	37	52.7	0.0001	0.109
Gastrointestinal					
High	3,938	188	21.0	0.0001	0.005
Ostomy	2,440	214	11.4	0.0001	0.004
Medium	1,778	69	25.6	0.0001	0.027
Low	849	47	18.0	0.0001	0.062
Diabetes					
Type 1 or 2 with rare complications	5,007	125	40.0	0.0001	0.008
Type 1 with common complications	3,822	60	63.7	0.0001	0.006
Type1	3,822	60	63.7	0.0001	0.031
Type 2 with common complications	1,358	38	36.2	0.0001	0.009
Type 2	1,358	38	36.2	0.0001	0.090

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Skin					
High	4,192	131	32.1	0.0001	0.010
Low	2,657	75	35.2	0.0001	0.023
Renal					
Extra high	12,949	635	20.4	0.0001	0.000[1]
Very high	3,695	150	24.7	0.0001	0.007
Medium	2,738	101	27.2	0.0001	0.008
Low	2,738	101	27.2	0.0001	0.005
Very low	758	51	15.0	0.0001	0.053
Substance abuse					
Low	1,728	300	5.8	0.0001	0.004
Very low	876	184	4.8	0.0001	0.008
Cancer					
Very high	7,968	119	67.1	0.0001	0.009
High	3,688	106	34.6	0.0001	0.011
Medium	2,084	77	26.9	0.0001	0.021
Low	1,019	64	15.9	0.0001	0.032
Very low	294	51	5.8	0.0001	0.050
Metabolic					
High	3,048	87	35.1	0.0001	0.018
Low	566	74	7.6	0.0001	0.023
Cerebrovascular					
High	4,093	113	36.3	0.0001	0.010
Medium	1,947	64	30.6	0.0001	0.033
Low	1,131	56	20.1	0.0001	0.037
Very low	1,131	56	20.1	0.0001	0.005
Extra low	809	99	8.1	0.0001	0.013
Infectious disease					
AIDS	4,639	210	22.1	0.0001	0.001
High	4,639	210	22.1	0.0001	0.002
HIV	2,820	100	28.2	0.0001	0.000
Medium	2,820	100	28.2	0.0001	0.013
Hematological					
Very high	6,910	217	31.9	0.0001	0.000
High	6,910	217	31.9	0.0001	0.002
Medium	3,602	185	19.5	0.0001	0.005
Low	1,338	115	11.6	0.0001	0.012
Anemia	899	42	21.2	0.0001	0.083
Interactions with disabled					
Disabled and Psychiatric high	465	135	3.4	0.0006	0.013
Disabled and Psychiatric medium	-543	141	-3.9	0.0001	0.011
Disabled and M.S., muscular dystrophy, and others	1,025	249	4.1	0.0001	0.004
Disabled and Pulmonary high	2,911	233	12.5	0.0001	0.003
Disabled and Gastrointestinal high	1,949	358	5.4	0.0001	0.001
Disabled and Ostomy	2,740	434	6.3	0.0001	0.001
Disabled and Skin high	2,640	273	9.7	0.0001	0.002
Disabled and Renal very high	2,671	303	8.8	0.0001	0.002
Disabled and Substance Abuse low	3,014	370	8.1	0.0001	0.003
Disabled and Substance Abuse very low	1,200	259	4.6	0.0001	0.004
Disabled and Hematological very high	7,052	809	8.7	0.0001	0.000
Disabled and Hematological medium	2,162	399	5.4	0.0001	0.001
Disabled and Hematological low	1,869	260	7.2	0.0001	0.002

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Originally disabled	1,167	48	24.1	0.0001	0.063
Medicaid beneficiary	937	36	25.9	0.0001	0.144
Medicaid beneficiary, age < 45	-363	119	-3.0	0.0024	0.024
Male, age 0 to 34	-1,558	154	-10.1	0.0001	0.008
Male, age 35 to 44	-1,482	117	-12.6	0.0001	0.016
Male, age 45 to 54	-1,322	92	-14.4	0.0001	0.019
Male, age 55 to 59	-946	120	-7.9	0.0001	0.010
Male, age 60 to 64	-492	109	-4.5	0.0001	0.013
Male, age 65 to 69	-459	56	-8.2	0.0001	0.076
Male, age 70 to 74 *	0	-	-	-	0.140
Male, age 75 to 79	589	56	10.5	0.0001	0.077
Male, age 80 to 84	1,118	64	17.5	0.0001	0.048
Male, age 85 to 89	1,872	85	22.0	0.0001	0.022
Male, age 90 to 94	2,496	140	17.9	0.0001	0.007
Male, age 95 and older	1,827	278	6.6	0.0001	0.002
Female, age 0 to 34	-1,382	182	-7.6	0.0001	0.005
Female, age 35 to 44	-1,245	139	-9.0	0.0001	0.010
Female, age 45 to 54	-1,208	108	-11.1	0.0001	0.013
Female, age 55 to 59	-979	133	-7.3	0.0001	0.008
Female, age 60 to 64	-374	121	-3.1	0.0020	0.010
Female, age 65 to 69	-806	52	-15.4	0.0001	0.094
Female, age 70 to 74	-409	48	-8.5	0.0001	0.134
Female, age 75 to 79	149	50	3.0	0.0029	0.116
Female, age 80 to 84	684	54	12.7	0.0001	0.087
Female, age 85 to 89	1,258	63	20.1	0.0001	0.053
Female, age 90 to 94	1,607	84	19.1	0.0001	0.024
Female, age 95 and older	881	132	6.7	0.0001	0.008
Intercept	1,789	38	46.8	0.0001	
R^2	0.111				

* The age-gender group "Male, age 70 to 74" is the reference category.

[1] The frequency of the renal extra high subcategory is 0.0003.

SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Table 3-3
Frequency and Subsequent-Year Annual Expenditure Effects
of CDPS-Medicare Subcategories and Other Variables
for Medicare Population: Full Model

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Cardiovascular					
Very high	$7,628	229	33.4	0.0001	0.002
Ischemic heart disease, high	2,140	53	40.7	0.0001	0.101
Ischemic heart disease, low	1,198	43	27.9	0.0001	0.082
Valvular, conductive and other heart disease, medium	2,078	202	10.3	0.0001	0.003
Valvular, conductive and other heart disease, low	1,329	38	35.1	0.0001	0.121
Valvular, conductive and other heart disease, very low	643	47	13.6	0.0001	0.062
Peripheral vascular, medium	1,607	40	40.0	0.0001	0.094
Psychiatric					
High	2,357	86	27.4	0.0001	0.016
Medium	2,357	86	27.4	0.0001	0.026
Low	669	52	12.9	0.0001	0.052
Skeletal and connective					
Medium	1,984	49	40.8	0.0001	0.060
Very Low	887	43	20.5	0.0001	0.075
Extra Low	594	39	15.1	0.0001	0.090
Nervous system					
High	7,217	219	32.9	0.0001	0.003
Peripheral, high	2,054	86	24.0	0.0001	0.018
Peripheral, low	732	95	7.7	0.0001	0.014
Multiple sclerosis, muscular dystrophy and others	2,014	166	12.2	0.0001	0.008
Parkinson's disease	2,060	100	20.5	0.0001	0.013
Convulsions and epilepsy	1,320	74	17.7	0.0001	0.024
Low	1,116	77	14.5	0.0001	0.022
Delirum and dementia					
Delirium	1,407	149	9.5	0.0001	0.006
Dementia	685	61	11.3	0.0001	0.040
Pulmonary					
High	7,566	121	62.5	0.0001	0.012
Medium	1,575	60	26.3	0.0001	0.039
Pneumonia, high	2,889	148	19.5	0.0001	0.006
Pneumonia, low	1,157	53	21.9	0.0001	0.052
Chronic obstructive disease, high	1,778	42	42.6	0.0001	0.109
Gastrointestinal					
High	3,612	188	19.2	0.0001	0.005
Ostomy	1,958	216	9.1	0.0001	0.004
Medium	1,620	70	23.2	0.0001	0.027
Low	874	47	18.5	0.0001	0.062
Diabetes					
Type 1 or 2 with rare complications	4,477	127	35.2	0.0001	0.008
Type 1 with common complications	3,322	64	51.5	0.0001	0.006
Type1	3,322	64	51.5	0.0001	0.031
Type 2 with common complications	1,126	41	27.4	0.0001	0.009
Type 2	1,126	41	27.4	0.0001	0.090
Skin					
High	3,751	132	28.4	0.0001	0.010
Low	2,515	76	33.2	0.0001	0.023

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Renal					
Extra high	12,418	636	19.5	0.0001	0.000[1]
Very high	2,649	169	15.7	0.0001	0.007
Medium	2,101	110	19.0	0.0001	0.008
Low	2,101	110	19.0	0.0001	0.005
Very low	783	51	15.5	0.0001	0.053
Substance abuse					
Low	1,732	300	5.8	0.0001	0.004
Very low	947	184	5.1	0.0001	0.008
Cancer					
Very high	7,896	119	66.4	0.0001	0.009
High	3,622	107	34.0	0.0001	0.011
Medium	2,038	78	26.3	0.0001	0.021
Low	1,041	64	16.2	0.0001	0.032
Very low	305	51	6.0	0.0001	0.050
Metabolic					
High	2,524	90	28.1	0.0001	0.018
Low	593	74	8.0	0.0001	0.023
Cerebrovascular					
High	3,713	116	32.1	0.0001	0.010
Medium	1,662	68	24.6	0.0001	0.033
Low	1,018	59	17.1	0.0001	0.037
Very low	1,018	59	17.1	0.0001	0.005
Extra low	718	101	7.1	0.0001	0.013
Infectious disease					
AIDS	3,997	212	18.8	0.0001	0.001
High	3,997	212	18.8	0.0001	0.002
HIV	2,339	103	22.8	0.0001	0.000
Medium	2,339	103	22.8	0.0001	0.013
Hematological					
Very high	6,536	217	30.1	0.0001	0.000
High	6,536	217	30.1	0.0001	0.002
Medium	3,408	185	18.4	0.0001	0.005
Low	1,335	115	11.6	0.0001	0.012
Anemia	920	42	21.7	0.0001	0.083
Interactions with disabled					
Disabled and Psychiatric high	555	135	4.1	0.0001	0.013
Disabled and Psychiatric medium	-500	141	-3.5	0.0004	0.011
Disabled and M.S., muscular dystrophy, and others	1,105	249	4.4	0.0001	0.004
Disabled and Pulmonary high	2,785	233	12.0	0.0001	0.003
Disabled and Gastrointestinal high	1,885	358	5.3	0.0001	0.001
Disabled and Ostomy	2,695	434	6.2	0.0001	0.001
Disabled and Skin high	2,565	273	9.4	0.0001	0.002
Disabled and Renal very high	2,507	303	8.3	0.0001	0.002
Disabled and Substance Abuse low	3,071	370	8.3	0.0001	0.003
Disabled and Substance Abuse very low	1,181	259	4.6	0.0001	0.004
Disabled and Hematological very high	7,335	808	9.1	0.0001	0.000
Disabled and Hematological medium	2,064	399	5.2	0.0001	0.001
Disabled and Hematological low	1,809	260	7.0	0.0001	0.002
Interactions between disease categories					
Diabetes and Ischemic heart disease high	1,042	88	11.9	0.0001	0.030
Diabetes and Cerebrovascular	632	90	7.0	0.0001	0.024
Ischemic high and Chronic obstructive disease high	1,074	89	12.1	0.0001	0.027

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Renal very high and Ischemic high	786	209	3.8	0.0002	0.007
Renal very high, Ischemic high and diabetes	1,308	277	4.7	0.0001	0.003
Four high-cost subcategories[2]	1,479	141	10.5	0.0001	0.008
Five high-cost subcategories	2,896	216	13.4	0.0001	0.003
Six high-cost subcategories	4,099	330	12.4	0.0001	0.001
Seven or more high-cost	6,294	430	14.6	0.0001	0.001
Originally disabled	1,191	48	24.7	0.0001	0.063
Medicaid beneficiary	951	36	26.2	0.0001	0.144
Medicaid beneficiary, age < 45	-351	119	-2.9	0.0032	0.024
Male, age 0 to 34	-1,573	154	-10.2	0.0001	0.008
Male, age 35 to 44	-1,478	117	-12.6	0.0001	0.016
Male, age 45 to 54	-1,307	92	-14.2	0.0001	0.019
Male, age 55 to 59	-923	120	-7.7	0.0001	0.010
Male, age 60 to 64	-466	109	-4.3	0.0001	0.013
Male, age 65 to 69	-469	56	-8.4	0.0001	0.076
Male, age 70 to 74*	0	-	-	-	0.140
Male, age 75 to 79	598	56	10.7	0.0001	0.077
Male, age 80 to 84	1,140	64	17.9	0.0001	0.048
Male, age 85 to 89	1,907	85	22.4	0.0001	0.022
Male, age 90 to 94	2,566	140	18.4	0.0001	0.007
Male, age 95 and older	1,930	278	6.9	0.0001	0.002
Female, age 0 to 34	-1,391	182	-7.6	0.0001	0.005
Female, age 35 to 44	-1,239	139	-8.9	0.0001	0.010
Female, age 45 to 54	-1,183	108	-10.9	0.0001	0.013
Female, age 55 to 59	-938	133	-7.0	0.0001	0.008
Female, age 60 to 64	-342	121	-2.8	0.0047	0.010
Female, age 65 to 69	-820	52	-15.7	0.0001	0.094
Female, age 70 to 74	-415	48	-8.6	0.0001	0.134
Female, age 75 to 79	153	50	3.1	0.0022	0.116
Female, age 80 to 84	707	54	13.1	0.0001	0.087
Female, age 85 to 89	1,311	63	20.9	0.0001	0.053
Female, age 90 to 94	1,697	84	20.2	0.0001	0.024
Female, age 95 and older	994	132	7.6	0.0001	0.008
Intercept	1,870	38	48.8	0.0001	
R^2	0.111				

* The age-gender group "Male, age 70 to 74" is the reference category.

[1] The frequency of the renal extra high subcategory is 0.0003.

[2] The high-cost subcategories were: cardiovascular very-high; cardiovascular ischemic heart disease high; cardiovascular valvular, conductive and other heart disease medium; psychiatric, high and medium; nervous system high; nervous system multiple sclerosis, muscular dystrophy and others; nervous system Parkinson's disease; pulmonary high; pulmonary pneumonia high; gastrointestinal high, medium, and ostomy; diabetes Type 1 or 2 with rare complications; diabetes Type 1; skin, high and low; renal, extra high, very high, and medium; cancer, very high, high, and medium; metabolic high; cerebrovascular, high and medium; AIDS high; infectious disease, high and medium; HIV medium; hematological, very high, high, and medium.

SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Table 3-4
Frequency and Subsequent-Year Annual Expenditure Effects of CDPS-Medicare Subcategories and Other Variables for Medicare Population: Inpatient Model

CDPS Category	Expenditure Effect	Standard Error	T-stat	P-value	Inpatient Frequency	Overall Frequency	Ratio
Cardiovascular							
Very high	$8,381	335	25.0	0.0001	0.001	0.002	0.46
Ischemic heart disease, high	4,143	76	54.7	0.0001	0.033	0.101	0.33
Ischemic heart disease, low	877	74	11.8	0.0001	0.028	0.082	0.34
Valvular, conductive and other heart disease, medium	1,643	377	4.4	0.0001	0.001	0.003	0.29
Valvular, conductive and other heart disease, low	1,398	68	20.7	0.0001	0.040	0.121	0.33
Valvular, conductive and other heart disease, very low	463	103	4.5	0.0001	0.013	0.062	0.21
Peripheral vascular, medium	2,547	98	26.0	0.0001	0.015	0.094	0.16
Psychiatric							
High	5,530	200	27.6	0.0001	0.004	0.016	0.28
Medium	5,530	200	27.6	0.0001	0.005	0.026	0.21
Low	2,228	114	19.5	0.0001	0.010	0.052	0.20
Skeletal and connective							
Medium	2,029	98	20.8	0.0001	0.015	0.060	0.25
Very Low	2,584	130	19.9	0.0001	0.008	0.075	0.10
Extra Low	921	119	7.7	0.0001	0.009	0.090	0.10
Nervous system							
High	10,952	380	28.8	0.0001	0.001	0.003	0.35
Peripheral, high	3,838	205	18.8	0.0001	0.003	0.018	0.18
Peripheral, low	3,411	414	8.2	0.0001	0.001	0.014	0.05
Multiple sclerosis, muscular dystrophy and others	3,068	537	5.7	0.0001	0.001	0.008	0.14
Parkinson's disease	3,681	200	18.4	0.0001	0.003	0.013	0.26
Convulsions and epilepsy	2,797	141	19.9	0.0001	0.007	0.024	0.28
Low	1,745	197	8.9	0.0001	0.003	0.022	0.15
Delirum and dementia							
Delirium	2,283	279	8.2	0.0001	0.002	0.006	0.29
Dementia	1,134	119	9.5	0.0001	0.010	0.040	0.24
Pulmonary							
High	7,537	200	37.6	0.0001	0.005	0.012	0.38
Medium	2,097	142	14.8	0.0001	0.007	0.039	0.17
Pneumonia, high	2,632	173	15.2	0.0001	0.004	0.006	0.75
Pneumonia, low	868	99	8.8	0.0001	0.015	0.052	0.28
Chronic obstructive disease, high	3,448	71	48.7	0.0001	0.032	0.109	0.29
Gastrointestinal							
High	4,959	324	15.3	0.0001	0.002	0.005	0.35
Ostomy	3,295	315	10.4	0.0001	0.002	0.004	0.48
Medium	1,806	116	15.6	0.0001	0.010	0.027	0.37
Low	1,132	104	10.9	0.0001	0.013	0.062	0.21
Diabetes							
Type 1 or 2 with rare complications	5,419	390	13.9	0.0001	0.001	0.008	0.10
Type 1 with common complications	6,698	115	58.0	0.0001	0.002	0.006	0.37
Type1	6,698	115	58.0	0.0001	0.009	0.031	0.27
Type 2 with common complications	2,747	80	34.4	0.0001	0.002	0.009	0.18
Type 2	2,747	80	34.4	0.0001	0.021	0.090	0.23
Skin							
High	7,388	265	27.9	0.0001	0.003	0.010	0.27
Low	6,649	233	28.6	0.0001	0.002	0.023	0.11
Renal							
Extra high	20,584	1235	16.7	0.0001	0.000[1]	0.000[1]	1.00
Very high	5,159	341	15.1	0.0001	0.001	0.007	0.20
Medium	3,462	151	22.9	0.0001	0.004	0.008	0.53
Low	3,462	151	22.9	0.0001	0.002	0.005	0.34
Very low	786	115	6.8	0.0001	0.010	0.053	0.19
Substance abuse							
Low	1,873	399	4.7	0.0001	0.002	0.004	0.60
Very low	739	249	3.0	0.0030	0.004	0.008	0.56

CDPS Category	Expenditure Effect	Standard Error	T-stat	P-value	Inpatient Frequency	Overall Frequency	Ratio
Cancer							
Very high	13,000	217	59.8	0.0001	0.003	0.009	0.30
High	8,534	249	34.2	0.0001	0.002	0.011	0.19
Medium	6,170	210	29.4	0.0001	0.003	0.021	0.14
Low	873	175	5.0	0.0001	0.004	0.032	0.13
Very low	713	257	2.8	0.0056	0.002	0.050	0.04
Metabolic							
High	3,093	123	25.1	0.0001	0.009	0.018	0.51
Low	1,602	188	8.5	0.0001	0.004	0.023	0.16
Cerebrovascular							
High	4,506	150	30.0	0.0001	0.006	0.010	0.58
Medium	1,759	221	8.0	0.0001	0.003	0.033	0.08
Low	2,167	108	20.0	0.0001	0.009	0.037	0.24
Very low	2,167	108	20.0	0.0001	0.003	0.005	0.49
Extra low	1,301	203	6.4	0.0001	0.003	0.013	0.24
Infectious disease							
AIDS	5,454	288	18.9	0.0001	0.000	0.001	0.27
High	5,454	288	18.9	0.0001	0.001	0.002	0.78
HIV	2,125	154	13.8	0.0001	0.000	0.000	0.73
Medium	2,125	154	13.8	0.0001	0.006	0.013	0.43
Hematological							
Very high	9,088	375	24.2	0.0001	0.000	0.000	0.31
High	9,088	375	24.2	0.0001	0.001	0.002	0.37
Medium	4,596	403	11.4	0.0001	0.001	0.005	0.22
Low	2,276	220	10.3	0.0001	0.003	0.012	0.29
Anemia	890	73	12.1	0.0001	0.030	0.083	0.36
Interactions with disabled							
Disabled and Psychiatric high	467	277	1.7	0.0915	0.004	0.013	0.29
Disabled and Psychiatric medium	-609	300	-2.0	0.0423	0.003	0.011	0.25
Disabled and M.S., muscular dystrophy, and others	3,024	688	4.4	0.0001	0.001	0.004	0.19
Disabled and Pulmonary high	3,727	365	10.2	0.0001	0.001	0.003	0.44
Disabled and Gastrointestinal high	2,976	597	5.0	0.0001	0.001	0.001	0.38
Disabled and Ostomy	2,799	617	4.5	0.0001	0.000	0.001	0.52
Disabled and Skin high	1,003	505	2.0	0.0470	0.001	0.002	0.33
Disabled and Renal very high	3,085	678	4.5	0.0001	0.000	0.002	0.21
Disabled and Substance Abuse low	1,981	491	4.0	0.0001	0.002	0.003	0.61
Disabled and Substance Abuse very low	358	353	1.0	0.3100	0.002	0.004	0.55
Disabled and Hematological very high	14,194	1164	12.2	0.0001	0.000	0.000	0.51
Disabled and Hematological medium	3,667	821	4.5	0.0001	0.000	0.001	0.25
Disabled and Hematological low	3,006	464	6.5	0.0001	0.001	0.002	0.33
Originally disabled	2,038	48	42.4	0.0001	0.063	0.063	
Medicaid beneficiary	1,631	36	44.9	0.0001	0.144	0.144	
Medicaid beneficiary, age < 45	-593	121	-4.9	0.0001	0.024	0.024	
Male, age 0 to 34	-2,204	156	-14.2	0.0001	0.008	0.008	
Male, age 35 to 44	-1,686	117	-14.4	0.0001	0.016	0.016	
Male, age 45 to 54	-1,419	92	-15.5	0.0001	0.019	0.019	
Male, age 55 to 59	-834	121	-6.9	0.0001	0.010	0.010	
Male, age 60 to 64	-179	110	-1.6	0.1036	0.013	0.013	
Male, age 65 to 69	-833	57	-14.6	0.0001	0.076	0.076	
Male, age 70 to 74 *	0	-	-	-	0.140	0	
Male, age 75 to 79	948	57	16.8	0.0001	0.077	0.077	
Male, age 80 to 84	1,798	65	27.9	0.0001	0.048	0.048	
Male, age 85 to 89	2,776	86	32.3	0.0001	0.022	0.022	
Male, age 90 to 94	3,494	141	24.7	0.0001	0.007	0.007	
Male, age 95 and older	2,721	282	9.7	0.0001	0.002	0.002	
Female, age 0 to 34	-1,994	184	-10.8	0.0001	0.005	0.005	
Female, age 35 to 44	-1,367	139	-9.8	0.0001	0.010	0.010	
Female, age 45 to 54	-1,037	108	-9.6	0.0001	0.013	0.013	
Female, age 55 to 59	-577	134	-4.3	0.0001	0.008	0.008	
Female, age 60 to 64	210	122	1.7	0.0857	0.010	0.010	
Female, age 65 to 69	-1,124	53	-21.3	0.0001	0.094	0.094	
Female, age 70 to 74	-472	49	-9.7	0.0001	0.134	0.134	
Female, age 75 to 79	343	50	6.8	0.0001	0.116	0.116	
Female, age 80 to 84	1,137	54	21.0	0.0001	0.087	0.087	
Female, age 85 to 89	1,939	63	30.8	0.0001	0.053	0.053	
Female, age 90 to 94	2,463	84	29.2	0.0001	0.024	0.024	
Female, age 95 and older	1,776	133	13.4	0.0001	0.008	0.008	

CDPS Category	Expenditure Effect	Standard Error	T-stat	P-value	Inpatient Frequency	Overall Frequency	Ratio
Intercept	3,483	37.3	93.4	0.0001			
R^2	0.085						

* The age-gender group "Male, age 70 to 74" is the reference category.

[1] The frequency of the renal extra high subcategory is 0.0003.

SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Table 3-5
Frequency and Subsequent-Year Annual Expenditure Effects
of CDPS-Medicare Subcategories and Other Variables
for Medicare Population: Restricted Model

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Cardiovascular					
Very high	$10,525	227	46.4	0.0001	0.002
Ischemic heart disease, high	5,006	39	127.7	0.0001	0.101
Psychiatric					
High	3,641	86	42.5	0.0001	0.016
Medium	3,641	86	42.5	0.0001	0.026
Nervous system					
High	8,239	221	37.2	0.0001	0.003
Peripheral, high	3,410	86	39.7	0.0001	0.018
Multiple sclerosis, muscular dystrophy and others	3,597	167	21.5	0.0001	0.008
Parkinson's disease	3,103	101	30.8	0.0001	0.013
Pulmonary					
High	9,023	118	76.3	0.0001	0.012
Gastrointestinal					
High	5,641	189	29.9	0.0001	0.005
Ostomy	4,460	216	20.7	0.0001	0.004
Diabetes					
Type 1 or 2 with rare complications	5,401	126	42.8	0.0001	0.008
Type 1 with common complications	4,136	60	68.7	0.0001	0.006
Type1	4,136	60	68.7	0.0001	0.031
Skin					
High	6,510	131	49.7	0.0001	0.010
Low	3,858	76	51.1	0.0001	0.023
Renal					
Extra high	14,555	643	22.6	0.0001	0.000[1]
Very high	5,459	151	36.3	0.0001	0.007
Medium	4,326	101	42.9	0.0001	0.008
Low	4,326	101	42.9	0.0001	0.005
Cancer					
Very high	9,302	120	77.8	0.0001	0.009
High	4,910	107	45.9	0.0001	0.011
Medium	2,805	78	36.0	0.0001	0.021
Cerebrovascular					
High	5,647	112	50.2	0.0001	0.010
Infectious disease					
AIDS	5,904	314	18.8	0.0001	0.001
HIV	1,651	1127	1.5	0.1431	0.000
Hematological					
Very high	8,292	219	37.9	0.0001	0.000
High	8,292	219	37.9	0.0001	0.002
Medium	4,543	187	24.3	0.0001	0.005

CDPS Category	Expenditure Effect	Standard Error	T-Statistic	P-Value	Frequency
Interactions with disabled					
Disabled and Psychiatric high	-262	136	-1.9	0.0538	0.013
Disabled and Psychiatric medium	-785	141	-5.6	0.0001	0.011
Disabled and M.S., muscular dystrophy, and others	290	252	1.1	0.2505	0.004
Disabled and Pulmonary high	2,727	235	11.6	0.0001	0.003
Disabled and Gastrointestinal high	1,830	362	5.1	0.0001	0.001
Disabled and Ostomy	2,532	439	5.8	0.0001	0.001
Disabled and Skin high	2,396	276	8.7	0.0001	0.002
Disabled and Renal very high	2,447	306	8.0	0.0001	0.002
Disabled and Hematological very high	7,056	819	8.6	0.0001	0.000
Disabled and Hematological medium	2,606	404	6.5	0.0001	0.001
Disabled and Hematological low	4,981	236	21.1	0.0001	0.002
Originally disabled	1,690	49	34.7	0.0001	0.063
Medicaid beneficiary	1,377	36	37.9	0.0001	0.144
Medicaid beneficiary, age < 45	-407	121	-3.4	0.0007	0.024
Male, age 0 to 34	-2,379	156	-15.3	0.0001	0.008
Male, age 35 to 44	-1,998	118	-16.9	0.0001	0.016
Male, age 45 to 54	-1,662	92	-18.0	0.0001	0.019
Male, age 55 to 59	-1,025	121	-8.5	0.0001	0.010
Male, age 60 to 64	-451	110	-4.1	0.0001	0.013
Male, age 65 to 69	-732	57	-12.9	0.0001	0.076
Male, age 70 to 74*	0	-	-	-	0.140
Male, age 75 to 79	838	56	14.8	0.0001	0.077
Male, age 80 to 84	1,611	64	25.0	0.0001	0.048
Male, age 85 to 89	2,495	86	29.0	0.0001	0.022
Male, age 90 to 94	3,146	141	22.3	0.0001	0.007
Male, age 95 and older	2,229	281	7.9	0.0001	0.002
Female, age 0 to 34	-2,123	184	-11.5	0.0001	0.005
Female, age 35 to 44	-1,725	140	-12.3	0.0001	0.010
Female, age 45 to 54	-1,457	109	-13.3	0.0001	0.013
Female, age 55 to 59	-1,000	135	-7.4	0.0001	0.008
Female, age 60 to 64	-249	122	-2.0	0.0415	0.010
Female, age 65 to 69	-1,104	53	-21.0	0.0001	0.094
Female, age 70 to 74	-508	49	-10.5	0.0001	0.134
Female, age 75 to 79	242	50	4.8	0.0001	0.116
Female, age 80 to 84	975	54	18.1	0.0001	0.087
Female, age 85 to 89	1,677	63	26.7	0.0001	0.053
Female, age 90 to 94	2,029	84	24.1	0.0001	0.024
Female, age 95 and older	1,146	132	8.7	0.0001	0.008
Intercept	3,055	37.3	81.9	0.0001	
R^2	0.089				

* The age-gender group "Male, age 70 to 74" is the reference category.

[1] The frequency of the renal extra high subcategory is 0.0003.

SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Table 3-6
Frequency and Subsequent-Year Annual Expenditure Effects
of CDPS-Medicare Subcategories and Other Variables
for Medicare Population: End-of-Life Model

CDPS Category	Expenditure Effect	Standard Error	T-Stat	P-Value	Frequency
Cardiovascular					
Very high	$7,263	218	33.3	0.0001	0.002
Ischemic heart disease, high	1,379	50	27.5	0.0001	0.101
Ischemic heart disease, low	1,398	41	34.2	0.0001	0.082
Valvular, conductive and other heart disease, medium	1,948	192	10.1	0.0001	0.003
Valvular, conductive and other heart disease, low	1,213	36	33.6	0.0001	0.121
Valvular, conductive and other heart disease, very low	767	45	17.1	0.0001	0.062
Peripheral vascular, medium	1,388	38	36.2	0.0001	0.094
Psychiatric					
High	2,337	82	28.5	0.0001	0.016
Medium	2,337	82	28.5	0.0001	0.026
Low	383	49	7.8	0.0001	0.052
Skeletal and connective					
Medium	1,917	46	41.4	0.0001	0.060
Very Low	930	41	22.6	0.0001	0.075
Extra Low	743	38	19.8	0.0001	0.090
Nervous system					
High	6,817	209	32.6	0.0001	0.003
Peripheral, high	2,145	81	26.3	0.0001	0.018
Peripheral, low	946	90	10.5	0.0001	0.014
Multiple sclerosis, muscular dystrophy and others	1,776	158	11.2	0.0001	0.008
Parkinson's disease	1,194	96	12.5	0.0001	0.013
Convulsions and epilepsy	1,203	71	17.0	0.0001	0.024
Low	1,151	73	15.7	0.0001	0.022
Delirum and dementia					
Delirium	614	142	4.3	0.0001	0.006
Dementia	-637	58	-11.0	0.0001	0.040
Pulmonary					
High	6,283	115	54.4	0.0001	0.012
Medium	1,163	57	20.4	0.0001	0.039
Pneumonia, high	1,838	141	13.0	0.0001	0.006
Pneumonia, low	806	50	16.0	0.0001	0.052
Chronic obstructive disease, high	1,348	40	33.9	0.0001	0.109
Gastrointestinal					
High	2,879	179	16.0	0.0001	0.005
Ostomy	1,137	206	5.5	0.0001	0.004
Medium	1,518	67	22.8	0.0001	0.027
Low	938	45	20.9	0.0001	0.062
Diabetes					
Type 1 or 2 with rare complications	4,050	121	33.4	0.0001	0.008
Type 1 with common complications	2,992	61	48.7	0.0001	0.006
Type1	2,992	61	48.7	0.0001	0.031
Type 2 with common complications	1,022	39	26.1	0.0001	0.009
Type 2	1,022	39	26.1	0.0001	0.090

CDPS Category	Expenditure Effect	Standard Error	T-Stat	P-Value	Frequency
Skin					
High	2,504	126	19.9	0.0001	0.010
Low	2,172	72	30.1	0.0001	0.023
Renal					
Extra high	11,869	606	19.6	0.0001	0.000[1]
Very high	1,826	161	11.3	0.0001	0.007
Medium	1,824	105	17.3	0.0001	0.008
Low	1,824	105	17.3	0.0001	0.005
Very low	839	48	17.4	0.0001	0.053
Substance abuse					
Low	1,721	285	6.0	0.0001	0.004
Very low	602	176	3.4	0.0006	0.008
Cancer					
Very high	4,389	114	38.6	0.0001	0.009
High	1,993	102	19.6	0.0001	0.011
Medium	1,574	74	21.3	0.0001	0.021
Low	1,021	61	16.7	0.0001	0.032
Very low	363	49	7.5	0.0001	0.050
Metabolic					
High	1,878	86	21.9	0.0001	0.018
Low	619	71	8.8	0.0001	0.023
Cerebrovascular					
High	3,053	110	27.7	0.0001	0.010
Medium	1,254	64	19.5	0.0001	0.033
Low	988	57	17.4	0.0001	0.037
Very low	988	57	17.4	0.0001	0.005
Extra low	831	96	8.7	0.0001	0.013
Infectious disease					
AIDS	3,483	202	17.2	0.0001	0.001
High	3,483	202	17.2	0.0001	0.002
HIV	2,118	98	21.7	0.0001	0.000
Medium	2,118	98	21.7	0.0001	0.013
Hematological					
Very high	4,819	207	23.3	0.0001	0.000
High	4,819	207	23.3	0.0001	0.002
Medium	2,539	176	14.4	0.0001	0.005
Low	1,216	110	11.1	0.0001	0.012
Anemia	794	40	19.7	0.0001	0.083
Interactions with disabled					
Disabled and Psychiatric high	611	129	4.7	0.0001	0.013
Disabled and Psychiatric medium	-415	134	-3.1	0.0020	0.011
Disabled and M.S.M.D.	1,136	238	4.8	0.0001	0.004
Disabled and Pulmonary high	2,367	222	10.7	0.0001	0.003
Disabled and Gastrointestinal high	1,529	342	4.5	0.0001	0.001
Disabled and Ostomy	2,727	413	6.6	0.0001	0.001
Disabled and Skin high	2,914	260	11.2	0.0001	0.002
Disabled and Renal very high	2,504	289	8.7	0.0001	0.002
Disabled and Substance Abuse low	2,953	352	8.4	0.0001	0.003
Disabled and Substance Abuse very low	1,195	246	4.8	0.0001	0.004
Disabled and Hematological very high	8,857	771	11.5	0.0001	0.000
Disabled and Hematological medium	2,122	380	5.6	0.0001	0.001
Disabled and Hematological low	1,769	248	7.1	0.0001	0.002

CDPS Category	Expenditure Effect	Standard Error	T-Stat	P-Value	Frequency
Interactions between disease categories					
Diabetes and Ischemic heart disease high	891	84	10.6	0.0001	0.030
Diabetes and Cerebrovascular	507	86	5.9	0.0001	0.024
Ischemic high and Chronic obstructive disease high	903	84	10.7	0.0001	0.027
Renal very high and Ischemic high	1	199	0.0	0.9968	0.007
Renal very high, Ischemic high and diabetes	1,283	264	4.9	0.0001	0.003
Four high-cost subcategories[2]	1,278	135	9.5	0.0001	0.008
Five high-cost subcategories	2,826	205	13.8	0.0001	0.003
Six high-cost subcategories	4,031	315	12.8	0.0001	0.001
Seven or more high-cost	6,540	410	16.0	0.0001	0.001
Died during the first six months of 1997	39,546	141	281.3	0.0001	0.021
Died during the last six months of 1997	21,056	87	242.6	0.0001	0.022
Died during the first six months of 1998	8,129	75	108.7	0.0001	0.022
Died during the last six months of 1998	4,278	77	55.5	0.0001	0.021
Died during the first six months of 1999	3,056	74	41.2	0.0001	0.020
Died during the last six months of 1999	2,296	77	29.8	0.0001	0.020
Died during the first six months of 2000	1,842	75	24.6	0.0001	0.020
Died during the last six months of 2000	1,630	77	21.2	0.0001	0.020
Originally disabled	642	46	13.9	0.0001	0.063
Medicaid beneficiary	921	35	26.7	0.0001	0.144
Medicaid beneficiary, age < 45	-272	114	-2.4	0.0167	0.024
Male, age 0 to 34	-1,108	147	-7.5	0.0001	0.008
Male, age 35 to 44	-1,070	112	-9.6	0.0001	0.016
Male, age 45 to 54	-1,018	88	-11.6	0.0001	0.019
Male, age 55 to 59	-801	114	-7.0	0.0001	0.010
Male, age 60 to 64	-534	104	-5.2	0.0001	0.013
Male, age 65 to 69	-292	54	-5.5	0.0001	0.076
Male, age 70 to 74*	0	-	-	-	0.140
Male, age 75 to 79	178	53	3.4	0.0008	0.077
Male, age 80 to 84	47	61	0.8	0.4383	0.048
Male, age 85 to 89	-283	82	-3.5	0.0005	0.022
Male, age 90 to 94	-1,101	134	-8.2	0.0001	0.007
Male, age 95 and older	-2,986	266	-11.2	0.0001	0.002
Female, age 0 to 34	-838	174	-4.8	0.0001	0.005
Female, age 35 to 44	-703	132	-5.3	0.0001	0.010
Female, age 45 to 54	-681	103	-6.6	0.0001	0.013
Female, age 55 to 59	-459	127	-3.6	0.0003	0.008
Female, age 60 to 64	84	115	0.7	0.4673	0.010
Female, age 65 to 69	-307	50	-6.2	0.0001	0.094
Female, age 70 to 74	43	46	0.9	0.3534	0.134
Female, age 75 to 79	488	47	10.3	0.0001	0.116
Female, age 80 to 84	787	51	15.3	0.0001	0.087
Female, age 85 to 89	976	60	16.3	0.0001	0.053
Female, age 90 to 94	777	80	9.7	0.0001	0.024
Female, age 95 and older	-524	125	-4.2	0.0001	0.008

CDPS Category	Expenditure Effect	Standard Error	T-Stat	P-Value	Frequency
Intercept	1,367	37	37.3	0.0001	
R^2	0.193				

* The age-gender group "Male, age 70 to 74" is the reference category.

[1] The frequency of the renal extra high subcategory is 0.0003.

[2] The high-cost subcategories were: cardiovascular very-high; cardiovascular ischemic heart disease high; cardiovascular valvular, conductive and other heart disease medium; psychiatric, high and medium; nervous system high; nervous system multiple sclerosis, muscular dystrophy and others; nervous system Parkinson's disease; pulmonary high; pulmonary pneumonia high; gastrointestinal high, medium, and ostomy; diabetes Type 1 or 2 with rare complications; diabetes Type 1; skin, high and low; renal, extra high, very high, and medium; cancer, very high, high, and medium; metabolic high; cerebrovascular, high and medium; AIDS high; infectious disease, high and medium; HIV medium; hematological, very high, high, and medium.

SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Table 3-7
Subsequent-Year Annual Expenditure Effects of CDPS-Medicare Subcategories and Other Variables for Medicare Population for Six Model Variants

CDPS Category	Base Model	Disability Interaction Model	Full Model	Inpatient Model	Restricted Model	End-of-Life Model
Cardiovascular						
Very high	$8,795	$8,662	$7,628	$8,381	$10,525	$7,263
Ischemic heart disease, high	2,788	2,804	2,140	4,143	5,006	1,379
Ischemic heart disease, low	1,202	1,210	1,198	877		1,398
Valvular, conductive and other heart disease, medium	2,453	2,450	2,078	1,643		1,948
Valvular, conductive and other heart disease, low	1,288	1,297	1,329	1,398		1,213
Valvular, conductive and other heart disease, very low	611	606	643	463		767
Peripheral vascular, medium	1,591	1,598	1,607	2,547		1,388
Psychiatric						
High	2,508	2,497	2,357	5,530	3,641	2,337
Medium	2,508	2,497	2,357	5,530	3,641	2,337
Low	628	645	669	2,228		383
Skeletal and connective						
Medium	1,962	1,966	1,984	2,029		1,917
Very Low	858	863	887	2,584		930
Extra Low	568	575	594	921		743
Nervous system						
High	7,861	7,434	7,217	10,952	8,239	6,817
Peripheral, high	2,103	2,101	2,054	3,838	3,410	2,145
Peripheral, low	714	715	732	3,411		946
Multiple sclerosis, muscular dystrophy and others	2,685	2,212	2,014	3,068	3,597	1,776
Parkinson's disease	2,152	2,176	2,060	3,681	3,103	1,194
Convulsions and epilepsy	1,352	1,328	1,320	2,797		1,203
Low	1,160	1,141	1,116	1,745		1,151
Delirum and dementia						
Delirium	1,339	1,419	1,407	2,283		614
Dementia	639	681	685	1,134		-637
Pulmonary						
High	8,655	7,938	7,566	7,537	9,023	6,283
Medium	1,582	1,584	1,575	2,097		1,163
Pneumonia, high	3,341	3,350	2,889	2,632		1,838
Pneumonia, low	1,154	1,152	1,157	868		806
Chronic obstructive disease, high	1,967	1,973	1,778	3,448		1,348
Gastrointestinal						
High	4,503	3,938	3,612	4,959	5,641	2,879
Ostomy	3,146	2,440	1,958	3,295	4,460	1,137
Medium	1,779	1,778	1,620	1,806		1,518
Low	848	849	874	1,132		938
Diabetes						
Type 1 or 2 with rare complications	5,050	5,007	4,477	5,419	5,401	4,050
Type 1 with common complications	3,829	3,822	3,322	6,698	4,136	2,992
Type1	3,829	3,822	3,322	6,698	4,136	2,992
Type 2 with common complications	1,353	1,358	1,126	2,747		1,022
Type 2	1,353	1,358	1,126	2,747		1,022
Skin						
High	4,786	4,192	3,751	7,388	6,510	2,504
Low	2,669	2,657	2,515	6,649	3,858	2,172
Renal						
Extra high	13,002	12,949	12,418	20,584	14,555	11,869
Very high	4,332	3,695	2,649	5,159	5,459	1,826
Medium	2,734	2,738	2,101	3,462	4,326	1,824
Low	2,734	2,738	2,101	3,462	4,326	1,824
Very low	756	758	783	786		839

CDPS Category	Base Model	Disability Interaction Model	Full Model	Inpatient Model	Restricted Model	End-of-Life Model
Substance abuse						
Low	3,788	1,728	1,732	1,873		1,721
Very low	1,529	876	947	739		602
Cancer						
Very high	7,900	7,968	7,896	13,000	9,302	4,389
High	3,661	3,688	3,622	8,534	4,910	1,993
Medium	2,066	2,084	2,038	6,170	2,805	1,574
Low	1,012	1,019	1,041	873		1,021
Very low	297	294	305	713		363
Metabolic						
High	3,051	3,048	2,524	3,093		1,878
Low	562	566	593	1,602		619
Cerebrovascular						
High	4,065	4,093	3,713	4,506	5,647	3,053
Medium	1,926	1,947	1,662	1,759		1,254
Low	1,123	1,131	1,018	2,167		988
Very low	1,123	1,131	1,018	2,167		988
Extra low	801	809	718	1,301		831
Infectious disease						
AIDS	4,839	4,639	3,997	5,454	5,904	3,483
High	4,839	4,639	3,997	5,454		3,483
HIV	2,824	2,820	2,339	2,125	1,651	2,118
Medium	2,824	2,820	2,339	2,125		2,118
Hematological						
Very high	7,404	6,910	6,536	9,088	8,292	4,819
High	7,404	6,910	6,536	9,088	8,292	4,819
Medium	4,074	3,602	3,408	4,596	4,543	2,539
Low	1,704	1,338	1,335	2,276		1,216
Anemia	891	899	920	890		794
Interactions with disabled						
Disabled and Psychiatric high		465	555	467	-262	611
Disabled and Psychiatric medium		-543	-500	-609	-785	-415
Disabled and M.S.M.D.		1,025	1,105	3,024	290	1,136
Disabled and Pulmonary high		2,911	2,785	3,727	2,727	2,367
Disabled and Gastrointestinal high		1,949	1,885	2,976	1,830	1,529
Disabled and Ostomy		2,740	2,695	2,799	2,532	2,727
Disabled and Skin high		2,640	2,565	1,003	2,396	2,914
Disabled and Renal very high		2,671	2,507	3,085	2,447	2,504
Disabled and Substance Abuse low		3,014	3,071	1,981		2,953
Disabled and Substance Abuse very low		1,200	1,181	358		1,195
Disabled and Hematological very high		7,052	7,335	14,194	7,056	8,857
Disabled and Hematological medium		2,162	2,064	3,667	2,606	2,122
Disabled and Hematological low		1,869	1,809	3,006	4,981	1,769
Interactions between disease categories						
Diabetes and Ischemic heart disease high			1,042			891
Diabetes and Cerebrovascular			632			507
Ischemic high and Chronic obstructive disease high			1,074			903
Renal very high and Ischemic high			786			1
Renal very high, Ischemic high and diabetes			1,308			1,283
Four high-cost subcategories[1]			1,479			1,278
Five high-cost subcategories			2,896			2,826
Six high-cost subcategories			4,099			4,031
Seven or more high-cost			6,294			6,540

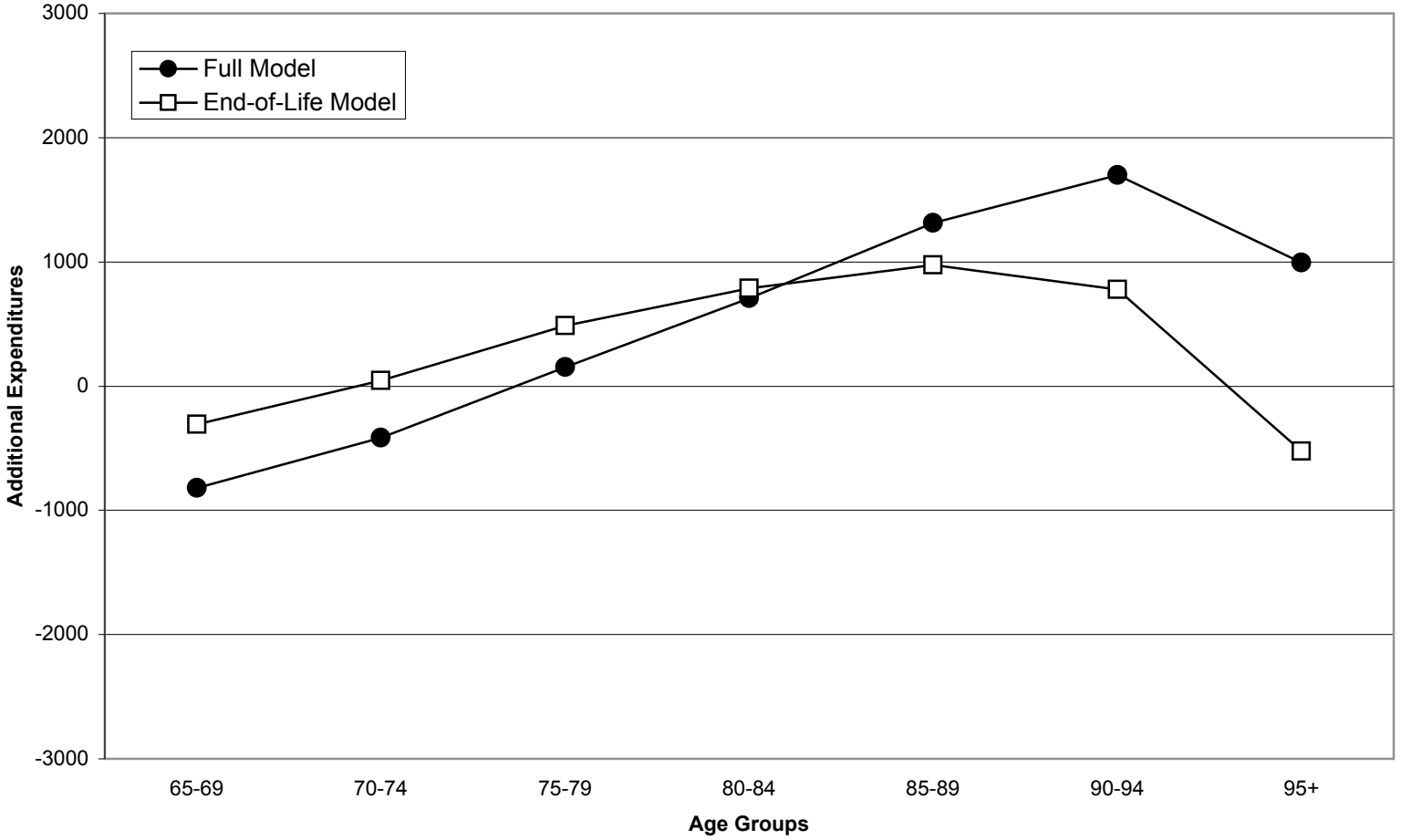
CDPS Category	Base Model	Disability Interaction Model	Full Model	Inpatient Model	Restricted Model	End-of-Life Model
Died during the first six months of 1997						39,546
Died during the last six months of 1997						21,056
Died during the first six months of 1998						8,129
Died during the last six months of 1998						4,278
Died during the first six months of 1999						3,056
Died during the last six months of 1999						2,296
Died during the first six months of 2000						1,842
Died during the last six months of 2000						1,630
Originally disabled	1,387	1,167	1,191	2,038	1,690	642
Medicaid beneficiary	943	937	951	1,631	1,377	921
Medicaid beneficiary, age < 45	-273	-363	-351	-593	-407	-272
Male, age 0 to 34	-1,398	-1,558	-1,573	-2,204	-2,379	-1,108
Male, age 35 to 44	-1,287	-1,482	-1,478	-1,686	-1,998	-1,070
Male, age 45 to 54	-1,111	-1,322	-1,307	-1,419	-1,662	-1,018
Male, age 55 to 59	-760	-946	-923	-834	-1,025	-801
Male, age 60 to 64	-302	-492	-466	-179	-451	-534
Male, age 65 to 69	-460	-459	-469	-833	-732	-292
Male, age 70 to 74*	0	0	0	0	0	0
Male, age 75 to 79	582	589	598	948	838	178
Male, age 80 to 84	1,110	1,118	1,140	1,798	1,611	47
Male, age 85 to 89	1,857	1,872	1,907	2,776	2,495	-283
Male, age 90 to 94	2,474	2,496	2,566	3,494	3,146	-1,101
Male, age 95 and older	1,801	1,827	1,930	2,721	2,229	-2,986
Female, age 0 to 34	-1,247	-1,382	-1,391	-1,994	-2,123	-838
Female, age 35 to 44	-1,100	-1,245	-1,239	-1,367	-1,725	-703
Female, age 45 to 54	-1,033	-1,208	-1,183	-1,037	-1,457	-681
Female, age 55 to 59	-807	-979	-938	-577	-1,000	-459
Female, age 60 to 64	-186	-374	-342	210	-249	84
Female, age 65 to 69	-800	-806	-820	-1,124	-1,104	-307
Female, age 70 to 74	-406	-409	-415	-472	-508	43
Female, age 75 to 79	150	149	153	343	242	488
Female, age 80 to 84	681	684	707	1,137	975	787
Female, age 85 to 89	1,249	1,258	1,311	1,939	1,677	976
Female, age 90 to 94	1,594	1,607	1,697	2,463	2,029	777
Female, age 95 and older	867	881	994	1,776	1,146	-524
Intercept	1,760	1,789	1,870	3,483	3,055	1,367
R^2	0.110	0.111	0.111	0.085	0.089	0.193
Percent with no CDPS Category	29.8%	29.8%	29.8%	83.2%	72.6%	29.8%

* The age-gender group "Male, age 70 to 74" is the reference category.

[1] The high-cost subcategories were: cardiovascular very-high; cardiovascular ischemic heart disease high; cardiovascular valvular, conductive and other heart disease medium; psychiatric, high and medium; nervous system high; nervous system multiple sclerosis, muscular dystrophy and others; nervous system Parkinson's disease; pulmonary high; pulmonary pneumonia high; gastrointestinal high, medium, and ostomy; diabetes Type 1 or 2 with rare complications; diabetes Type 1; skin, high and low; renal, extra high, very high, and medium; cancer, very high, high, and medium; metabolic high; cerebrovascular, high and medium; AIDS high; infectious disease, high and medium; HIV medium; hematological, very high, high, and medium.

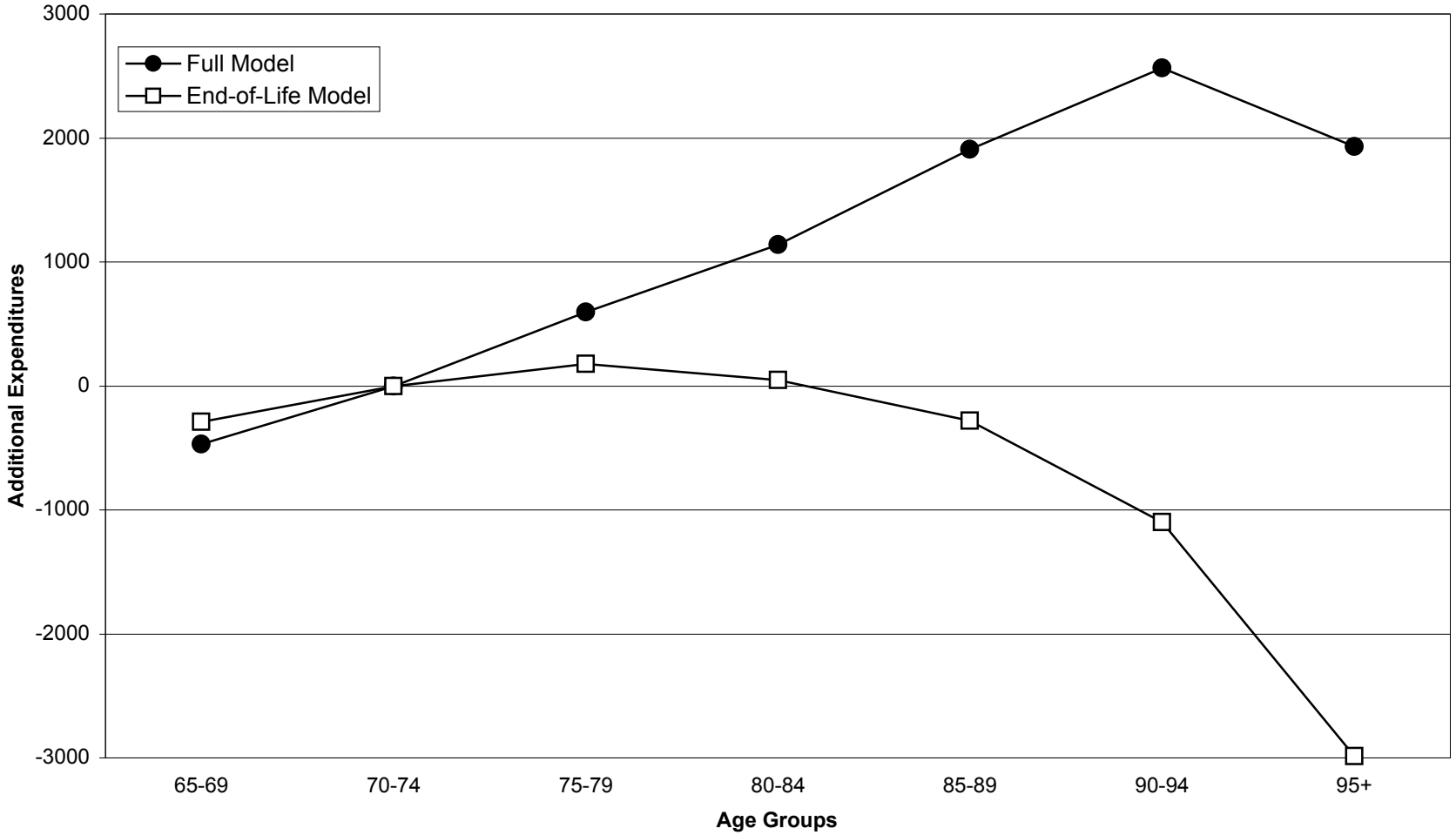
SOURCE: Authors' analysis of 1996 diagnoses and 1997 expenditures.

Figure 3-1
Additional Expenditures for Females Age 65 and Over, for Full and End-of-Life Models



Note: The additional expenditures shown for the age groups in the full and end-of-life models are coefficients from regressions of the full CDPS-Medicare model and the full model supplemented with eight variables indicating death in the eight half years of 1997-2000. Both the full model and end-of-life model include diagnostic subcategories, interaction variables between disability and selected diagnostic subcategories, interactions among selected diagnoses, variables for beneficiaries with four or more high-cost subcategories, and demographic variables. In both regressions males age 70-74 are the omitted, or reference, category. Estimates of additional expenditures are relative to the reference category.

Figure 3-2
Additional Expenditures for Males, Age 65 and Over, for Full and End-of-Life Models



Note: The additional expenditures shown for the age groups in the full and end-of-life models are coefficients from regressions of the full CDPS-Medicar model supplemented with eight variables indicating death in the eight half years of 1997-2000. Both the full model and end-of-life model include diagnos interaction variables between disability and selected diagnostic subcategories, interactions among selected diagnoses, variables for beneficiaries with fe subcategories, and demographic variables. In both regressions males age 70-74 are the omitted, or reference, category. Estimates of additional expend reference category.

Table 4-1
Predictive Ratios for Six CDPS-Medicare Model Variants

Group	Base Model	Disability Interaction Model	Full Model	End-of-Life Model	Restricted Model	Inpatient Model
All Enrollees	1.00	1.00	1.00	1.00	1.00	1.00
Demographics						
Aged	1.00	1.00	1.00	1.00	1.00	1.00
Disabled	1.00	1.00	1.00	1.00	1.00	1.00
Female, less than 34	1.00	1.00	1.00	1.00	1.00	1.00
Female, 35-44	1.00	1.00	1.00	1.00	1.00	1.00
Female, 45-54	1.00	1.00	1.00	1.00	1.00	1.00
Female, 55-59	1.00	1.00	1.00	1.00	1.00	1.00
Female, 60-64	1.00	1.00	1.00	1.00	1.00	1.00
Female, 65-69	1.00	1.00	1.00	1.00	1.00	1.00
Female, 70-74	1.00	1.00	1.00	1.00	1.00	1.00
Female, 75-79	1.00	1.00	1.00	1.00	1.00	1.00
Female, 80-84	1.00	1.00	1.00	1.00	1.00	1.00
Female, 85-89	1.00	1.00	1.00	1.00	1.00	1.00
Female, 89-94	1.00	1.00	1.00	1.00	1.00	1.00
Female, 95 Or Older	1.00	1.00	1.00	1.00	1.00	1.00
Male, less than 34	1.00	1.00	1.00	1.00	1.00	1.00
Male, 35-44	1.00	1.00	1.00	1.00	1.00	1.00
Male, 45-54	1.00	1.00	1.00	1.00	1.00	1.00
Male, 55-59	1.00	1.00	1.00	1.00	1.00	1.00
Male, 60-64	1.00	1.00	1.00	1.00	1.00	1.00
Male, 65-69	1.00	1.00	1.00	1.00	1.00	1.00
Male, 70-74	1.00	1.00	1.00	1.00	1.00	1.00
Male, 75-79	1.00	1.00	1.00	1.00	1.00	1.00
Male, 80-84	1.00	1.00	1.00	1.00	1.00	1.00
Male, 85-89	1.00	1.00	1.00	1.00	1.00	1.00
Male, 89-94	1.00	1.00	1.00	1.00	1.00	1.00
Male, 95 Or Older	1.00	1.00	1.00	1.00	1.00	1.00
Race: Black	1.04	1.04	1.04	0.99	1.06	1.04
Race: Other	1.00	1.00	1.00	1.00	1.00	1.00
Ever Disabled	1.00	1.00	1.00	1.00	1.00	1.00
Medicaid	1.00	1.00	1.00	1.00	1.00	1.00
Diagnoses						
Any Year 1 Chronic Condition	0.99	0.99	0.98	0.98	0.93	0.91
Depression	0.92	0.92	0.93	0.92	0.79	0.84
Alcohol or Drug Dependence	0.94	0.96	0.95	0.96	0.66	0.88
Hypertensive Heart/Renal Disease	0.94	0.94	0.94	0.92	0.86	0.84
Benign/Unspecified Hypertension	0.97	0.97	0.97	0.95	0.91	0.91
Diabetes With Complications	0.89	0.89	0.90	0.91	0.83	0.73
Diabetes Without Complications	0.99	0.99	0.99	1.00	0.89	0.82
Heart Failure / Cardiomyopathy	0.98	0.98	0.98	0.98	0.97	0.81
Acute Myocardial Infarction	0.97	0.97	0.98	0.99	0.79	0.90
Other Heart Disease	0.97	0.97	0.97	0.98	0.84	0.85
Chronic Obstructive Pulmonary Disease	0.97	0.97	0.97	0.97	0.79	0.84
Colorectal Cancer	0.97	0.97	0.97	1.00	0.85	0.84
Breast Cancer	1.00	1.00	1.00	1.01	0.95	0.86
Lung/Pancreas Cancer	0.91	0.91	0.91	1.00	0.86	0.68
Other Stroke	0.96	0.96	0.96	0.96	0.77	0.80
Intracerebral Hemorrhage	1.02	1.02	1.02	0.99	0.80	0.88
Hip Fracture	1.03	1.02	1.02	1.03	0.78	0.95
Arthritis	0.92	0.92	0.92	0.90	0.84	0.85

Group	Base Model	Disability Interaction Model	Full Model	End-of-Life Model	Restricted Model	Inpatient Model
Diabetes, Coronary Artery Disease	0.93	0.93	0.95	0.95	0.80	0.79
Diabetes, Cerebrovascular Disease	0.93	0.93	0.97	0.97	0.77	0.78
Heart Failure, Copd	0.92	0.92	0.95	0.96	0.80	0.79
Coronary Artery Disease, Vascular Disease	0.93	0.93	0.93	0.94	0.74	0.77
COPD, Coronary Artery Disease	0.93	0.93	0.94	0.95	0.72	0.80
Heart Failure, Renal Failure	0.92	0.92	0.98	0.98	0.90	0.79
Diabetes, Heart Failure, Renal Failure	0.86	0.86	0.97	0.97	0.84	0.77
Copd, Cerebrovascular Disease, Coronary Artery Disease	0.91	0.91	0.93	0.93	0.67	0.79
Diabetes, Cerebrovascular Disease, Vascular Disease	0.92	0.92	0.97	0.97	0.74	0.77
Expenditures						
First (Lowest) Quintile, Year1 Expenditures	1.15	1.14	1.18	1.22	1.75	1.97
Second Quintile, Year1 Expenditures	1.22	1.22	1.23	1.21	1.46	1.45
Middle Quintile, Year1 Expenditures	1.16	1.16	1.16	1.14	1.20	1.05
Fourth Quintile, Year1 Expenditures	1.04	1.04	1.04	1.03	0.98	0.81
Fifth (Highest) Quintile, Year1 Expenditures	0.86	0.86	0.86	0.86	0.73	0.82
Top 5 Percent Year1	0.76	0.76	0.77	0.77	0.63	0.75
Top 1 Percent Year1	0.66	0.66	0.68	0.68	0.56	0.64
No Home Health Spending Year1	1.10	1.10	1.10	1.09	1.13	1.11
Some Home Health Spending > 0 Year1	0.74	0.74	0.74	0.76	0.65	0.70
Home Health Spending>0:First Quintile, Year1	0.99	0.99	0.98	0.99	0.85	0.94
Home Health Spending>0:Second Quintile, Year1	0.99	0.99	0.98	0.99	0.85	0.94
Home Health Spending>0:Middle Quintile, Year1	0.88	0.88	0.88	0.90	0.76	0.84
Home Health Spending>0:Fourth Quintile, Year1	0.75	0.75	0.75	0.78	0.65	0.71
Home Health Spending>0:Fifth Quintile, Year1	0.46	0.46	0.46	0.49	0.42	0.43
Home Health Spending>0: 10% Of Spending Year1	0.38	0.38	0.38	0.42	0.35	0.35
Home Health Spending>0: 5% Of Spending Year1	0.32	0.32	0.33	0.36	0.30	0.30
No Home Health Spending Year2	1.54	1.54	1.54	1.51	1.57	1.57
Some Home Health Spending > 0 Year2	0.41	0.41	0.41	0.44	0.37	0.37
Home Health Spending>0:First Quintile, Year2	0.53	0.53	0.53	0.56	0.49	0.50
Home Health Spending>0:Second Quintile, Year2	0.47	0.47	0.47	0.50	0.44	0.44
Home Health Spending>0:Middle Quintile, Year2	0.43	0.43	0.43	0.47	0.39	0.39
Home Health Spending>0:Fourth Quintile, Year2	0.39	0.39	0.39	0.44	0.36	0.36
Home Health Spending>0:Fifth Quintile, Year2	0.32	0.32	0.32	0.36	0.29	0.29
Home Health Spending>0: 10% Of Spending Year2	0.29	0.29	0.29	0.32	0.27	0.27
Home Health Spending>0: 5% Of Spending Year2	0.26	0.26	0.26	0.29	0.24	0.24
No DME Spending Year1	1.09	1.09	1.09	1.08	1.13	1.13
Some DME Spending > 0 Year1	0.82	0.82	0.82	0.84	0.74	0.73
DME Spending>0:First Quintile, Year1	0.96	0.96	0.96	0.96	0.87	0.87
DME Spending>0:Second Quintile, Year1	0.91	0.91	0.90	0.90	0.81	0.82
DME Spending>0:Middle Quintile, Year1	0.89	0.89	0.89	0.90	0.81	0.78
DME Spending>0:Fourth Quintile, Year1	0.82	0.82	0.82	0.84	0.74	0.71
DME Spending>0:Fifth Quintile, Year1	0.64	0.64	0.65	0.71	0.57	0.57
DME Spending>0: 10% Of Spending Year1	0.58	0.58	0.59	0.66	0.52	0.51
DME Spending>0: 5% Of Spending Year1	0.56	0.56	0.56	0.62	0.50	0.49
No DME Spending Year2	1.41	1.41	1.41	1.38	1.45	1.47
DME Spending > 0 Year2	0.57	0.57	0.57	0.61	0.53	0.51
DME Spending>0:First Quintile, Year2	0.77	0.77	0.77	0.75	0.72	0.71
DME Spending>0:Second Quintile, Year2	0.59	0.58	0.58	0.59	0.55	0.52
DME Spending>0:Middle Quintile, Year2	0.66	0.66	0.65	0.68	0.61	0.58
DME Spending>0:Fourth Quintile, Year2	0.54	0.54	0.54	0.58	0.50	0.47
DME Spending>0:Fifth Quintile, Year2	0.47	0.47	0.47	0.54	0.41	0.41
DME Spending>0: 10% Of Spending Year2	0.49	0.49	0.50	0.56	0.43	0.44
DME Spending>0: 5% Of Spending Year2	0.43	0.43	0.43	0.49	0.38	0.38
DME						
Oxygen Supplies/Equipment (DME)	0.64	0.64	0.64	0.73	0.55	0.58
Wheelchairs (DME)	0.67	0.67	0.68	0.72	0.61	0.62
Walkers (DME)	0.84	0.84	0.84	0.85	0.71	0.81

Group	Base Model	Disability Interaction Model	Full Model	End-of-Life Model	Restricted Model	Inpatient Model
Hospital Admissions						
0 Year1 Hosp Admissions	1.03	1.03	1.03	1.03	1.13	1.01
1 Year1 Hosp Admissions	1.03	1.03	1.01	1.01	0.87	1.05
2 Year1 Hosp Admissions	0.98	0.98	0.97	0.97	0.80	1.01
3+ Year1 Hosp Admissions	0.80	0.80	0.82	0.82	0.65	0.84
0 Year2 Hosp Admissions	3.53	3.53	3.53	3.28	3.66	3.65
1 Year2 Hosp Admissions	0.57	0.57	0.56	0.63	0.53	0.52
2 Year2 Hosp Admissions	0.34	0.34	0.34	0.40	0.31	0.31
3+ Year2 Hosp Admissions	0.24	0.24	0.24	0.30	0.22	0.23
First (Lowest) Quintile, Year2 Expend	100.83	100.39	102.38	95.59	131.92	147.50
Second Quintile, Year2 Expend	13.71	13.72	13.74	12.42	14.90	15.26
Middle Quintile, Year2 Expend	5.76	5.76	5.74	5.26	5.68	5.48
Fourth Quintile, Year2 Expend	1.99	1.99	1.98	1.86	1.87	1.79
Fifth (Highest) Quintile, Year2 Expend	0.37	0.37	0.37	0.44	0.34	0.34
DTH97 = Died in 1997	0.31	0.31	0.31	1.00	0.29	0.28
DTH98 = Died in 1998	0.70	0.70	0.70	1.00	0.66	0.64
DTH99 = Died in 1999	0.93	0.93	0.93	1.00	0.88	0.86
DTH00 = Died in 2000	1.01	1.01	1.01	1.00	0.97	0.95
ALIVE	1.21	1.21	1.21	1.00	1.23	1.24

Source: Authors' analysis of 1996 diagnoses on 1997 expenditures.

Table 4-2
Predicted and Actual Expenditures for Beneficiaries Grouped by Number of ADL Impairments and Medicaid Status

Number of ADL Impairments	Number of Beneficiaries	CDPS-Predicted Expenditures	Actual Expenditures	Predictive Ratio
All beneficiaries				
0	5,217	$4,509	$3,832	1.18
1	1,048	6,636	6,391	1.04
2	608	7,092	8,060	0.88
3	368	8,615	12,067	0.71
4	309	8,369	11,566	0.72
5	386	10,030	14,399	0.70
6	436	10,287	11,609	0.89
Total, All beneficiaries	**8,372**	**5,588**	**5,588**	**1.00**
Without Medicaid				
0	4,361	$4,338	$3,641	1.19
1	827	6,447	6,194	1.04
2	434	6,802	7,769	0.88
3	226	7,781	12,635	0.62
4	217	7,806	11,643	0.67
5	235	9,719	15,513	0.63
6	223	9,119	12,098	0.75
Total Without Medicaid	**6,523**	**5,170**	**5,163**	**1.00**
With Medicaid				
0	856	$5,844	$5,324	1.10
1	221	7,566	7,366	1.03
2	174	7,968	8,938	0.89
3	142	10,155	11,019	0.92
4	92	9,980	11,347	0.88
5	151	10,594	12,376	0.86
6	213	11,652	11,038	1.06
Total With Medicaid	1,849	7,747	7,788	0.99

ADL stands for activities of daily living. The six ADLs are bathing, sitting in a chair, dressing, walking, toileting and eating.

SOURCE: Medicare Current Beneficiary Survey, 1996. ADLs are from 1996, diagnoses are from 1996 and expenditures from 1997.

Table 4-3
Mortality Rates of Beneficiaries Grouped by Number of ADL Impairments

Number of ADL Impairments	Number of Beneficiaries	1997 Mortality Rate	1998 Mortality Rate	1999 Mortality Rate
0	5,217	0.025	0.026	0.041
1	1,048	0.068	0.059	0.084
2	608	0.071	0.081	0.085
3	368	0.100	0.079	0.095
4	309	0.119	0.121	0.095
5	386	0.155	0.149	0.143
6	436	0.308	0.179	0.121
All beneficiaries	8,372	0.055	0.049	0.060

Note: Analysis restricted to beneficiaries who were eligible for all of 1996 and at least one month of 1997 and thus excludes beneficiaries who died prior to January 31. As a result, 1997 mortality rates are underestimated.The mortality rates for 1998 and 1999 are equal to 1998 and 1999 deaths divided by the total number of beneficiaries in 1996, not the number of beneficiaries alive at the beginning of 1998.

Source: ADLs from 1996 Medicare Current Beneficiary Survey, mortality data from an extract from the Denominator file.

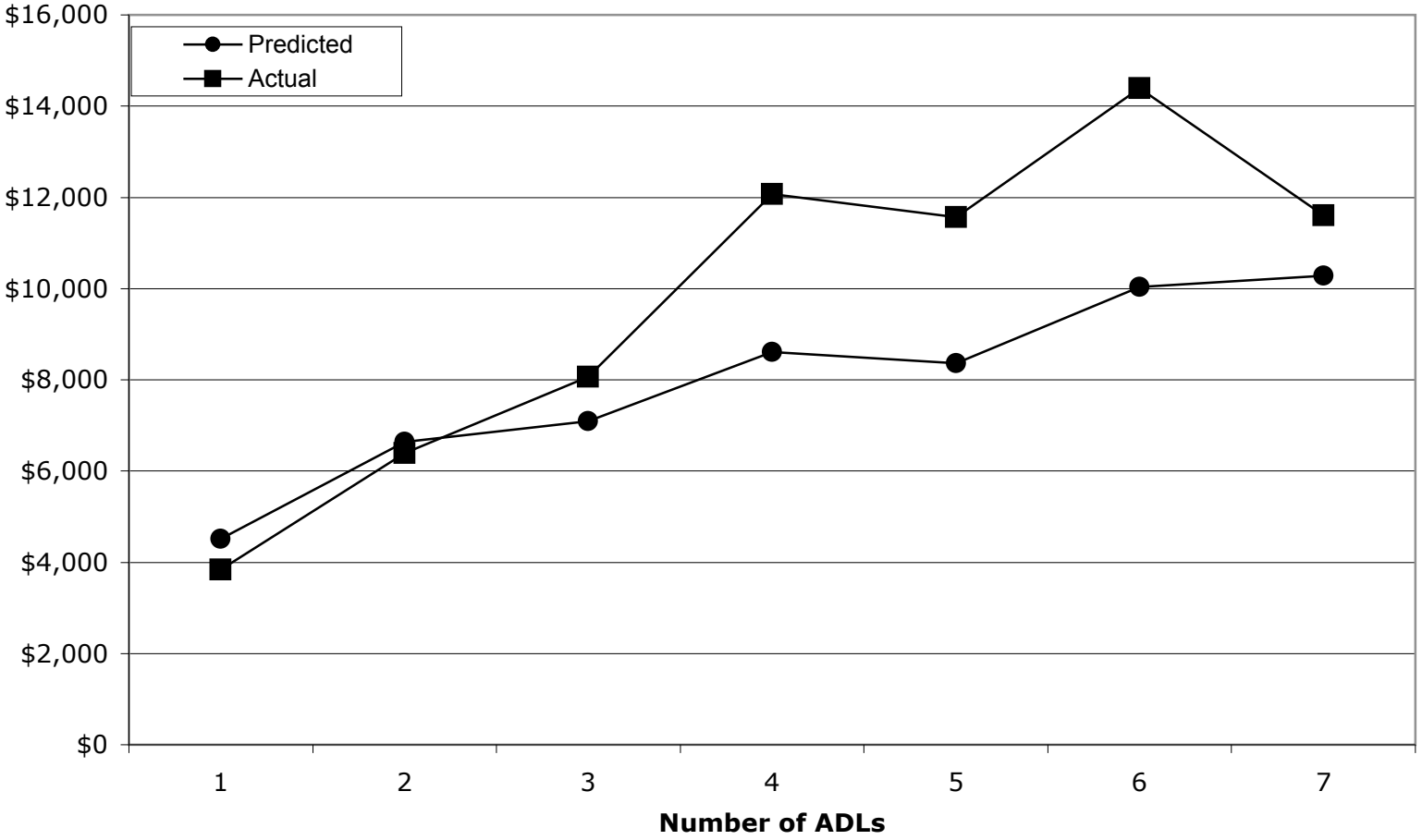
Table 4-4
Expenditures Predicted by CDPS-Medicare Model and by End-of-Life Model Compared with Actual Expenditures for Beneficiaries Grouped by Number of ADL Impairments

Number of ADL Impairments	Number of Beneficiaries	CDPS-Medicare Predicted Expenditures	End-of-Life Model Predicted Expenditures	Actual Expenditures	CDPS-Medicare Predictive Ratio	End-of-Life Model Predictive Ratio
All beneficiaries						
0	5,217	$4,509	$4,199	$3,832	1.18	1.10
1	1,048	6,636	6,771	6,391	1.04	1.06
2	608	7,092	7,189	8,060	0.88	0.89
3	368	8,615	8,735	12,067	0.71	0.72
4	309	8,369	9,063	11,566	0.72	0.78
5	386	10,030	11,204	14,399	0.70	0.78
6	436	10,287	13,865	11,609	0.89	1.19
Total all beneficiaries	**8,372**	**$5,588**	**$5,588**	**$5,588**	**1.00**	**1.00**
Without Medicaid						
0	4,361	$4,338	$4,012	$3,641	1.19	1.10
1	827	6,447	6,605	6,194	1.04	1.07
2	434	6,802	6,963	7,769	0.88	0.90
3	226	7,781	7,884	12,635	0.62	0.62
4	217	7,806	8,669	11,643	0.67	0.74
5	235	9,719	10,865	15,513	0.63	0.70
6	223	9,119	12,686	12,098	0.75	1.05
Total Without Medicaid	**6,523**	**$5,170**	**$5,098**	**$5,163**	**1.00**	**0.99**
With Medicaid						
0	856	$5,844	$5,662	$5,324	1.10	1.06
1	221	7,566	7,594	7,366	1.03	1.03
2	174	7,968	7,872	8,938	0.89	0.88
3	142	10,155	10,307	11,019	0.92	0.94
4	92	9,980	10,187	11,347	0.88	0.90
5	151	10,594	11,820	12,376	0.86	0.96
6	213	11,652	15,244	11,038	1.06	1.38
Total With Medicaid	**1,849**	**$7,747**	**$8,120**	**$7,788**	**0.99**	**1.04**
Survivors						
0	5082	4667	3800	3357	1.39	1.13
1	976	6462	5650	5200	1.24	1.09
2	563	6967	6084	6967	1.00	0.87
3	329	8218	7034	8911	0.92	0.79
4	275	8315	7428	10434	0.80	0.71
5	322	9573	8793	13159	0.73	0.67
6	295	9676	9139	8321	1.16	1.10
Total Survivors	**7,842**	**$5,408**	**$4,704**	**$4,680**	**1.16**	**1.01**
Decedents						
0	135	9414	32410	37474	0.25	0.86
1	72	10747	33345	34658	0.31	0.96
2	45	9834	31481	32076	0.31	0.98
3	39	14705	34849	60550	0.24	0.58
4	34	9186	33696	28636	0.32	1.18
5	64	14624	35462	26873	0.54	1.32
6	141	13137	35938	26972	0.49	1.33
Total Decedents	**530**	**$11,340**	**$33,758**	**$34,545**	**0.33**	**0.98**

ADL stands for activities of daily living. The six ADLs are bathing, sitting in a chair, dressing, walking, toileting and eating.

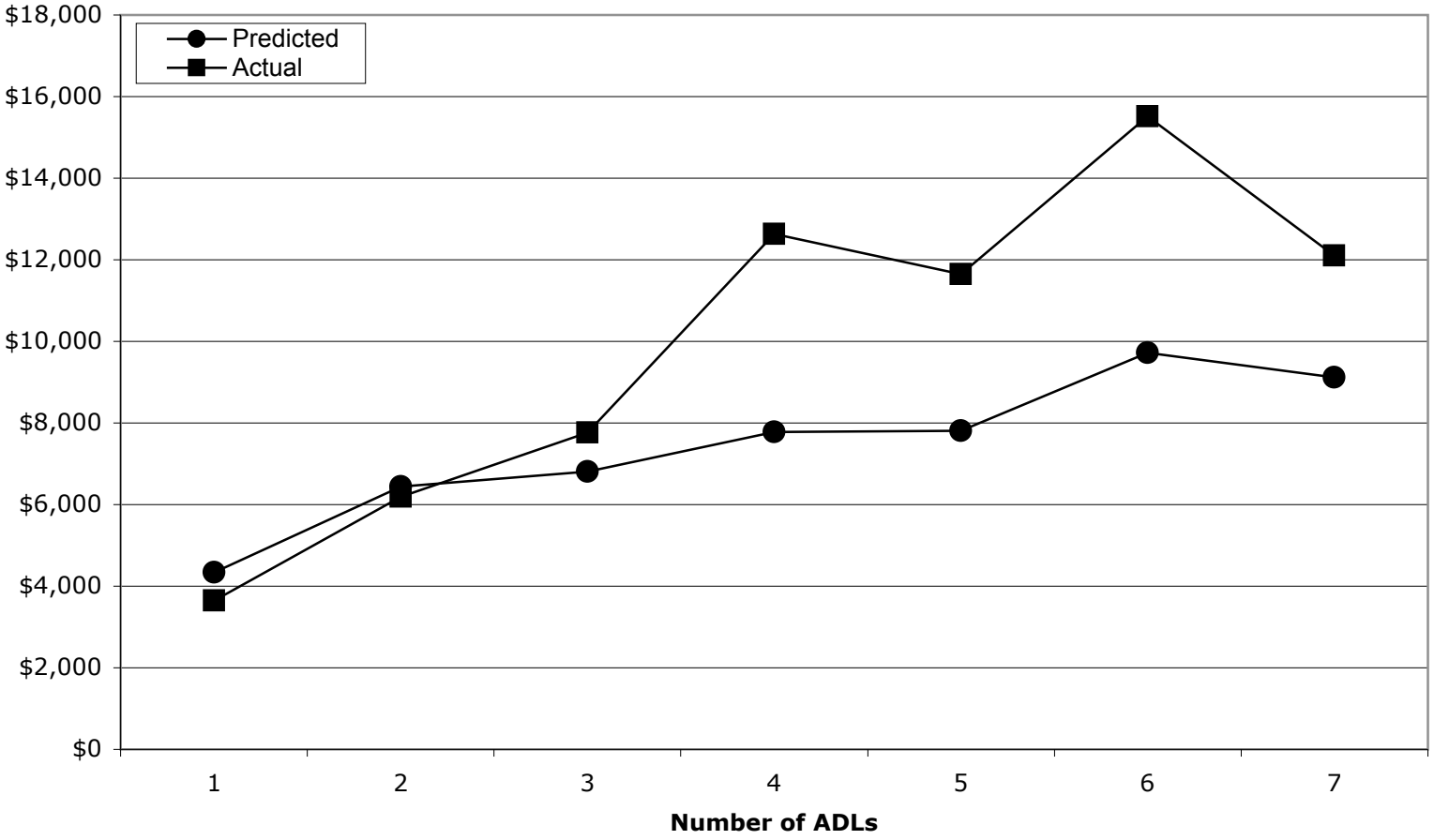
SOURCE: Medicare Current Beneficiary Survey, 1996. ADLs are from 1996, diagnoses are from 1996 and expenditures from 1997.

Figure 4-1
Actual and CDPS-Medicare Predicted Expenditures, by Number of ADLs



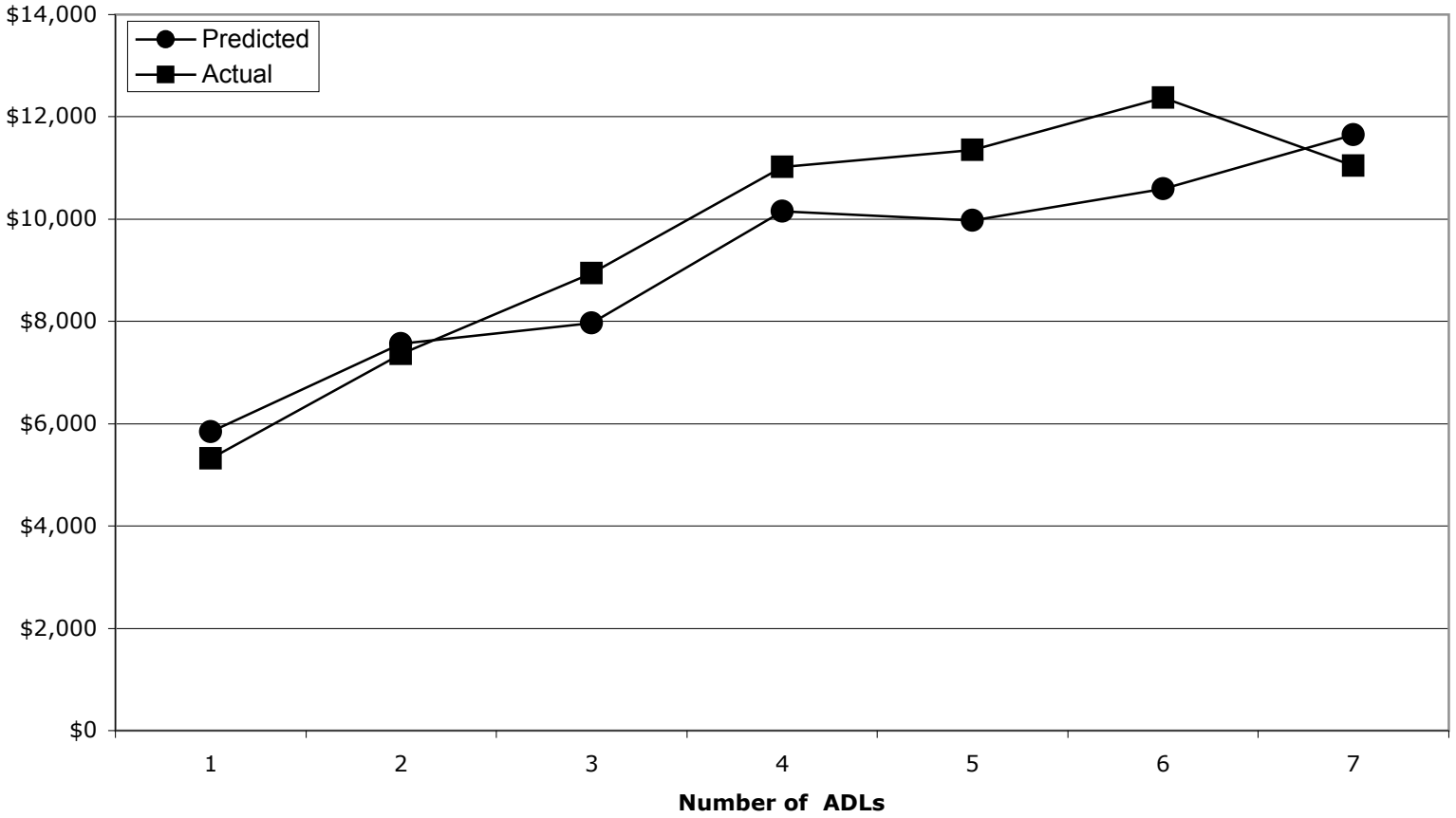
SOURCE: Medicare Current Beneficiary Survey, 1996. ADLs are from 1996, diagnoses are from 1996 and expenditures from 1997.

Figure 4-2
Actual and CDPS-Medicare Predicted Expenditures, by Number of ADLs, Beneficiaries Without Medicaid



SOURCE: Medicare Current Beneficiary Survey, 1996. ADLs are from 1996, diagnoses are from 1996 and expenditures from 1997.

Figure 4-3
Actual and CDPS-Medicare Predicted Expenditures, by Number of ADLs, Beneficiaries With Medicaid



SOURCE: Medicare Current Beneficiary Survey, 1996. ADLs are from 1996, diagnoses are from 1996 and expenditures from 1997.

Table 6-1
Relative Mortality Rate of HMO Beneficiaries, by Age and Medicaid Status, 1997

Beneficiary Groups	HMO Beneficiaries	HMO Decedents	HMO Mortality	Expected FFS Mortality	Relative Mortality Rate
All beneficiaries	1,242,844	39,716	0.032	0.038	0.848
age 0 to 64	140,103	1,813	0.013	0.014	0.908
age 65 to 69	345,467	5,204	0.015	0.017	0.888
age 70 to 74	303,819	6,958	0.023	0.027	0.861
age 75 to 79	224,780	7,756	0.035	0.042	0.822
age 80 to84	136,267	7,750	0.057	0.069	0.829
age 85 and over	92,408	10,235	0.111	0.131	0.847
Not on Medicaid	1,176,216	35,716	0.030	0.036	0.840
On Medicaid	66,628	4,000	0.060	0.064	0.935
Not on Medicaid					
age 0 to 64	125,314	1,594	0.013	0.014	0.913
age 65 to 69	332,296	4,846	0.015	0.016	0.889
age 70 to 74	291,056	6,391	0.022	0.026	0.851
age 75 to 79	215,082	7,129	0.033	0.041	0.812
age 80 to84	128,944	7,021	0.054	0.067	0.817
age 85 and over	83,524	8,735	0.105	0.125	0.836
On Medicaid					
age 0 to 64	14,789	219	0.015	0.017	0.875
age 65 to 69	13,171	358	0.027	0.031	0.871
age 70 to 74	12,763	567	0.044	0.045	0.996
age 75 to 79	9,698	627	0.065	0.068	0.951
age 80 to84	7,323	729	0.100	0.102	0.975
age 85 and over	8,884	1,500	0.169	0.185	0.914

SOURCE: Twenty-percent sample of the 1997 Denominator file.

Note: Expected FFS mortality is adjusted for age, gender, county of residence, and Medicaid buy-in status. It is not adjusted for institutional status or hospice enrollment.

Table 6-2
Relative Mortality Rate of HMO Beneficiaries, by Age and Medicaid Status, 1997–2000, Combined

Beneficiary Groups	HMO Beneficiaries	HMO Decedents	HMO Mortality	Expected FFS Mortality	Relative Mortality Rate
All beneficiaries	5,658,044	195,948	0.035	0.040	0.870
age 0 to 64	626,832	9,000	0.014	0.015	0.941
age 65 to 69	1,539,767	24,400	0.016	0.017	0.914
age 70 to 74	1,365,411	33,238	0.024	0.028	0.883
age 75 to 79	1,045,219	38,656	0.037	0.043	0.854
age 80 to84	632,438	37,889	0.060	0.071	0.850
age 85 and over	448,377	52,765	0.118	0.137	0.860
Not on Medicaid	5,324,524	174,601	0.033	0.038	0.863
On Medicaid	333,520	21,347	0.064	0.069	0.932
Not on Medicaid					
age 0 to 64	551,452	7,704	0.014	0.015	0.938
age 65 to 69	1,477,700	22,565	0.015	0.017	0.918
age 70 to 74	1,303,106	30,388	0.023	0.027	0.877
age 75 to 79	993,869	35,191	0.035	0.042	0.847
age 80 to84	595,604	34,050	0.057	0.068	0.838
age 85 and over	402,793	44,703	0.111	0.131	0.849
On Medicaid					
age 0 to 64	75,380	1,296	0.017	0.018	0.958
age 65 to 69	62,067	1,835	0.030	0.034	0.870
age 70 to 74	62,305	2,850	0.046	0.048	0.955
age 75 to 79	51,350	3,465	0.067	0.073	0.927
age 80 to84	36,834	3,839	0.104	0.108	0.969
age 85 and over	45,584	8,062	0.177	0.192	0.921

SOURCE: Twenty-percent sample of the 1997–2000 Denominator files.

Note: Expected FFS mortality is adjusted for age, gender, county of residence, and Medicaid buy-in status. It is not adjusted for institutional status or hospice enrollment.

Table 6-3
Relative Mortality Rate in 2000
by Year of First HMO Enrollment

Year of First HMO Enrollment	Frequency	HMO Deaths	HMO Mortality	Expected FFS Mortality	Relative Mortality Rate
2000	127,443	1,809	0.014	0.018	0.788
1999	177,390	4,780	0.027	0.031	0.857
1998	210,324	6,458	0.031	0.036	0.860
1997	205,726	6,938	0.034	0.039	0.871
1996 or before*	761,784	34,418	0.045	0.049	0.914
All years combined	1,482,667	54,403	0.037	0.041	0.892

*Includes all beneficiaries in an HMO in January of 1997.

SOURCE: Twenty-percent sample of the 1997–2000 Denominator files.

Note: Expected FFS mortality is adjusted for age, gender, county of residence, and Medicaid buy-in status and number of months of HMO enrollment in 2000. It is not adjusted for institutional status or hospice enrollment.

Table 6-4
Relative Mortality Rates for HMO Beneficiaries, 1997–2000

Beneficiary Groups	HMO Beneficiaries	HMO Decedents	HMO Mortality	Expected FFS Mortality	Relative Mortality Rate
1997	1,242,844	39,716	0.032	0.038	0.848
1998	1,429,186	48,015	0.034	0.039	0.861
1999	1,503,347	53,814	0.036	0.041	0.874
2000	1,482,667	54,403	0.037	0.041	0.892
1997-2000 combined	5,658,044	195,948	0.035	0.040	0.870

SOURCE: Twenty-percent sample of the 1997–2000 Denominator files.

Note: Expected FFS mortality is adjusted for age, gender, county of residence, and Medicaid buy-in status. It is not adjusted for institutional status or hospice enrollment.

Table 6-5
Expenditures in the Last Four Years of Life and Predicted Expenditures Based on Demographic and Diagnostic Characteristics

Time Period	1997 Expenditures	Predicted Expenditures, Controlling for: Demographic Characteristics	Predicted Expenditures, Controlling for: Demographic and Diagnostic Characteristics	Additional Expenditures for End-of-Life Care, Controlling for: Demographic Characteristics	Additional Expenditures for End-of-Life Care, Controlling for: Demographic and Diagnostic Characteristics
Last 12 months of life	$25,235	$4,271	$7,080	$20,964	$18,155
Months 13-24 before death	10,030	4,250	6,355	5,780	3,675
Months 25-36 before death	8,027	4,264	5,999	3,763	2,028
Months 37-48 before death	7,065	4,220	5,641	2,845	1,424
Total for last 48 months of life	–	–	–	$33,352	$25,281

SOURCE: Authors' analysis of 1996 diagnostic and demographic data and 1997 expenditure data.

Table 6-6
Effect of Differential Mortality for HMO Beneficiaries on Expected Resource Needs

Year	Overprediction of HMO Expenditures Due to Differential Mortality If Expected Expenditures Are Adjusted For: Demographic Characteristics	Demographic and Diagnostic Characteristics
1997	0.036	0.027
1998	0.034	0.026
1999	0.032	0.025
2000	0.028	0.021

SOURCE: Authors' analysis of five-percent sample of 1996 diagnostic and demographic data, 1997 expenditure data, and twenty-percent sample of the 1997–2000 Denominator files.

Note: Expected FFS mortality is adjusted for age, gender, county of residence, and Medicaid buy-in status. It is not adjusted for institutional status or hospice enrollment.

Table 7-1
1996 and 1997 Disease Burden by Age and Gender

Female

Age in 1996	Number of Beneficiaries	1996 Disease Burden	1997 Disease Burden	Percent Change 1996 to 1997
0-34	7,130	$4,771	$4,904	2.8%
35-44	13,942	5,167	5,386	4.2%
45-54	18,561	5,612	5,974	6.4%
55-59	11,693	5,998	6,479	8.0%
60-64	14,500	6,419	7,016	9.3%
65-69	133,170	4,395	4,837	10.1%
70-74	192,790	4,703	5,234	11.3%
75-79	168,118	5,228	5,895	12.8%
80-84	126,470	5,836	6,660	14.1%
85-89	79,120	6,383	7,358	15.3%
90-94	36,773	6,722	7,782	15.8%
95 +	13,244	6,709	7,724	15.1%
All ages	815,511	5,302	5,954	12.3%

Male

Age in 1996	Number of Beneficiaries	1996 Disease Burden	1997 Disease Burden	Percent Change 1996 to 1997
0-34	11,215	$4,591	$4,696	2.3%
35-44	22,161	4,985	5,144	3.2%
45-54	26,962	5,060	5,413	7.0%
55-59	14,742	5,442	5,999	10.2%
60-64	18,282	5,738	6,374	11.1%
65-69	108,892	4,573	5,119	11.9%
70-74	144,493	4,928	5,615	13.9%
75-79	112,986	5,588	6,470	15.8%
80-84	70,996	6,283	7,404	17.8%
85-89	34,180	6,786	8,240	21.4%
90-94	11,491	7,014	8,606	22.7%
95 +	2,791	6,912	8,177	18.3%
All ages	579,191	5,357	6,123	14.3%

Combined

Age in 1996	Number of Beneficiaries	1996 Disease Burden	1997 Disease Burden	Percent Change 1996 to 1997
0-34	18,345	$4,661	$4,777	2.5%
35-44	36,103	5,055	5,237	3.6%
45-54	45,523	5,285	5,642	6.7%
55-59	26,435	5,688	6,211	9.2%
60-64	32,782	6,040	6,658	10.2%
65-69	242,062	4,475	4,964	10.9%
70-74	337,283	4,799	5,397	12.5%
75-79	281,104	5,373	6,126	14.0%
80-84	197,466	5,997	6,927	15.5%
85-89	113,300	6,505	7,624	17.2%
90-94	48,264	6,791	7,978	17.5%
95 +	16,035	6,745	7,803	15.7%
All ages	1,394,702	5,325	6,024	13.1%

Note: Disease burden is predicted using diagnostic information, and excluding age and gender variables. 1996 Disease burden uses 1996 diagnoses; 1997 disease burden, 1997 diagnoses. For each beneficiary in the analysis, disease burden was computed twice.

SOURCE: 1996 and 1997 diagnostic data and parameter estimates from regression using 1997 expenditure data and 1996 diagnoses.

Table 7-2
Annual Increase in Disease Burden Among Successive Cohorts of Medicare Beneficiaries

Age Group	Females	Males	Combined
35-44	—	—	—
45-54	1.0%	0.5%	0.7%
55-59	1.1%	1.4%	1.3%
60-64	1.6%	1.2%	1.4%
65-69	–	–	–
70-74	1.6%	1.9%	1.7%
75-79	2.4%	2.9%	2.6%
80-84	2.5%	2.7%	2.5%
85-89	2.0%	2.2%	1.9%
90-94	1.1%	0.9%	0.9%
95 +	-0.1%	-1.0%	-0.4%

Note: Entries are estimates of the annual rate of change in 1997 disease burden from one five-year age cohort to the next. For example, from Table 7-1 1997 disease burden for 75-79 year old men is $6,126 and for 80-84 year old men is $6,927, an increase of 13.1% over a five-year span. The annual rate of increase is the fifth root of 1.131, which is 1.027. Because the composition of the group of beneficiaries changes so dramatically at age 65, we do not calculate a rate of change for 60-64 year olc compared to 65-69 year olds.

SOURCE: 1997 diagnostic data and parameter estimates from a regression using 1997 expenditure data and 1996 diagnoses.

Table 7-3
1996 and 1997 Disease Burden, by Year of Death

Year of Death	Number of Beneficiaries	Disease Burden in 1996	Disease Burden in 1997	Percent Change 1996 to 1997
1997	57,376	$10,059	$16,936	68%
1998	58,030	8,657	11,356	31%
1999	57,916	7,781	8,939	15%
2000	56,907	7,159	8,035	12%
Alive in Jan. 2001	1,155,209	4,791	5,190	8%

Note: Disease burden is predicted using diagnostic information, and excluding age and gender variables. 1996 Disease burden uses 1996 diagnoses; 1997 disease burden, 1997 diagnoses. For each beneficiary in the analysis, disease burden was computed twice.

SOURCE: 1996 and 1997 diagnostic data and parameter estimates from a regression using 1997 expenditure data and 1996 diagnoses.