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Impact of Prescription Drug Coverage on Medicare Program Expenditures – A Case Study of the UMWA (Also Includes Predictability of Drug Expenditures for Medicare Beneficiaries)

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Executive Summary

Increasing the Medicare population's access to drug coverage was one of the highest domestic political priorities of 2003. In the late fall, the Congress passed and the President signed legislation intended to increase access to drug coverage for Medicare beneficiaries. This report contains three chapters, each featuring a research study focused on different aspects of providing drug benefits to the Medicare population. All three studies used the Medicare Current Beneficiary Survey as their primary data source. The Medicare Current Beneficiary Survey is the premier dataset for assessing this issue as it contains extensive health care and insurance information on a representative sample of Medicare beneficiaries. Domains include demographic characteristics, health status, insurance coverage, and utilization and expenditures for a range of health services, notably prescription drugs and medical services covered by Medicare Parts A and B.

The first study examined the impact of drug coverage on drug expenditures and other expenditures covered by the Medicare program from 1995 to the latest available data of 2000. Many commentators have argued that higher rates of drug coverage will lower expenditures elsewhere in the Medicare program as access to appropriate drug utilization improves health and consequently may substitute for avoidable hospitalizations and expensive non-pharmacological therapies. This chapter extensively addresses that conjecture. The second study explored critical research design issues (most importantly statistical techniques for selecting comparison groups) that will be encountered in any evaluation of the prescription drug benefit currently available to members of the United Mine Workers of America (UMWA) Health and Retirement Funds. This analysis provides an essential counterpoint to observational research that examines causation in the presence of self-selection, such as described in Chapter 1. The final study in this report assessed the predictability of drug expenditures and the performance of Medicare's current risk adjustment methodology (the HCC/DCG). These results are relevant both to incorporating prescription drug expenditures into new Medicare spending forecasts and to developing reimbursement methodologies for entities providing drug coverage.

Essential results of each chapter are summarized below.

Aim 1: The Impact of Drug Coverage on Medicare Program Expenditures

The first chapter used data from the 1995-2000 Medicare Current Beneficiary Survey (MCBS) to address the question of whether prescription drug coverage produces cost offsets in Medicare Part A and B spending. Commentators have argued that drug benefits are an important factor in assuring access to necessary medicines, which if used appropriately may reduce avoidable hospitalizations and other more expensive non-pharmacological therapies. We tested this hypothesis using both cross-sectional and longitudinal study designs. Our rationale is that if the two approaches produce similar findings it will mitigate analytic concerns associated with either approach considered individually.

Under the cross-sectional approach, we conducted a series of analyses designed to assess each link in the causal chain between drug coverage and Medicare spending using data from 2000. We first estimated the impact of coverage on drug spending, reasoning that unless the pattern of medication use changes, prescription coverage cannot logically affect spending on other services. Next, we assessed the impact of coverage on various measures of health care spending by Medicare

beneficiaries. We estimated this series of models for all Medicare beneficiaries and then for the subset with employer-sponsored health insurance (ESHI). We focused on beneficiaries with ESHI in the belief that estimates derived from this group are less likely to be biased by selection effects compared to beneficiaries with other forms of prescription coverage. Also, employer-sponsored coverage tends to be more generous than other forms of private drug benefits available to Medicare beneficiaries, and thus is more likely to induce the hypothesized changes in use of Medicare-covered services. Lastly, we assessed the effect of prescription coverage on Medicare spending for beneficiaries with chronic obstructive pulmonary disease (COPD), the rationale being that if drug coverage does produce cost offsets in Medicare spending, the impact should be most apparent for beneficiaries with a medication-sensitive condition, such as COPD.

Under the longitudinal design, we focused attention on beneficiaries who either gained or lost drug coverage during their observation period in the MCBS dataset between 1995 and 2000. We followed the same individuals before and after a change in coverage and compared their spending for drugs, hospital care, and physician services to beneficiaries who consistently maintained coverage or had none at all. We reasoned that the relationship between drug insurance and Medicare spending would be most evident for persons gaining drug insurance as improved access to medications would result in reduced need for non-medication spending. We also hypothesized that persons losing drug coverage would reduce medication spending and compensate for their loss through increased reliance on Medicare-covered services.

The primary challenge to establishing the true relationship between drug coverage and Medicare spending is the fact that beneficiaries may self-select prescription benefits based on foreknowledge of their anticipated need for drug therapy. This selection may be static, i.e., individuals with an ongoing need for drug therapy maintain insurance, or dynamic, i.e., individuals respond to a change in their drug expenditures by changing their coverage choices. While our analysis emphasizes selection on the part of the insured, it should be remembered that insurers may also practice selection, seeking to attract those with lower expenditures into their pool.

If the need for drug therapy is positively correlated to Medicare spending (which is likely) and if significant selection exists at the individual level (which is also likely), then simple cross-sectional tests of the relationship between drug insurance and Medicare expenditure will be upwardly biased (i.e., drug coverage will appear to cause higher Medicare spending). Our cross-sectional methods address selection bias through sample stratification, extensive control variables, and statistical techniques that are robust to bias (propensity scoring). We reasoned that longitudinal analysis would provide the best direct evidence of selection behavior in terms of anticipatory increases in expenditures prior to gaining drug coverage or declining spending prior to losing it. Using multivariate panel analyses, we are able to control for any pre-switch spending changes that might otherwise bias the estimated impact on drug coverage on post-switch spending levels.

The cross-sectional analyses indicated that drug coverage was associated with much higher spending on prescription medications: 94 percent higher in the unadjusted comparison, dropping to 49 percent after risk adjustment, and 66 percent after adjustment for propensity scores (all differences statistically significant at $p<.05$). Unadjusted Medicare Part A and B spending was 27 percent higher for beneficiaries with drug coverage than for those with no coverage. Controlling for risk factors reduced the difference to 6 percent, and matching the samples on propensity scores reduced it still further to minus 2 percent; however, none of the differences were statistically significant. Only in the case of the COPD sample did we find evidence of a significant negative association between drug

coverage and Medicare spending. Unadjusted Medicare spending for COPD patients with drug coverage was 7 percent lower compared to those without coverage in 2000. However, a repeat of the COPD analysis using 1996 MCBS data failed to find any significant Medicare savings.

The longitudinal models corroborated the findings of the cross-sectional analysis for the Medicare population as a whole and for those with employer-sponsored drug benefits. Beneficiaries who gained drug coverage spent 66 percent more on medications in the year after getting insurance compared to the period before, a magnitude similar to that found in the cross-sectional comparisons. Visual inspection of the time plots for hospital and physician services spending for persons losing or gaining drug coverage provided no evidence of overt selection behavior on these variables prior to the switch. Moreover, the visual plots and multivariate models showed no systematic post-switch change in either hospital or physician/supplier spending that could reasonably be attributed to the change in drug coverage.

We draw three conclusions from these findings. First, there is no question that drug coverage induces additional spending on prescribed medications by Medicare beneficiaries. This was expected, but the size of the estimated effect is larger than we had anticipated based on prior research. Second, the higher spending on drugs among those with coverage appears to have little aggregate impact on spending for Medicare-covered services. We found no consistent evidence that drug coverage either increases or reduces spending for hospital and physician services. This does not necessarily mean that drug therapy cannot substitute or complement other therapies, but rather that neither effect predominates across the Medicare population as a whole. Third, our results suggest that drug coverage may potentially produce cost offsets for persons with particular medication-sensitive conditions, but the level of savings may also change over time.

Aim 2: Design Issues

The second chapter addresses design issues for the evaluation of prescription drug programs, specifically for the evaluation of the United Mineworkers of America (UMWA) demonstration. This CMS demonstration provides partial funding for a drug benefit for the UMWA retirees, and the Congress has mandated an evaluation of its impact on the services covered by Parts A and B of Medicare and on Medicare expenditures.

The chapter begins by outlining an evaluation design for the UMWA demonstration. There are two necessary conditions for that design to provide an accurate measure of demonstration effects. First, the comparison group for the evaluation must be similar to the UMWA beneficiaries in terms of factors that affect Medicare spending, apart from insurance coverage and other factors that can be measured and controlled for in the Medicare claims. Second, the comparison group must contain a large number of individuals with employer-provided supplemental coverage but without drug coverage, because this group would be used to estimate the marginal impact of the UMWA drug benefit.

The main part of the chapter describes work with the MCBS to develop two possible procedures for comparison group selection and to assess these procedures relative to the two necessary conditions just noted. The advantage of using the MCBS (rather than Medicare data) for this purpose was the presence of data regarding drug and supplemental coverage and drug utilization. The disadvantage was the relatively small sample size and the resulting need to use a broader base group than the UMWA beneficiaries to develop the procedures. Males and females were analyzed separately

because of the presumption that it might be more feasible to select a valid comparison group for females.

The base group was defined as individuals who received drug and supplemental coverage from a previous employer (or a spouse's previous employer) in mining or in another industry requiring physically demanding outdoor work. The authors then drew comparison groups for this base group, first using matching on propensity scores, then using exact match techniques. Finally, these procedures were assessed in terms of the match between base and comparison groups on measured covariates and on drug and Medicare-covered expenditures controlling for insurance status. A mismatch in expenditures, controlling for insurance, would be *prima facie* evidence that the two groups were not comparable. We also examined rates of drug and supplemental coverage in the comparison groups.

The first procedure was matching on propensity scores, the approach favored by many recent non-experimental evaluations. In brief, this procedure was successful in terms of metrics that compared the base and comparison samples on observable characteristics that would be present in the Medicare claims and would serve as independent variables in predicting Medicare expenditures. However, it was less successful in that, even when supplemental and drug coverage were held constant between the base and comparison samples, the miner-plus group appeared to have higher expenditures than the propensity –matched comparison group. The difference in drug expenditures for males was statistically significant. The differences in drug expenditures for females and in Medicare-covered expenditures for both genders were not statistically significant but the pattern of higher expenditures for the miner-plus group was consistent across many percentiles of the expenditure distribution.

The second of the procedures involved an exact match. This may be an attractive option for the UMWA evaluation because of the large sample of Medicare beneficiaries and the manageable number of independent variables. Unfortunately, MCBS sample sizes forced the authors to use a one-to-one (rather than a three-to-one match) and the results were too poorly measured to effectively analyze discrepancies in expenditures or to compare this procedure with the propensity match procedure.

In addition, this study established the rates of drug and supplemental coverage within comparison groups created in these ways. Approximately, six percent of males and five percent of females had employer-provided supplemental coverage but not employer-provided drug coverage.

This study makes three important contributions to those interested in the UMWA evaluation. First, it spells out procedures that could be used. Second, it offers a preliminary response to the concern that it may be difficult to find a credible comparison group for the Funds' beneficiaries. Subject to certain limitations, these findings support that concern. Finally, the study estimated rates of insurance coverage. The rates observed here suggest there would be a subgroup of observations within a UMWA comparison group that would have employer-provided supplemental coverage but not drug coverage but that large initial sample sizes would be needed to assure that this subgroup was large enough to provide accurate estimates of the demonstration effect.

Aim 3: The Predictability of Prescription Drug Expenditures

The third and final chapter used the 1999 and 2000 Medicare Current Beneficiaries Survey (MCBS) to address how well drug expenditures can be predicted for the Medicare population and how effective the Hierarchical Conditions Categories (HCC) methodology is in this setting.[1] The HCC is CMS' existing framework for predicting the expenditures covered by Parts A and B of Medicare.[2]

We estimated concurrent models in which drug expenditures in 1999 or 2000 were modeled as a function of individual characteristics (including health status) in that same year and prospective models in which 2000 drug expenditures were modeled as a function of individual characteristics in the previous year. The dependent variables were the level and natural logarithm of annual drug expenditures calculated using average wholesale prices (AWP) as opposed to retail prices.
The concurrent models showed that health conditions were key predictors of drug expenditures and that, while many of the same conditions that predicted physician and hospital expenditures were also important predictors of drug expenditures, the relative weights of the conditions differed notably between drug and Medicare-covered expenditures. Demographic variables alone explained less than two percent of drug expenditures (adjusted R-square); adding the single summary measure of predicted Medicare expenditures (ybase) raised this figure to 16 percent, replacing that single summary measure with 128 indicators for specific conditions further increased the share of expenditures predicted to 30 percent.

The prospective models showed that the predictable component of drug expenditures was driven primarily by conditions that persisted from year to year and that the previous year's drug expenditures were an even more powerful predictor of current year's drug expenditures than the HCC indicators. Indicators for conditions observed in 1999 proved just as effective in predicting 2000 drug expenditures as did indicators for conditions observed in 2000. Moreover, adding a measure of lagged drug expenditures to the prospective model containing the individual condition indicators caused the percentage of variation explained to more than double, from 29 to 70 percent.

These findings have several policy implications. First it would be possible to develop a case-mix adjustment methodology for privately provided drug benefits that would mitigate a substantial proportion of case-mix risk. Second, the summary measure of predicted Parts A and B expenditure provided by the HCC/DCG methodology (ybase) would not be the optimal risk adjustment methodology for drug benefits (provided either alone or as part of a package) but the indicators for individual conditions might be a point of departure for the development of such a methodology. The persistence of drug expenditures underscored the potentials for adverse selection, when beneficiaries are free to decide whether to purchase drug insurance, and for risk-selection or "cherry-picking," when firms compete for beneficiaries. Hence there is a need for very careful design of policies intended to improve beneficiaries' access to drug insurance via free markets.

[1] A version of this chapter will also be published in the Winter 2002/2003 Issue of Health Care Financing Review.

[2] In our application, the HCC/DCG model uses the diagnoses recorded on the Medicare claims to create indicators for 189 medical problems (the HCCs). The model then uses about 100 of these indicators and patient characteristics to create "ybase" a single summary measure of predicted Medicare expenditure.

1.0 Aim 1: The Impact of Prescription Drug Coverage on Medicare Program Expenditures

1.1 Background and Aims

Previous research and policy analyses on the impact of prescription drug coverage have focused primarily on the direct relationship between coverage and use of medications. This study examines the broader issue of how prescription coverage influences the use of medical care as drug therapy substitutes for or complements other medical services. The clinical literature cites many examples where pharmacological interventions reduce emergency and acute care treatments. Our objective in this research is to assess the impact of prescription coverage of Medicare beneficiaries on program expenditures for Part A and Part B services.

Economic theory posits that medical care is a "normal good" i.e., that demand is inversely related to price. Because health insurance lowers the effective cost to consumers at the time health care services are utilized, theory predicts that insured persons will use more health care than uninsured persons, all else being equal. In cases where one type of health service can substitute for another, theory also predicts that a drop in price for one good will lower the demand for the substitute. We know from prior research that prescription coverage increases use, but we do not know whether drugs substitute for physician services, hospitalizations, and other services, or how the generosity of prescription coverage affects this relationship. Substitution could be of two types. Drugs might be the therapy of choice, but individuals who have no drug coverage select less optimal services. Alternatively, avoidance of expensive drug therapy by those without coverage could have negative health consequences, leading to higher Medicare service use to address the problems.

Economic theory also posits that when the price of a complementary good falls, the demand for both the good itself and its complement will rise. This leads to a second way in which Medicare supplementation might affect Part A and B spending. Because physician services are a complement to prescription drug fills, we expect that persons with prescription coverage would be more likely to visit physicians and thereby spend more on Medicare Part B services.[3] The question of whether substitution or complementary effects are stronger is ultimately an empirical rather than a theoretical issue.

1.2 Literature Review

In a recently published report, *Issues in Designing a Prescription Drug Benefit for Medicare*, the Congressional Budget Office conducted an extensive literature review to assess the evidence that drug coverage affects use and cost of other health services (CBO, 2002). The report concluded that, "Little

[3] We also expect that beneficiaries with medical supplements that cover the 20 percent Medicare coinsurance for physician services (most do) would be more likely to visit physicians and thus receive prescriptions. In this case, the direct price effect of medical supplementation on Medicare spending is expected to be positive. Although our objective is not to estimate the impact that supplemental medical insurance coverage has on Medicare spending, it is critical that the effect be taken into account. Otherwise, the estimated impact of drug coverage will be biased toward zero to the extent that beneficiaries with drug coverage also have medical supplementation. Except for a small fraction of beneficiaries enrolled in state pharmaceutical assistance plans, most beneficiaries with drug coverage have supplementary medical insurance.

good evidence exists from which to determine the net effect of drug coverage on other Medicare services; but overall, costs of other services would probably not change significantly," (CBO, 2002, p. xv). The CBO reviewed three types of studies: (1) research on particular drugs and drug classes, (2) studies of the impact of prescription coverage on vulnerable populations, and (3) analyses of populations using older versus newer medications.

By far the largest number of studies falls into the first category. This is not surprising because pharmaceutical manufacturers in conjunction with Phase III and Phase IV clinical trials finance most of the published research on drug effectiveness. Publications showing that new drug products reduce hospitalization and other negative consequences of disease are valued marketing tools for the companies. However, even when reported findings from such studies are technically accurate, it is difficult to generalize them to Medicare. In part, this is due to the selection criteria used to enlist subjects in clinical trials. It is well known that the elderly are usually under-represented in trials, as are those who may be expected to gain little or be potentially harmed by the drug under review. There is also the problem of publication bias, "the tendency of authors to submit, and journals to publish, studies with findings that suggest improvements from therapy," (CBO, 2002, p. 49). But the most compelling reason why trial data represent a poor basis for measuring cost-offsets to drug use is the fact that they are available for only a small fraction of the drug products on the market, and then only for the indicated uses for which the drugs have been approved. Thus, even if Medicare beneficiaries with prescription drug coverage had higher utilization of all of the products shown to be associated with cost-offsets, that would not, by itself, guarantee overall cost savings for the Medicare program.

The second type of evidence that drug coverage might result in cost-offsets comes from a few studies that have found significant adverse events following reductions in coverage. The well-known studies by Soumerai and colleagues that attributed increased nursing home admissions (Soumerai, et al, 1991) and acute mental health services (Soumerai, et al, 1994) to the imposition of a three-per-month limit on prescriptions in the New Hampshire Medicaid program, fall into this category. More recent work by Tamblyn, et al (2001) found evidence that increased cost sharing for drug products resulted in higher rates of emergency visits and hospitalizations for elderly and poor recipients of Quebec's provincial health insurance program. As the authors of the CBO report note, it is difficult to generalize these findings to the Medicare population because of sample differences, data limitations, and methodological shortcomings. Moreover, it is not clear that just because there are bad effects associated with restricting access to pharmaceuticals, that increased access to drugs will necessarily result in improved care and attendant cost savings.

To our knowledge, the only study that has directly addressed the question of whether giving people drug coverage results in reduced utilization of other health care services is an analysis of Vermont's pharmacy assistance programs by Gillman, Gage, and Mitchell (2003). This CMS-supported analysis (Contract No. 500-95-0040) examined Medicare spending on inpatient hospital, outpatient hospital, and physician services for low-income Medicare beneficiaries before and after enrolling in the Vermont Health Access Plan (VHAP) or an expanded assistance program known as VScript. The results were compared to changes in Medicare spending for a control group of beneficiaries who had not enrolled in these programs. The study found no evidence of cost-offsets associated with either the VHAP or VScript program—in fact, Medicare spending was higher after enrollment for all service types, albeit the difference declined with time. The study authors attributed these findings to adverse selection (e.g., persons with precipitating events requiring both more Medicare services and prescription drugs are more likely to enroll), but the inability to control for other relevant factors

(such as whether the control group had drug coverage) undoubtedly also played a role. The main lesson from the Vermont study is that unless the coverage-selection decision can be adequately modeled, it will be difficult, if not impossible, to tease out the true effects of drug coverage on Medicare spending.

The final piece of evidence that drugs may produce cost-offsets comes from two studies by Frank Lichtenberg (1996, 2000) that compare Medicare spending for beneficiaries using older and newer drugs. Findings from both a longitudinal and a cross-sectional model indicate that beneficiaries taking newer drugs have lower hospitalization admission rates, length of stay, and surgical interventions compared to those using older therapies. Although CBO noted a number of technical limitations with Lichtenberg's work (CBO, 2002, p. 51-52), the review accepted his central conclusions. We also reviewed these studies and find that alternative explanations could plausibly account for Lichtenberg's findings. Specifically, the case for savings depends on a strong and untested assumption that new drug introductions are not correlated in time with other non-drug-related influences on inpatient treatment patterns.

In sum, while it is clear that appropriate drug use can result in reduced expenditures associated with avoidable hospitalizations and emergency treatments, it requires a major leap of faith to argue, based on the published literature, that drug coverage will save Medicare money in Part A and B spending. One critical missing link in the causal chain is research showing that drug coverage promotes appropriate medication use. There is some literature suggesting that people with prescription coverage are more likely to receive newer and more expensive drugs (Blustein, 2000), which is a key requirement for Medicare cost-offsets under Lichtenberg's scenario that use of new drugs represents the source of potential savings. On the other hand, there has been no published research on the question of whether drug coverage increases utilization of inappropriate medications. If it does, the effect would be to moderate or even reverse the cost-offsets associated with appropriate use.

Beyond this missing causal link, the literature on substitution effects and complementarities of drug coverage suffers from a lack of methodological consistency. The central problem is how best to estimate insurance effects using secondary datasets where subjects may self-select coverage based on potentially non-observable factors. In the Gilman study (2003) noted above, the authors concluded that there was no evidence of Medicare cost-offsets generated by the Vermont pharmacy assistance program. They also noted evidence of adverse selection among those who joined, which would have tended to neutralize the effects of cost-offsets. One lesson from Gillman's work is the importance of formally assessing the likelihood of selection bias first, and then selecting an appropriate methodological approach based on that assessment. Where selection is considered likely, the next step would be to determine if it could be modeled on observable factors. If so, matching samples of beneficiaries with and with prescription coverage using propensity scores or a longitudinal switching model would both be logical approaches.

1.3 Methods

This section describes the study methodology and is organized as follows. Our analytic strategy is presented first, followed by a brief description of the MCBS dataset used in the analysis. Next, we describe our sample inclusion and exclusion criteria. Last is a list of study variables.

1.3.1 Analytic Approach

Our analytic strategy is to address the study question using both cross-sectional and longitudinal designs. The first approach focuses on a static comparison of beneficiaries who either have continuous drug coverage or none at all. The second approach rests on two dynamic comparisons: (1) the experience of beneficiaries who gain coverage to those who do not have it and (2) the experience of beneficiaries who lose drug coverage to those with continuous benefits. We reasoned that if the two approaches produce similar findings, that will help mitigate analytic concerns associated with either approach considered individually.

We assessed the impact of prescription coverage on Medicare spending through a series of descriptive and multivariate analyses. First, we estimate the impact of coverage on drug spending, reasoning that unless the pattern of medication use changes, prescription coverage cannot logically affect spending on other services. Next, we assess the impact of coverage on various measures of health care spending by Medicare beneficiaries, including total Medicare Part A and B spending combined, spending for inpatient hospital care (a potential substitute for drug therapy), and spending for physician services (a potential complement to drug use).

In the cross-sectional analyses, we examine differences in spending attributable to drug coverage in the year 2000 for all community-dwelling Medicare beneficiaries (subject to exclusion criteria described in Section 3.1) and for two sub-samples of beneficiaries: those with Medicare supplemental health benefits from an employer and beneficiaries with evidence of COPD. The longitudinal approach focused on beneficiaries who gained or lost prescription coverage between 1995 and 2000 with a sub-analysis of persons with employer-sponsored coverage (there were too few COPD patients for a longitudinal study of this group).

The employer-insured sample was selected for three reasons. First, persons who obtain their drug benefits from an employer plan tend to have more generous coverage than those with other private sources of drug coverage. We hypothesize that any drug coverage-related impact on Medicare spending should be larger for this group than the Medicare population as a whole because of the overall generosity of coverage. The second reason to focus on this group is that most analysts believe employer-provided insurance is determined more by tenure and industry than individual self-selection. That may be changing, however. Data from the Kaiser/Hewitt 2002 Retiree Health Survey (Kaiser Family Foundation, 2002) show that 40 percent of large private-sector employers offer their retirees only one health plan, 29 percent offer a choice of two, and 31 percent offer a choice of three or more. We suspect that, on the one hand, the largest employers in the survey are more likely to offer multiple plans. On the other hand, small employers are not included in the Kaiser/Hewitt survey, and they are more likely to offer only one plan. We do not know which effect dominates. But whatever the true proportion, the availability of alternative health plans re-introduces the issue of selection bias. Because of this possibility, we use the same modeling strategy for the employer-sponsored sample as for the full beneficiary population (assuming, however, that the extent of selection will be less). Third, the employer sample excludes all beneficiaries with public sector coverage (Medicaid in particular), where selection effects are virtually guaranteed to arise.

In addition to the employer plan sample, we estimated cross-sectional models designed to test the impact of prescription coverage on spending for medications and Medicare-covered services on behalf of beneficiaries with chronic obstructive pulmonary disease (COPD). COPD includes chronic bronchitis and emphysema as well as forms of asthma not readily differentiable from the other types

of lung disease. We selected it for three reasons: (1) it is a prevalent problem affecting about 16 percent of the population over 65, (2) acute exacerbations of the disease are sensitive to medication therapy, and (3) there are reports that under-medication may be associated with lack of prescription coverage (Center on an Aging Society, 2002).

Our choice of estimators to measure prescription coverage effects for the various study samples is driven by a combination of theoretical and empirical issues. There is no single, widely accepted statistical approach to estimating insurance effects in secondary datasets. Among the various alternatives, we have selected techniques that we believe will produce the least biased and most precise estimates for policy makers. Under the cross-sectional approach, these include multivariate regression and propensity-score adjustment. Under the longitudinal model approach, these include fixed-effects and difference-in-difference models. Each approach has its strengths and limitations as described below.

We used SAS and STATA statistical software to conduct all analyses. None of the estimates used the MCBS sampling probability weights. Restrictions in the STATA survey estimator prohibit weighted estimates where there is but a single observation in a primary sampling unit (PSU). In the smaller samples of persons with COPD and employer-sponsored heath insurance, several PSUs were represented by a single observation. Moreover, there is no practicable way to use the survey weights in our pooled cross-sectional analyses. Thus, for consistency we estimate all relationships using unweighted survey data

Cross-sectional Models

Multiple Regression Models

The multiple regression models rely upon covariates to control for possible self-selection into drug coverage. These estimations take into account observed differences in the characteristics of beneficiaries with and without drug coverage. More specifically, we control for selection effects through a measure of predicted Medicare spending based on prior year diagnostic information from the DCG/HCC risk adjuster described in section 3.4 below. Written as a linear function, the equations take the following basic form,

$$(1)\quad Y_{it} = \alpha_i + D_{it}\beta_1 + X_{it}\beta_2 + H_{it-1}\beta_3 + \varepsilon_{it}$$

where Y is the expenditure variable, i indexes the person, t = 2000, D is a dummy variable for drug coverage, X is a vector of demographic characteristics, H is the risk adjuster derived from 1999 data, and the β's are coefficients to be estimated.

We estimate separate equations for each type of expenditure using a generalized linear model (GLM) with a gamma distribution and log link function, as suggested by Blough, et al (1999).[4] In the case of hospital care, we also estimate a two-part model. The first part uses logistic regression to estimate the

[4] An alternative approach that is frequently used to estimate expenditure models on data that are severely right skewed is the semi-log specification, ln(y) = XB + e. These can be estimated using ordinary least squares. However, transformation of the logged results back to natural form is mathematically difficult. The most common approach is to use a "smearing estimate," E(y)= e ^ (mu + 1/2 sigma^2) where mu is the mean and sigma is the variance of ln(y). However, calculating this estimator becomes challenging if one is interested in results conditional on x, because these results may be biased if sigma depends on x [i.e., E(y|x) = e ^ (mu(x) + 1/2 sigma(x)^2], and this dependence is not fully understood.

probability of any use; the second part uses the GLM model to estimate the level of spending for those with any use.[5]

Propensity Score Approach

Regression models of the type described above use covariates to reduce bias on estimates of the hypothesized relationship (in this case, that drug coverage will reduce Medicare spending). One issue arises in observational studies when "treated" subjects (having drug coverage) are not well matched to "controls" (having no drug coverage) on factors thought to be correlated with "treatment" selection (i.e., sicker people tend to choose drug coverage). In this case, covariate control will produce biased estimates even if individuals select coverage on measured variables.

The propensity score approach can be used to address this problem (Rosenbaum and Rubin, 1983). The propensity score is the conditional probability of exposure to a treatment given observed covariates. Matching (or weighting) subjects on the estimated propensity score, a single variable that summarizes the observed covariates, is more effective in controlling for differences between the treatment and the control group as compared to traditional regression methods.

Rubin (2001) specifies several conditions that must be met before traditional regression adjustment will provide reliable estimates:

The difference in the mean of the propensity scores in the two groups being compared must be small (i.e., less than half a standard deviation apart). As noted, the propensity score is the probability of receiving the treatment as a function of all relevant covariates in the original regression model.

The distributions of the covariates in both groups are nearly symmetric

The distributions of the covariates in both groups have nearly the same variances.

The sample sizes are approximately equal

The ratio of the variances of the propensity score in the two groups must be close to one

The ratio of the variances of the residuals of the covariates after adjusting for the propensity score must be close to one. (Rubin, 2001)

To determine how robust our regression estimates are to violations of these assumptions, we estimate propensity scores for drug coverage for all sample subjects as a function of the covariates in equation (1) using logistic regression. We output the predicted probability that each person in the sample had coverage. This measure, which varies between 0 and 1, is the propensity score. We then compare the distribution of propensity scores for those with and without drug coverage to make our initial assessment of balance. Applying the Rubin criteria listed above, we assess the relative reliability of the covariate adjusted multivariate model compared to the propensity score approach. Our final step is to force balance between the two groups by weighting observations for individuals without drug coverage by their propensity score and weighting those with coverage by 1 minus the propensity score. This assures equality in the mean values for all variables used to produce the propensity scores (Schneider, et al., 2001).

[5] In our study samples, between 88 percent and 100 percent of subjects had positive spending for service categories other than inpatient hospital care. With such small numbers of nonusers two-part models are inappropriate because the probability-of-use equations will produce unreliable estimates, which in turn will bias the total expenditure effects when the two parts of the model are re-combined. In the case of hospital care, however, between 15 and 32 percent of our study subjects had positive expenditures, thus providing the rationale for using the two-part approach.

Two considerations in using propensity score weighting (and similar designs using matching algorithms) should be kept in mind. First, the method does not control for selection on non-observed variables. For this reason, we use a Hausman test to assess the presence of selection on unmeasured variables. Second, because propensity weighting substantially reduces the contribution of observations at the extremes of the propensity range (close to 0 or 1) the estimated treatment effects cannot be generalized to persons falling in the tails of the propensity score distribution (but neither can traditional regression).

Longitudinal Models for Switchers

Our longitudinal approach allows us to explore the dynamic aspects of selection, i.e., individuals changing their drug coverage in response to changes in expenditures. This approach uses a three-step method to model changes in Medicare spending as beneficiaries take up or drop drug coverage. To the extent that there is selection on measurable variables, we can directly observe it in these models by comparing differences in the level and rates of change in Medicare and drug spending before and after beneficiaries switch coverage status. In the first step we identify all beneficiaries with a change in drug coverage status and isolate the month in which the change occurred (persons with multiple switches are excluded from the analysis). We then track monthly Medicare spending prior to the switch (up to 23 months prior) and after the switch (up to 23 months post) and plot the time-matched spending of gainers and losers relative to control groups of beneficiaries with continuous drug coverage and no drug coverage at all. To compare switchers with those without change in coverage status, we assigned a random month to serve as the "non-switch" reference period for the always covered and never covered control groups. Months before and after the reference month are coded the same as those for switchers.

In step two, we use a fixed effect panel model to analyze differences in expenditures between the switcher and non-switcher groups over time. The fixed effects model is well suited for our longitudinal data structure and its strengths include a single intercept term for each person that explicit handles individual-level influences.[6] The basic model can be summarized as:

$$(2)\quad Y_{it} = \alpha_i + Z_{it}*R_{it}\beta_1 + X_{it}\beta_2 + H_{it}\beta_3 + C_t\beta_4 + \varepsilon_{it}$$

where Y_{it} is monthly Medicare expenditures for beneficiary i in month t; α_i is the intercept for each individual; $Z_{it}*R_{it}$ is an interaction term indicating observations from the switchers relative to switch month[7], X_{it} represents a vector of time-varying beneficiary-level characteristics (age, rural/urban

[6] Limitations of the fixed effects panel model include no estimates for time-invariant effects such as gender or race, and restricted generalizability. Strictly speaking, the fixed parameters of the individual-level intercept terms mean that common-level coefficients are conditional upon the members of the sample. We accepted this limitation rather than present the results from random effects panel models as the correlation between the individual-level errors and regressors was quite highly, exceeding 0.84 in some cases. We also assessed the fixed effects models for autocorrelated disturbances as it seemed likely that the pattern of spending (and residuals) in one month may be a fair indicator of spending in the next period. Our evaluation found that the autocorrelation never exceeded 0.10 in estimators with first-order correction for autoregression and the resulting changes in the coefficients and standard errors were quite modest.

[7] The Z variable measures the observation month in relation to the switch month and can take 46 values from –23 to +23, with the reference period being the month of the switch. The R variable is a dummy =1 for actual switchers and 0 for the comparison group.

residence, geographic residence); H_{it} is the annual HCC risk adjustment index measured concurrently with spending; and C_t is a set of dummy indicators for calendar time period.

The main coefficients of interest are the β_1's, which express the difference in Medicare spending between switchers and non-switchers in each month relative to the reference month. These coefficients capture differences in spending conditioned on the model covariates, X, H, C, and the fixed effects. We plot these coefficients to provide a visual expression of the likelihood that the post-switch effects are influenced by non-controlled factors in the pre-period (i.e., adverse selection). That is to say, if conditioning on X, H, and C removes any significant differences in Medicare spending prior to the switch, then we conclude that significant differences after the switch are due to drug coverage. If, on the other hand, significant differences are present in the pre-switch coefficients, then an additional step is needed to control for them.

This third step is a traditional difference-in difference (DD) model that compares both the pre- and post-spending of switchers as well as the period-matched spending of non-switchers. This model is reasonable if any changes in spending over time would have been the same for both groups except for those attributable to the switch in coverage. The table below describes the basic DD relationship:

	Model 1	**Period 1**	**Period 2**
A	Part A & B spending for people who always maintain drug coverage	Covered	Covered
L	Part A&B spend for people who lose drug coverage	Covered	Not Covered
	Model 2		
N	Part A & B spending for people who never have drug coverage	Not Covered	Not Covered
G	Part A & B spending for people who gain drug coverage	Not Covered	Covered

Controlling for observable factors in Model 1, if (A2-L2) = insurance effect and period-related factors, and (A1-L1) = period-related factors, then (A2-L2) - (A1-L1) = insurance effect for losers. Similarly, in Model 2, (N2-G2) – (N1-G1), represents the insurance effect for gainers

This formulation could, of course, be estimated by simply adding the main effect variable for R (switchers) and post period observations for Z into equation 2; in that case the β_1 coefficients on the interaction terms, $Z_{it}*R_{it}$ would capture the net difference-in-difference effects of interest. However, we prefer a simpler formulation in which all observations for each subject are collapsed into single observations representing the pre-period and post-period respectively. This formulation provides a clear test of the hypothesis that a switch in drug coverage affects Medicare spending in cases where, for example, the monthly β_1 coefficients are insignificant but consistently signed.

1.3.2 Data Source

The Medicare Current Beneficiary Survey (MCBS) Cost and Use files serve as the primary dataset for our analyses. The MCBS is a longitudinal panel survey of a representative national sample of the Medicare population conducted under the auspices of CMS. Begun in the fall of 1991, over 12,000 Medicare beneficiaries, both aged and disabled, living in the community or in institutions are sampled from Medicare enrollment files and surveyed three times a year using computer assisted personal

interviewing. MCBS interviewers collect extensive information on each individual's use and expenditures for health services including source of payment, as well as information on health insurance, health and functional status, socioeconomic status, and demographic characteristics. The MCBS files link Medicare claims to survey-reported events and provide complete expenditure and source of payment data on all health care services, including those not covered by Medicare, namely prescription drugs and long term care.

This analysis drew on the MCBS survey data for all measures of drug coverage and individual characteristics except the HCC risk adjustment, which came from the diagnostic variables in the appended Medicare claims files. For the cross-sectional analyses, expenditure data for total Medicare Part A and B spending and prescription spending were taken from the MCBS annual summary files. Data on inpatient hospital and physician/supplier expenditures were computed directly from the Medicare claims files for both the cross-sectional and longitudinal analyses.

1.3.3 Sample Selection Criteria

Cross-sectional Model Samples

The selection criteria for the cross-sectional samples are listed below with accompanying notes describing the rationale for each criterion.

- *Beneficiary present in both the 1999 and 2000 Cost and Use samples.* The primary control variable in the adjusted models (the HCC index) uses 1999 data to predict 2000 spending. Given the rotating panel design of the MCBS, 25 percent of beneficiaries surveyed in 1999 are dropped from the 2000 sample and there is additional loss due to deaths and failure to follow up.
- *Full-year Medicare entitled for both Parts A and B in both years*. A full year of Medicare A and B claims is required to specify the dependent variable in the Part A and B spending equation. In addition, a full year of claims is necessary to accurately assign HCC scores. We thus exclude persons who were newly Medicare entitled, persons with Part A but no Part B coverage, and decedents in 1999 or 2000.
- *Community-dwelling entire year*. Because MCBS does not collect drug expenditure data on institutionalized beneficiaries, we exclude all MCBS respondents who were in a LTC facility for all or part of the year.
- *In fee-for-service Medicare entire year*. There are no Medicare claims data for M+C enrollees, thus making it impossible to specify the dependent variable or to derive HCC scores. We thus exclude all respondents with any M+C enrollment in either 1999 or 2000.
- *Had Medicare supplementation in both years*. Since a small and unrepresentative fraction of beneficiaries had no Medicare supplementation whatever, we excluded them from the analysis as opposed to including them and adjusting for the effect of no supplementation through dummy variables and interaction terms.
- *For the group with drug coverage, the coverage is continuous throughout the year in both years (1999 and 2000).* For the group with no drug coverage, there is absence of drug coverage in both years. These conditions assured that behavior observed during the study year (2000) will not be biased by a change in coverage in the preceding year.
- *For the group with ESHI, the coverage is continuous throughout both years and there is no other coverage.* In this sample the group with drug coverage includes beneficiaries with continuous employer-sponsored drug coverage in both years. It excludes beneficiaries with

any source of prescription coverage other than employer-sponsored coverage. The group with no drug coverage includes beneficiaries with ESHI but no prescription benefits in both years.

- *For the group with COPD, there is evidence of COPD (HCC108) in 1999.* This ensures that all sample subjects were prevalent rather than incident cases in the study year (2000).

The above selection criteria resulted in sample sizes of 3,365 beneficiaries in the overall population, 1,262 beneficiaries in the ESHI sample, and 462 beneficiaries in the COPD sample. Except for the sub-analysis of ESHI beneficiaries, small sample sizes precluded analysis of coverage effects by source of benefit. Also small cell sizes were problematic for the group without drug coverage in the ESHI and the COPD samples which could result in large standard errors in our analyses.

In order to avoid Type 2 error associated with small sample sizes, we also developed a larger pooled sample comprising four cross-sectional samples (1996-1997, 1997-1998, 1998-1999, 1999-2000) with each sample defined as above. Not only is the pooled dataset much larger and hence able to potentially detect smaller differences, but it also permits a sensitivity test of the stability of the main findings for 2000.

Longitudinal Model Samples

For the longitudinal models of switchers, we included all fee-for-service beneficiaries with Part A and B coverage for all years (1995-2000) in which they are represented in the MCBS files. We excluded persons whose drug coverage had no beginning or end dates and persons with gaps in coverage or multiple switches. We categorized the remaining sample into four mutually-exclusive groups based upon the stability of their drug coverage up to two-years prior to switching (or non-switching in the case of the controls) and two years post switching: (L) lost coverage, (G) gained coverage, (A) held coverage always, and (N) never had coverage. The unit of observation for this set of models is the person-month. Lastly, we identified the sub-sample of persons with calendar year-end switches (November to February) in their drug coverage in order to compare pre-switch and post-switch differences in drug spending.[8] Given the rotating sample design of the MCBS, each beneficiary can be included in up to two study panels. Our final samples sizes for the longitudinal models were: 12,066 (Always), 1,275 (Losers), 1,488 (Gainers), 4,366 (Nevers). (See Appendix 1.A.1 for sample sizes by observation months).

It should be noted that although the cross-sectional and longitudinal samples share persons in the A and N groups, the L and G groups only appear in the longitudinal models. For this reason the results from the two types of models are not strictly comparable.

[8] This strategy is necessary because drug spending in the MCBS is not dated; therefore, it is impossible to compare pre- and post-switch behavior among beneficiaries who switch during the calendar year.

1.3.4 Study Variables

Cross-sectional Model Variables

There are four dependent variables in the cross-sectional models:

- Prescription drug expenditures (AWP)
- Total Medicare expenditures
- Inpatient hospital expenditures
- Physician/supplier expenditures

Note that prescription drug expenditures are measured in terms of the average wholesale price (AWP) rather than the event-level expenditures reported in the MCBS. Prices for the same drug may vary across different insurance groups based on negotiated discounts and rebates. The AWP provides a convenient, standardized price that can be applied to each drug event so that the aggregate "expenditure" represents variation in utilization (reflecting the number of prescriptions filled, the type of products obtained, and whether they are brand or generic) but not variation in prices negotiated by payers.

The independent variables in the cross-sectional analyses are shown below. All are measured in the study year (2000) except for the HCC risk adjuster, which is measured in 1999.

- Drug coverage (a binary indicator variable)
- Age (<65 years, i.e., Medicare disabled, 65-69 years, 70-74 years, 75-79 years, 80+ years)
- Race (white/nonwhite)
- Gender
- Marital status (married/nonmarried with non-married including those who are single, widowed, divorced or separated)
- Income (<$10k, $10 - $20k, $20 - $30k, >$30k)
- Educational attainment (high school graduate or not)
- Geographic region of residence (metro status and 4 census regions)
- An indicator variable identifying beneficiaries who were previously entitled to Medicare under SSDI but are now 65 or older the Diagnostic Cost Group Hierarchical Condition Category or (DCG/HCC) risk adjuster.

The main control variable in the cross-sectional models is the Diagnostic Cost Group Hierarchical Condition Category (DCG/HCC) risk adjuster developed by Health Economics Research Inc. under contract with CMS. The DCG/HCC is the current CMS methodology for predicting Medicare expenditures and is the basis for the "selected significant disease model" that will be used to reimburse the Medicare+Choice plans starting in January 2004. In our application, the HCC software creates indicators for the presence of 189 medical conditions based on the diagnoses recorded on a patient's Medicare claims (physician, outpatient, and inpatient). It then applies previously calibrated weights (based on regression coefficients) to approximately 100 of these conditions to create a single risk score (denoted "ybase") that is proportional to the patient's expected Medicare expenditure. In our models, we normalize "ybase" by dividing each predicted value by the mean "ybase" in the main population-based sample. Thus, a person with mean predicted expenditure equal to the actual average is scored 1.0. Those with above and below the mean predicted spending are scored accordingly.

The HCC effectively controls for the prevalence of disease but not its severity or the intensity of its treatment. In our opinion, this risk adjuster offers the best feasible balance between controlling for selection and preserving a full and unbiased estimate of the insurance effect. It is a reasonable control for selection because it captures the diagnoses that influence expenditures but may also influence individuals' decisions to enroll in insurance. It allows for a full and unbiased estimate of the effect of drug insurance on expenditures if one accepts the assumptions that insurance affects the use of services conditional on diagnoses but does not affect the diagnoses themselves. Among other things, these assumptions imply that the drug utilization induced by insurance affects the severity and progression of disease but not its onset. While we believe the HCC is the strongest feasible risk adjuster, we acknowledge that some potential for selection and other bias remain. There may be residual selection bias to the extent that individuals opt into drug insurance based on an individual taste or need for care beyond that captured in diagnoses. There may be other residual bias to the extent that drug insurance affects diagnoses. For example, drug coverage may actually induce the prevalence of disease through adverse effects (e.g., adverse drug reactions, drug-drug interactions or inappropriate drugs) or reduce the prevalence of disease through primary prevention (e.g., immunization), secondary prevention (e.g., diabetics not developing nephropathy) or cure. In either of these instances, the HCC will effectively control away only part of the insurance effect, leading to a biased estimate. We would expect that any net residual bias associated with using the HCC risk adjuster would more likely be downward rather than upward since diagnoses specifying ADRs or drug-drug interactions are not captured, but there is no way to empirically test that assumption.

Longitudinal Model Variables

The dependent variables for the longitudinal models are similar to those used in the cross-sectional models, except in the following ways. First, we use the MCBS survey summary measures for prescription drug spending rather than AWP priced-expenditures since AWP price files were not available for the early years of the study. Second, we assess Medicare spending just for inpatient hospital and physician/supplier expenditures from the claims records. We believe that these two spending categories will be most sensitive to drug coverage and, therefore, did not create a total Medicare A and B variable by combining all of the Medicare bill records. Finally, for the multivariate longitudinal analyses, we trimmed the expenditure data at 2 standard deviations above the mean (>$3684 for inpatient and >548 for physician/supplier). This was done to address extreme variability in the person-month observations.

The principal independent variable in the longitudinal analyses are 23 indicator variables representing the time period (measured in months) relative to the time of the change in coverage. For example, an indicator of "+4" means four months after the drug coverage switch, -4 means four months before the switch. As noted previously, we randomly generated a "switch date" to index pre and post months for non-switchers. In the final presentation, we collapse the monthly indicators into quarterly averages for ease of display and to improve the stability of the estimates. The other independent variables are the same time-varying characteristics as in the cross-sectional analysis except for age (which we code as a continuous variable and as age squared) and a set of dummy variables indicating the calendar year for which the observation pertains as a means of controlling for inflation and other calendar-specific events.

1.4 Results

1.4.1 Cross-sectional Models

Descriptive Results

Exhibits .1 to 1.5 present descriptive characteristics of the four cross-sectional samples for 2000. The first column in Exhibit 1.1[9] describes the Medicare beneficiaries who met sample inclusion and exclusion criteria for the population-level analysis. The next two columns show characteristics of persons with employer-sponsored health insurance (ESHI) and COPD, respectively. The samples varied in expected ways. The ESHI sample, for example, has significantly fewer disabled and formerly disabled beneficiaries than any of the other samples. The ESHI group was also more likely to live in urban areas and were much more likely to have prescription coverage. Beneficiaries with COPD had the highest rates of Medicare-entitled disability; nearly 20 percent were either currently or had formerly received SSDI. Beneficiaries with COPD were also more likely to have drug coverage as compared to the typical Medicare beneficiary. For beneficiaries with drug coverage, we also compute the average proportion of drug spending paid for by third parties as an ex post proxy for generosity of the drug benefit. There is very little difference in this proportion among those in the full population sample (69.3%) and the ESHI group (69.4%). The COPD sample with prescription benefits had the most generous coverage (74.4%). The final row in Exhibit 1.1 presents the HCC index values for each group, normalized to 1.0 for the full population sample. The HCC risk index is close to 1.0 for the ESHI group (0.93), but is much higher (1.68) for COPD patients, reflecting the greater medical needs of this group.

Exhibits 1.2 to 1.4 present means and standard errors for all of the drug and Medicare spending variables used in the cross-sectional analyses, arrayed according to prescription coverage status. In addition, these exhibits show the proportion of each sample with any spending by type of service and the mean spending levels for those beneficiaries. These three exhibits present a consistent picture of higher spending levels for all service types among Medicare beneficiaries with continuous drug benefits. We expected to find that the proportion of beneficiaries using any prescription medicine would be higher among those with drug coverage. Over all three samples, between 88 and 99 percent of beneficiaries reported some prescription use in 2000. The groups with drug coverage averaged 3 to 7 percentage points higher user rates than those without drug benefits.

The unadjusted relationships between drug coverage and the likelihood of using any Medicare services are mixed. For the population sample (Exhibit 1.2), the proportion of users varied little by drug coverage status. On the other hand, the proportion of Medicare service users in the ESHI sample (Exhibit 1.3) was consistently lower among beneficiaries with prescription coverage with the exception of inpatient service wherein there was no significant difference. While the proportion of physician Medicare service users in the COPD sample (Exhibit 1.4) varied little with drug coverage status, the proportion of inpatient service users in this sample was much lower among beneficiaries with prescription coverage.

[9] Note that the data shown in Exhibit 1.1 have been weighted to reflect actual population proportions. All remaining data presentations are unweighted for reasons summarized in Section 1.3.1.

Multivariate and Propensity Score Weighted Results

Exhibit 1.5 compares the unadjusted differences in drug and Medicare spending (column 1) with estimates from the GLM regressions (column 2) and weighted propensity score analyses (column 3). Full GLM regression results for the overall population are provided in Appendix A (Exhibits 1.A.2 to 1.A.5). The top row in each sample panel reports unadjusted and adjusted differences in AWP drug spending between those with and without prescription drug coverage. The differences are large, positive, and significant across the three samples. The difference in unadjusted spending was greatest (+94%) for the population sample and least (+80%) for the COPD sample. The differences are lower in the regression–adjusted models (+37% to +58%) and the propensity-weighted estimates (+61% to +74%), but they remain statistically significant.

The second row in each sample panel of Exhibit 1.5 presents estimated differences in total Medicare (Part A and Part B) spending as a function of drug coverage. The unadjusted differences (column 1) are all positive but not significantly different from zero, except for the COPD sample wherein the difference is negative (but insignificant). As with the drug spending regressions, the GLM models (column 2) produced much lower estimates of the drug insurance effect, which are not significantly different from zero except in the case of COPD patients, where drug coverage is associated with a significant reduction in Medicare spending of 40 percent. The propensity-weighted differences in total Medicare spending between those with and without drug benefits were close to the GLM results and were not statistically significant for any of the three samples.

The findings for Medicare inpatient hospital spending comparisons follow a similar pattern of positive differences associated with drug coverage in the unadjusted comparisons (albeit none are statistically significant) and smaller or negative associations in the adjusted estimates. Indeed, in two of the three GLM models, drug insurance is associated with reduced Medicare hospital spending (however, none reach conventional levels of statistical significance). Two of the three propensity-weighted comparisons also produced negative, but insignificant associations of drug coverage with hospital expenditures. The two-part models for inpatient hospital spending (results not shown) indicate that beneficiaries with drug coverage have lower probabilities of any inpatient hospital stay compared to those with no coverage for the population and COPD samples, while drug coverage had no impact on the probability of hospitalization in the employer-sponsored sample. The odds ratios were 0.90 for the population sample and 0.66 for the COPD group, but neither was statistically significant. The second part of these two-part models estimating the level of expenditures among beneficiaries with any inpatient hospital spending produced mixed results. The effect of drug coverage was negative and small in the population sample, positive and large in the ESHI group, and close to zero for those with COPD. As in the probability models, none of these results was statistically significant.

As shown in the third row of each sample panel in Exhibit 1.5, physician/supplier spending under Medicare is significantly higher among beneficiaries with drug coverage in two of the three unadjusted comparisons, and lower (but insignificantly so) for COPD patients. The positive associations remained positive in the GLM regressions and are significantly different from zero for the population sample but non-significant for the ESHI sample. The negative unadjusted relationship among COPD patients became more negative in the GLM model and reached statistical significance at $p<0.05$. Again, the propensity-weighted results are generally similar to the GLM results except that the significant positive association found between drug coverage and physician spending for the population sample in the GLM model was smaller and non-significant in the propensity model.

All analyses were then re-estimated in a larger sample of beneficiaries obtained by pooling data from 1996-2000. These findings are shown in Exhibit 1.6. For the population sample, increasing the sample size did not significantly improve model precision, but did confirm the stability of the 2000 estimates. In fact, the estimated differences in drug spending associated with insurance were virtually identical for the two sets of models. There were somewhat larger differences in the estimates for the ESHI samples, and major differences in the COPD samples. For example, comparison of the propensity-adjusted estimates in the ESHI samples reveals that although the pooled data estimates had the same signs, they were half to one-third the magnitude compared to year 2000 results shown in Exhibit 1.5. For COPD patients, results from the pooled sample produced various sign reversals and loss of significance compared to the 2000 findings. To further explore the reasons for this finding, we re-estimated all analyses for the 1996-1997 COPD sample from the pooled dataset. Surprisingly, we found drug coverage to be positively associated with total Part A and B spending and inpatient expenditures regardless of the estimator employed. This is in stark contrast to the negative associations observed in the 2000 time period (Exhibit 1.5). While drug coverage was still negatively associated with physician Medicare spending in 1997, the findings were not statistically significant in either the unadjusted or adjusted models.

1.4.2 Longitudinal Models for Switchers

Exhibits 1.7 to 1.9 present descriptive characteristics of the switching samples drawn from the 1995 through 2000 MCBS. Exhibit 1.7 compares selected demographic characteristics for the four switching groups. The samples are distributed as follows: 63% Always held drug coverage, 23% Never held coverage, 8% Gained it, and 7% Lost drug coverage. Between 1995 and 2000, the composition of the panels shifted toward more beneficiaries having drug coverage, especially stable forms. For example, the Always group represented 59% of the first panel (y9596) but 67% of the last one (y9900).[10] Conversely, the Never group comprised 26% of the first panel but only 19% of the final panel. As for individual characteristics, the Gainer and Loser groups tended to look similar to each other in terms of age, Medicare entitlement status, and geographic residence, but fall in between the more extreme distributions of the Always and Never groups. For example, about 65% of both switcher samples lived in metropolitan areas compared to 58% of the Never sample and 71% of the Always sample. Likewise, over 55% of the switcher groups were age 75 or older compared to 64% and 45% of the Never and Always samples, respectively. The Always covered group generated the highest average HCC risk score ($12,408), followed by the Gainers ($11,102), the Never covered ($10,799), and then Losers ($10,746).

Exhibit 1.8 shows the means and standard errors for all of the drug and Medicare spending variables used in the longitudinal analysis, arrayed according to switching status. This exhibit also shows the proportion of each sample with any spending by type of service.[11] As in the earlier exhibits, spending on all services was uniformly highest among Medicare beneficiaries with continuous drug benefits.

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[10] We know from previous research that most of the increase in new drug benefits obtained by the Medicare beneficiary population as a whole over this period was a result of the Medicare+Choice program (Briesacher, et al., 2002). However, the exclusion of M+C enrollees from the study sample means other sources of change are reflected in these results.

[11] The spending in this Exhibit represents the average annual spending of each group during the 2-year panel, recognizing that the Loser and Gainer samples may experience large changes relative to their coverage switches.

Spending levels from the other groups varied in conformance with expectations. The Never sample had the lowest drug expenditures and yet higher inpatient spending than Losers and higher physician spending than Gainers. Losers and Gainers had comparable drug spending ($682 and $711, respectively) but Losers had the lowest inpatient spending ($1,276) while Gainers had the lowest physician/supplier spending ($1,006).

Exhibits 1.9 and 1.10 provide information on changes in medication use before and after a switch in coverage. In Exhibit 1.9, we compared annual drug spending for groups whose drug coverage switch occurred at the end of the calendar year. (The estimates are for the subsample of beneficiaries with end-of-year coverage switches because the MCBS provides only annual drug spending figures.) On average, Losers spent only 7% more on prescription drugs in the year following the loss of the drug coverage, compared to the Always sample, which spent 14% more. Gainers spent 66% more on prescription drugs in the year following the acquisition of drug coverage, compared to the Never sample, which spent only 8% more. In Exhibit 1.10, the change is presented in a graph to highlight the direction and magnitude of changes in drug spending as individuals lose or gain drug coverage. The difference in drug spending between the Loser group and the Always group increased by a third in the post-period relative to the pre-period (-$260 vs. -$351). With the Gainers and Never samples, the difference in drug spending triples following the switch: the Gainers spent $117 more on average than the Never group before the switch, but $502 more afterward.

The next set of figures (Exhibits 1.11–1.18) describe patterns in quarterly Medicare inpatient and physician spending by the switcher groups before and after the change in drug coverage. The first graph compares the Losers to the Always sample, while the second set compares the Gainers to the Never sample. These comparisons have been selected so that the drug coverage status is the same for both groups before the switch but different afterward. In Exhibit 1.11, Losers spent less, on average, for inpatient services throughout the study period. In comparing the inpatient spending of the Gainer and the Never samples, we see a nearly identical rise during the period with no apparent sensitivity to drug coverage changes (Exhibit 1.12). In Exhibits 1.13 and 14, the inpatient spending estimates have been adjusted for calendar time, demographics, and health status, and the grey bars show 95 percent confidence intervals (regression output for these models is presented in Appendix Exhibit 1.A.6 and 1.A.7). The general effect of the multivariate models was to remove most of the unadjusted differences in spending, especially between Always and Losers where only the 6th quarter following the switch is statistically significant. Taken together, the unadjusted and unadjusted patterns of inpatient spending suggest no overt relationship to drug coverage.

We see similar patterns for Medicare physician/supplier spending. In Exhibit 1.15, physician expenditures by the Loser and Always groups were similar until the 2nd quarter following the loss of drug coverage. Then Losers began spending less than the Always sample, and the difference widened in the post-period. In comparing the physician/supplier spending of the Gainer and the Never samples (Exhibit 1.16), we see a nearly identical rise during the period without any apparent sensitivity to drug coverage changes. In Exhibits 1.17 and 1.18, the physician/supplier spending estimates have been adjusted as described above (regression results are presented in Appendix Exhibits 1.A.8 and 1.A.9). Here too, the multivariate models removed most of the unadjusted differences in spending, especially between Always and Losers, where only the 7th quarter following the switch is statistically significant. Taken together, the unadjusted and unadjusted patterns of physician/supplier spending suggest no obvious relationship to drug coverage.

We re-estimated the longitudinal models in the sample of beneficiaries with employer-sponsored drug benefits and found similar results as in the larger sample, although there were no pre-switch observations for Gainers in quarters 7–4 (see Appendix Exhibits 1.A.10 to 1.A.13 for the regression output). None of the switching coefficients approached statistical significance nor was there evidence of a consistent pattern in inpatient or physician/supplier spending behavior.

The last exhibit (Exhibit 1.19) summarizes the findings of the difference-in-difference models in comparison to unadjusted annual estimates (regression output from these models is reproduced in Appendix Exhibits 1.A.14 to 1.A.17). Unadjusted differences in drug spending are also reproduced in Exhibit 1.19 for comparison purposes, albeit there were too few observations to conduct any multivariate analyses for this group. Each estimate in this exhibit shows the residual spending of persons with drug coverage in the post-period relative to spending both in the pre-period and by persons without drug coverage (a difference-in-difference estimate). For instance, the first column shows that the Always group spent $91 more on medications than Losers after subtracting out the pre-period spending [Post-period ($1234-$883) – Pre-period ($1084-$824)=$91]. In the next column, we calculated these differences with a multivariate model to account for the effects of calendar time, age, martial status, income, urban residence and health status.

The unadjusted difference in annual inpatient spending between beneficiaries with and without drug coverage ranges from $215 for Gainers versus Nevers to $711 for Always versus Losers. In the adjusted comparisons, the inpatient spending differences become smaller ($95 for Always versus Losers) and negative in the case of Gainers versus Nevers (-$176), although the estimates are not statistically significant. For unadjusted physician/supplier spending, those with drug coverage spent between $18 and $370 more compared to those without drug coverage. In the adjusted comparisons, the difference drops to $77 for Always versus Losers and -$32 for Gainers versus Nevers, but again, the difference is not statistically significant.

1.5 Discussion

Taken together, the findings from this study support the conventional view that providing all Medicare beneficiaries with drug coverage will almost surely result in a significant increase in demand for prescription medications and may (or may not) result in savings elsewhere in the Medicare budget. The estimated magnitude of the effects must be interpreted in light of both technical and contextual issues.

On the technical side is the question of which of the analytic approaches employed in the study produces the least biased and most precise estimates of treatment effects. For the cross-sectional analyses, we applied Rubin's criteria (see Section 3.1 above) to assess whether the GLM or propensity-weighted results are more reliable. Based on a strict application of these rules,[12] we

[12] In the population sample, the mean propensity score for those who actually had prescription coverage was .79 (SD=.12) versus .70 (SD=.12) for those without coverage. The difference in mean scores is about three-fourths of a standard deviation, or somewhat above Rubin's rule of a half standard deviation or less. Rubin's second criterion pertains to the nearly symmetric distribution of the covariates in both groups. Examination of our main covariate to control for selection, (the mean ybase or predicted Medicare spending in 2000 based on 1999 HCC) revealed a 24% difference between the no drug coverage [Mean ybase=$4,962 (SD=3,849)] and drug coverage [Mean ybase=$6,154 (SD=5,124)] groups in the population sample. The standard deviations of the mean ybase in the two groups were also highly different, thus violating Rubin's rule on nearly same variances of the covariates in both groups. Another of Rubin's rules specifies that the sample

conclude that the propensity-weighted results are somewhat more reliable than the GLM regression-adjusted findings. This would suggest that, on balance, regression-adjustment tends to slightly underestimate the direct demand-inducing (moral hazard) effect of drug coverage on drug spending, and may slightly over-estimate the effect of coverage on the demand for substitutes. Of course, this assumes that any residual bias in the GLM findings arises from a failure of covariate adjustment to account for lack of balance in observable characteristics between those with and without drug benefits. If selection is conditioned by unobserved factors, then both regression and propensity scoring will produce biased results. To assess this possibility, we used the Durbin-Wu-Hausman (DWH) test suggested by Davidson and MacKinnon (1993) to test for endogeneity. The test statistic was negative.[13]

The second step of the longitudinal switching model also provides information about the likelihood that unobserved selection effects bias our findings. The longitudinal approach directly assesses the presence of dynamic selection into drug coverage, that is individuals changing their coverage status in response to changes in their expenditures. We observed no pre-switch patterns in Medicare spending that would indicate selection on observable measures (i.e., a bump up in spending for Gainers or a trough in spending for Losers). These findings increase our confidence in the cross-sectional estimates.

By focusing on the time patterns in Medicare and drug spending before and after changes in drug coverage, the longitudinal switching model produces perhaps the most policy-relevant findings of all of our analytic approaches. The results from the Gainer versus Never models are particularly relevant to CMS, because this comparison most closely equates to changes that can be expected to occur once a Medicare drug benefit is implemented. Our findings suggest that Medicare beneficiaries without any drug coverage will incur a steep increase (possibly as high as 60% or more) in drug expenditures in the year following acquisition of coverage. However, during the same period, physician/supplier spending should increase by only a slight amount while inpatient spending may also rise a bit and

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sizes of the two groups should be approximately equal which is clearly not met by the population sample [no drug coverage (N=762) and drug coverage (N=2,603)]. However, the ratio of the variances of the propensity scores in the two groups was equal to one (SD=0.12 in both groups), thus satisfying that criterion. The other samples (beneficiaries with ESHI, COPD, and cataracts) exhibited similar differences in the mean propensity scores, covariate distributions, variances of the covariate distributions, and sample sizes.

[13] The Durbin-Wu-Hausman test, also known as the augmented regression test, is a two-step process. In the first step, the potentially endogeneous explanatory variable (drug coverage) is regressed against all of the exogeneous variables in the original regression (equation 1 above). The residuals from this regression are then included in an augmented version of the original regression. The coefficient on the residuals variable is then tested against zero using an F test. If this coefficient were significantly different from zero, then we would infer that the GLM is not consistent. However, in our data the p-value on the residuals was 0.944, and the null hypothesis is not rejected.

The above test that failed to indicate drug coverage to be endogenous was conducted using the HCC index as one of the exogenous variables in the original regression. We hypothesize that beneficiaries would select into drug coverage based on health status, and we control for this selection bias using the HCC index. We believe that if the HCC index were omitted as a control variable, then drug coverage would be potentially endogenous. To test this assumption, we re-conducted the Durbin-Wu-Hausman test without the HCC index included as an exogenous variable. An F-test resulted in a p-value of 0.07 on the residuals. Given that the DWH test is a low power test, we conclude that there is marginal evidence of endogeneity in drug coverage if the HCC index is not controlled for.

then begin dropping modestly after about a year and a half, although these predictions are statistically nonsignificant.

The consensus finding across the various models is that prescription coverage increases drug expenditures by between 50 and 75 percent.[14] This is not to suggest that if Medicare were to extend coverage to all beneficiaries that drug cost would rise by this amount. In the first place, except for the switching models, our estimated effects are measured in terms of AWP prices. Managed care organizations today typically pay AWP less 12 to 14 percent. Public payers including the Veterans Administration, DOD, state Medicaid programs, and state pharmaceutical assistance plans get even better price breaks. Presumably, similar price reductions could be expected with a Medicare drug benefit. Secondly, our cross-sectional estimates compared drug spending between insured and uninsured beneficiaries in the year 2000 when payers had just begun to institute cost-saving benefit design features like 3-tier copayments and formulary-driven prior-authorization requirements. To the extent that these features are incorporated in a federal Medicare benefit, the spending differential would also fall below our estimate. Finally, it is clear that the Medicare drug benefit will be less generous than the typical plan available to beneficiaries today through employers or the public sector. That would ameliorate the demand-inducing effect of coverage and thus limit additional spending.

These same factors are likely to influence the impact that drug coverage will have on Medicare Part A and B spending in the future. Assuming that the average generosity of a Medicare drug benefit is significantly below that held by current beneficiaries, then the potential savings from substitution of drugs for hospital care would also be lower. On the other hand, assuming that the Medicare drug benefit incorporates incentives for more efficient use of drug products, that would enhance the value of drug coverage across the whole spectrum of health services.

Our analysis of COPD patients was designed in part to determine whether drug benefits (potentially packaged with disease management or other services) might have extra payoffs to the Medicare program for populations with certain chronic conditions. We found evidence of cost offsets in 2000 but not in an earlier year. The instability in these findings may be due to the small number of COPD beneficiaries with no drug coverage in which a few observations could have a substantial impact on the magnitude and direction of the estimates. Another reason for the different results may be due to changes in the disease management of COPD over time by physicians and insurance companies. In either case, the jury is still out regarding the returns to drug coverage for particular disease groups within the Medicare population.

1.6 Conclusions

We draw three conclusions from this study. First, there is no question that drug coverage induces additional spending on prescribed medications by Medicare beneficiaries. This was expected, but the size of the estimated effect is larger than we had anticipated based on prior research. Second, the higher spending on drugs among those with coverage appears to have little aggregate impact on spending for Medicare-covered services. We found no consistent evidence that drug coverage either increases or reduces spending for hospital and physician services. This does not necessarily mean that drug therapy cannot substitute or complement other therapies, but rather that neither effect

[14] This translates into an arc price elasticity of approximately 0.74 for the population and ESHI samples, both of which have equal generosity of drug benefits (See Exhibit 1). The elasticity for the COPD sample is lower, between 0.36 and 0.6.

predominates across the Medicare population as a whole. Third, our results suggest that drug coverage can potentially produce cost offsets for persons with particular medication-sensitive conditions. The primary implication of our COPD findings is that future analyses on cost savings associated with drug coverage for persons with particular diseases may need larger sample sizes than available in the MCBS. Also, researchers must be sensitive to the time period covered by their analysis. If nothing else, our attempt to discover whether drug coverage produce net cost savings for one disease group should spur research on other conditions that may be sensitive to medications.

The usual caveats apply to drawing causal inference from limited samples based on observational data. Our exclusion criteria mean that the study results cannot be generalized to the entire Medicare population. For example, we might expect systematic differences between beneficiaries in fee-for-service drug plans and M+C plans where the drug benefits are more likely to be managed (we had to exclude beneficiaries in M+C plans because there are no Medicare Part A and B data for them). Our primary method of controlling for selection in the cross-sectional approach—matching on propensity scores—also limits the generalizability of findings to those at the extremes of the propensity range. Small sample sizes were problematic. Except for a sub-analysis of employer-sponsored drug benefits, small sample sizes precluded analysis of coverage effects by source of benefit. Thus, we cannot say whether the average effect of drug coverage based on our findings would apply to different payors. Small cell sizes were most severe for the group without drug coverage, resulting in high standard errors for relatively rare events like hospitalization. However, as the results from our pooled analyses show, small cell size was not the primary reason for the failure to find any statistically significant association between drug coverage and Medicare spending

The longitudinal analyses also had limitations, albeit the consistency in overall findings between the two approaches serves to strengthen our main conclusion that increasing the proportion of the Medicare population with drug coverage is unlikely to produce Medicare cost offsets. It is possible that the longitudinal observation period was simply too short in duration to capture the clinical benefits of medications that influence use of hospitals and physicians, although these long-term effects would potentially be captured in the cross-sectional approach. Many of the prescription drugs used by Medicare beneficiaries are taken over the course of many years to slow the effects of disabling disease. It is important to remember that both the cross-sectional and the longitudinal results reflect the marginal impact of drug benefits and not the full impact of drug therapy. Our results show high levels of medication use even among the uninsured.

We believe that future research in this area should focus on additional medication sensitive conditions and seek to establish the relationship between drug coverage and treatments specific to these conditions. Clinicians would find it helpful to have an empirically derived list of these conditions in order to counsel patients about medication use. Payers (including CMS) and health plans could use such a list to target conditions with the highest potential for cost offsets in other service areas.

Exhibits

Exhibit 1.1

2000 Cross-Sectional Characteristics of the Three MCBS Study Samples[a]

Characteristic	All Beneficiaries	Beneficiaries with Employer-sponsored Health Insurance	Beneficiaries with COPD
Total, Unweighted N	**3365**	**1262**	**462**
Weighted N (millions)	9.7	4.0	1.4
Gender			
Female	58.5%	54.1%	53.7%
Male	41.5	45.9	46.3
Medicare Entitlement Status			
Aged/no prior disability	81.7	88.6	81.2
Disabled	11.4	5.8	10.2
Aged/previously disabled	6.9	5.6	8.6
Age, (Years)			
< 65	11.4	5.8	10.2
65-69	12.1	12.1	12.8
70-74	28.7	32.7	30.2
75-79	23.7	28.4	25.3
80+	24.1	21.0	21.3
Metropolitan Status			
Rural	27.8	21.8	29.6
Urban	72.2	78.2	70.4
Census Regions			
Northeast	20.6	22.7	19.3
Midwest	25.9	28.8	25.9
South	38.0	34.5	39.5
West	15.6	14.0	15.3
Drug Coverage			
Full-year drug coverage	77.5	95.2	83.7
% of drug spending paid by third party	69.3	69.4	74.4
No drug coverage	22.5	4.8	16.3
HCC index* in previous years	1.00	0.93	1.68

a. Population proportions using the MCBS weights

b. Predicted Medicare Part A & B payment from DCG-HCC risk adjuster normalized to 1.0

Source: Medicare Current Beneficiary Survey, 1999-2000

Exhibit 1.2

Univariate Statistics on Total Drug and Medicare Expenditures Among All MCBS Sample Beneficiaries with and without Drug Coverage

2000 Expenditures	Supplemental Insurance with No Drug Coverage (Unweighted N=762)	Supplemental Insurance with Full-year Drug Coverage (Unweighted N=2603)
Drug (AWP)		
Mean (se)	$1,068 (41)	$2,074 (47)
Percent with expenditure	88.3%	95.5%
Mean (se) among those with any expenditure	$1,210 (44)	$2,172 (48)
Medicare A & B		
Mean (se)	$3,899 (330)	$4,952 (209)
Percent with expenditure	94.5%	95.1%
Mean (se) among those with any expenditure	$4,126 (348)	$5,206 (218)
Inpatient Medicare		
Mean (se)	$1,835 (246)	$2,099 (129)
Percent with expenditure	19.3%	19.9%
Mean (se) among those with any expenditure	$9,514 (1,064)	$10,529 (497)
Physician Medicare		
Mean (se)	$1,243 (72)	$1,537 (49)
Percent with expenditure	93.4%	93.6%
Mean (se) among those with any expenditure	$1,331 (76)	$1,643 (52)

Source: Medicare Current Beneficiary Survey, 1999-2000

Exhibit 1.3

Univariate Statistics on Total Drug and Medicare Expenditures Among MCBS Sample Beneficiaries with Employer-Sponsored Health Insurance with and without Drug Coverage

2000 Expenditures	Supplemental Insurance with No Drug Coverage (Unweighted N=62)	Supplemental Insurance with Full-year Drug Coverage (Unweighted N=1,200)
Drug (AWP)		
Mean (se)	$1,026 (147)	$1,922 (53)
Percent with expenditure	91.9%	95.3%
Mean (se) among those with any expenditure	$1,117 (154)	$2,018 (54)
Medicare A & B		
Mean (se)	$2,911 (712)	$4,220 (253)
Percent with expenditure	100.0%	95.8%
Mean(se) among those with any expenditure	$2,911 (712)	$4,407 (263)
Inpatient Medicare		
Mean (se)	$1,054 (547)	$1,773 (168)
Percent with expenditure	14.5%	16.9%
Mean (se) among those with any expenditure	$7,260 (3,178)	$10,477 (735)
Physician Medicare		
Mean (se)	$998 (158)	$1,584 (74)
Percent with expenditure	100.0%	94.8%
Mean (se) among those with any expenditure	$998 (158)	$1,671 (77)

Source: Medicare Current Beneficiary Survey, 1999-2000

Exhibit 1.4

Univariate Statistics on Total Drug and Medicare Expenditures Among MCBS Sample Beneficiaries with COPD with and without Drug Coverage

2000 Expenditures	Supplemental Insurance with No Drug Coverage (Unweighted N=78)	Supplemental Insurance with Full-year Drug Coverage (Unweighted N=384)
Drug (AWP)		
Mean (se)	$1,536 (138)	$2,760 (192)
Percent with expenditure	96.2%	99.2%
Mean (se) among those with any expenditure	$1,597 (139)	$2,781 (193)
Medicare A & B		
Mean (se)	$7,243 (1,231)	$6,751 (637)
Percent with expenditure	100.0%	99.7%
Mean (se) among those with any expenditure	$7,243 (1231)	$6,769 (638)
Inpatient Medicare		
Mean (se)	$2,670 (723)	$2,864 (386)
Percent with expenditure	32.1%	26.6%
Mean (se) among those with any expenditure	$8,330 (1,807)	$10,780 (1,135)
Physician Medicare		
Mean (se)	$2,375 (336)	$1,889 (138)
Percent with expenditure	100.0%	98.2%
Mean (se) among those with any expenditure	$2,375 (336)	$1,924 (140)

Source: Medicare Current Beneficiary Survey, 1999-2000

Exhibit 1.5

Differences in Drug and Medicare Expenditures Among Beneficiaries with and without Drug Coverage Across the Three MCBS Study Samples, 1999-2000

Expenditures	Difference in Expenditures (Drug Coverage vs. No Drug Coverage)		
	Unadjusted Difference	GLM Adjusted Difference	Propensity Adjusted Difference
All Beneficiaries			
Drug (AWP)	+94%*	+49%*	+66%*
Medicare A & B	+27%	+6%	-2%
Inpatient Medicare	+14%	-2%	-14%
Beneficiaries with Employer-sponsored Health Insurance			
Drug (AWP)	+87%*	+58%*	+74%*
Medicare A & B	+45%	+21%	+25%
Inpatient Medicare	+68%	+36%	+42%
Physician Medicare	+59%*	+32%	+40%
Beneficiaries with COPD			
Drug (AWP)	+80%*	+37%*	+61%*
Medicare A & B	-7%	-40%*	-25%
Inpatient Medicare	+7%	-63%	-23%
Physician Medicare	-20%	-35%*	-29%*

Source: Medicare Current Beneficiary Survey, 1999-2000
* $p < 0.05$

Exhibit 1.6

Differences in Drug and Medicare Expenditures Among Beneficiaries with and without Drug Coverage Across the Three MCBS Study Samples, Pooled Data for 1996-2000

	Difference in Expenditures (Drug Coverage Vs. No Drug Coverage)		
Expenditures	**Unadjusted Difference**	**GLM Adjusted Difference**	**Propensity Adjusted Difference**
All Beneficiaries			
Drug (AWP)	+93%*	+49%*	+67%*
Medicare A & B	+19%*	+7%	+3%
Inpatient Medicare	+12%	+3%	-3%
Physician Medicare	+16%*	+7%	+6%
Beneficiaries with Employer-sponsored Health Insurance			
Drug (AWP)	+72%*	+45%*	+58%*
Medicare A & B	+13%	+23%*	+16%
Inpatient Medicare	+22%	+37%	+24%
Physician Medicare	+19%	+13%	+13%
Beneficiaries with COPD			
Drug (AWP)	+68%*	+37%*	+54%*
Medicare A & B	+6%	-5%	+0.2%
Inpatient Medicare	+5%	-7%	-5%
Physician Medicare	-2%	-11%	-9%

Source: Medicare Current Beneficiary Survey, 1996-2000
* $p < 0.05$

Exhibit 1.7

Sample Size and Characteristics of 2-Year Panels for the Longitudinal Switching Analysis, n=20,554

	Status of Drug Coverage During 2 years							
Sample Size (unweighted)	**Always Had**		**Lost**		**Gained**		**Never Had**	
Total (n)	**12,066**		**1,275**		**1,488**		**4,366**	
Panel y9596	2168		240		282		960	
Panel y9697	2291		232		269		951	
Panel y9798	2490		260		308		900	
Panel y9899	2537		287		311		839	
Panel y9900	2580		256		318		716	
Baseline Characteristics								
Gender	**(n)**	**%**	**(n)**	**%**	**(n)**	**%**	**(n)**	**%**
Male	5,117	42.4	544	42.7	617	41.5	1,709	39.1
Female	6,949	57.6	731	57.3	871	58.5	2,657	60.9
Age								
<65	2,280	18.9	99	7.8	145	9.7	100	2.3
65-69	1,525	12.6	159	12.5	165	11.1	430	9.8
70-74	2,733	22.7	299	23.5	359	24.1	1,004	23.0
75-79	2,210	18.3	246	19.3	290	19.5	921	21.1
80+	3,318	27.5	472	37.0	529	35.6	1,911	43.8
Medicare Entitlement Status								
Not disabled	9,825	81.4	1,177	92.3	1,345	90.4	4,265	97.7
Disabled	2,241	18.6	98	7.7	143	9.6	101	2.3
Medicare Entitlement Status								
Only Aged	11,218	93.0	1,199	94.0	1,400	94.1	4,203	96.3
Aged but previous disabled	848	7.0	76	6.0	88	5.9	163	3.7
Metropolitan Status								
Non-metro area	3,484	28.9	445	34.9	532	35.8	1,819	41.7
Metro area	8,582	71.1	830	65.1	956	64.2	2,547	58.3
Detailed Census Region								
New England	388	3.2	41	3.2	59	4.0	117	2.7
Middle Atlantic	2,217	18.4	212	16.6	247	16.6	537	12.3
East North Central	2,183	18.1	247	19.4	259	17.4	897	20.5
West North Central	655	5.4	104	8.2	119	8.0	587	13.4
East South Central	694	5.8	84	6.6	102	6.9	341	7.8
West South Central	1,225	10.2	120	9.4	159	10.7	471	10.8
Mountain	622	5.2	65	5.1	82	5.5	229	5.2
Pacific	1,350	11.2	97	7.6	135	9.1	285	6.5
South Atlantic	2,732	22.6	305	23.9	326	21.9	902	20.7
Ybase								
Panel average	12,408.99		10,746.39		11,102.36		10,799.07	

Source: Medicare Current Beneficiary Survey, 1995-2000

Exhibit 1.8

Univariate Statistics on Annual Drug and Medicare Expenditures by MCBS Beneficiaries in the Longitudinal Panel Sample by Drug Coverage Status

	Status of Drug Coverage During 2years							
Medical Expenditures	**Always Had (Unweighted N=12,066)**		**Lost (Unweighted N=1,275)**		**Gained (Unweighted N=1,488)**		**Never Had (Unweighted N=4,366)**	
Drug								
Mean (se)	$1,082	(13)	$682	(25)	$711	(26)	$565	(10)
Percent with expenditures	92.9%		85.7%		86.9%		88.2%	
Mean(se) among those with any expenditures	$1,165	(13)	$795	(28)	$818	(29)	$641	(10)
Inpatient Medicare								
Mean (se)	$1,814	(57)	$1,276	(118)	$1,560	158)	$1,527	(84)
Percent with expenditures	18.0%		14.8%		16.9%		16.0%	
Mean (se) among those with any expenditures	$10,103	(246)	$8,608	(548)	$9,247	(773)	$9,549	(404)
Physician/Supplier Medicare								
Mean (se)	$1,151	(17)	$1,050	(47)	$1,006	(38)	$1,024	(24)
Percent with expenditures	91.6%		90.0%		89.9%		92.0%	
Mean (se)among those with any expenditures	$1,256	(18)	$1,168	(51)	$1,119	(41)	$1,114	(25)

Source: Medicare Current Beneficiary Survey, 1995-2000

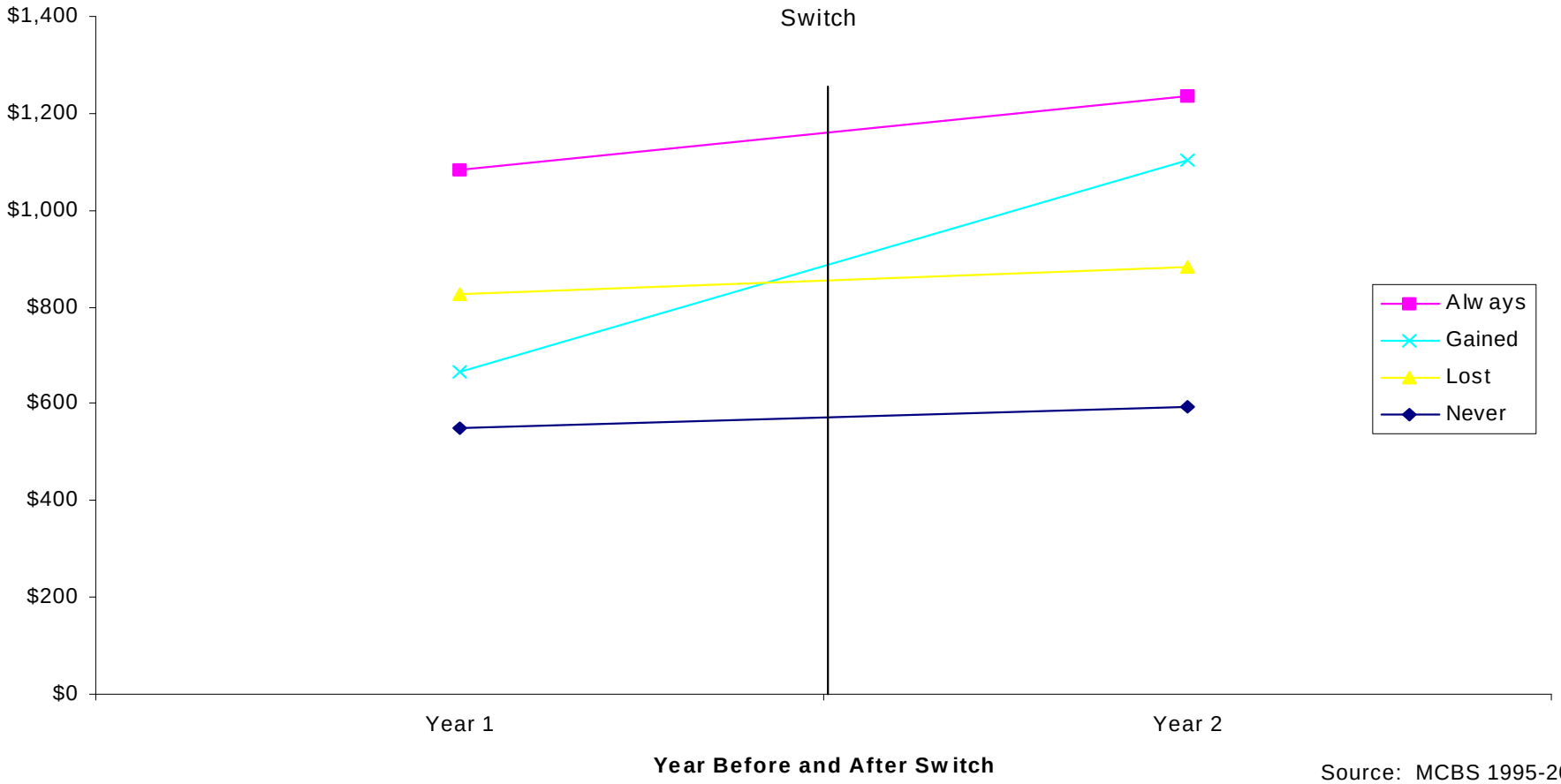
Exhibit 1.9

Sample Size and Average Annual Drug Spending Before and After Drug Coverage Switch for MCBS Beneficiaries with Calendar-End Changes in Drug Coverage

Sample Size (unweighted)	Year Before Switch	Year After Switch	Difference
N	**499**	**499**	**–**
Always	237	237	–
Lost	25	25	–
Gained	60	60	–
Never	177	177	–
Average Rx Spending	**$830.3694**	**$973.1665**	**+17.2%**
Always	1084.16	1234.15	+13.8%
Lost	824.96	883.69	+7.1%
Gained	664.18	1101.28	+65.8%
Never	547.65	592.93	+8.3%

Source: Medicare Current Beneficiary Survey, 1995-2000

Exhibit 1.10
Average Annual Drug Spending Before and After Drug Coverage Switch for Calendar-End Changes



Source: MCBS 1995-2000

Exhibit 1.11
Unadjusted Average Monthly Inpatient Hospital Spending
Before and After Drug Coverage Switch for Losers vs. Always Covered

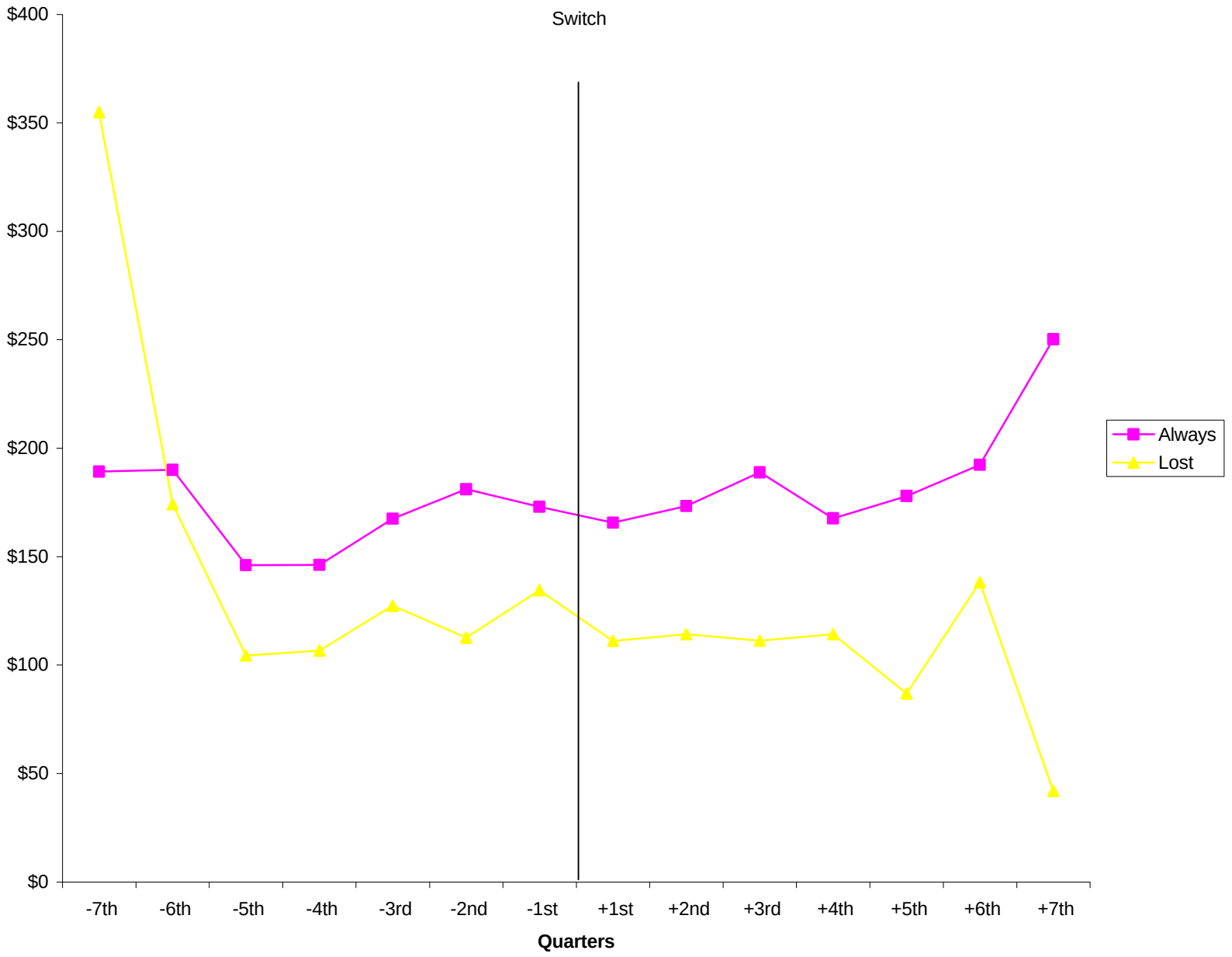


Exhibit 1.12
Unadjusted Average Monthly Inpatient Hospital Spending
Before and After Drug Coverage Switch for Gainers vs. Never Covered

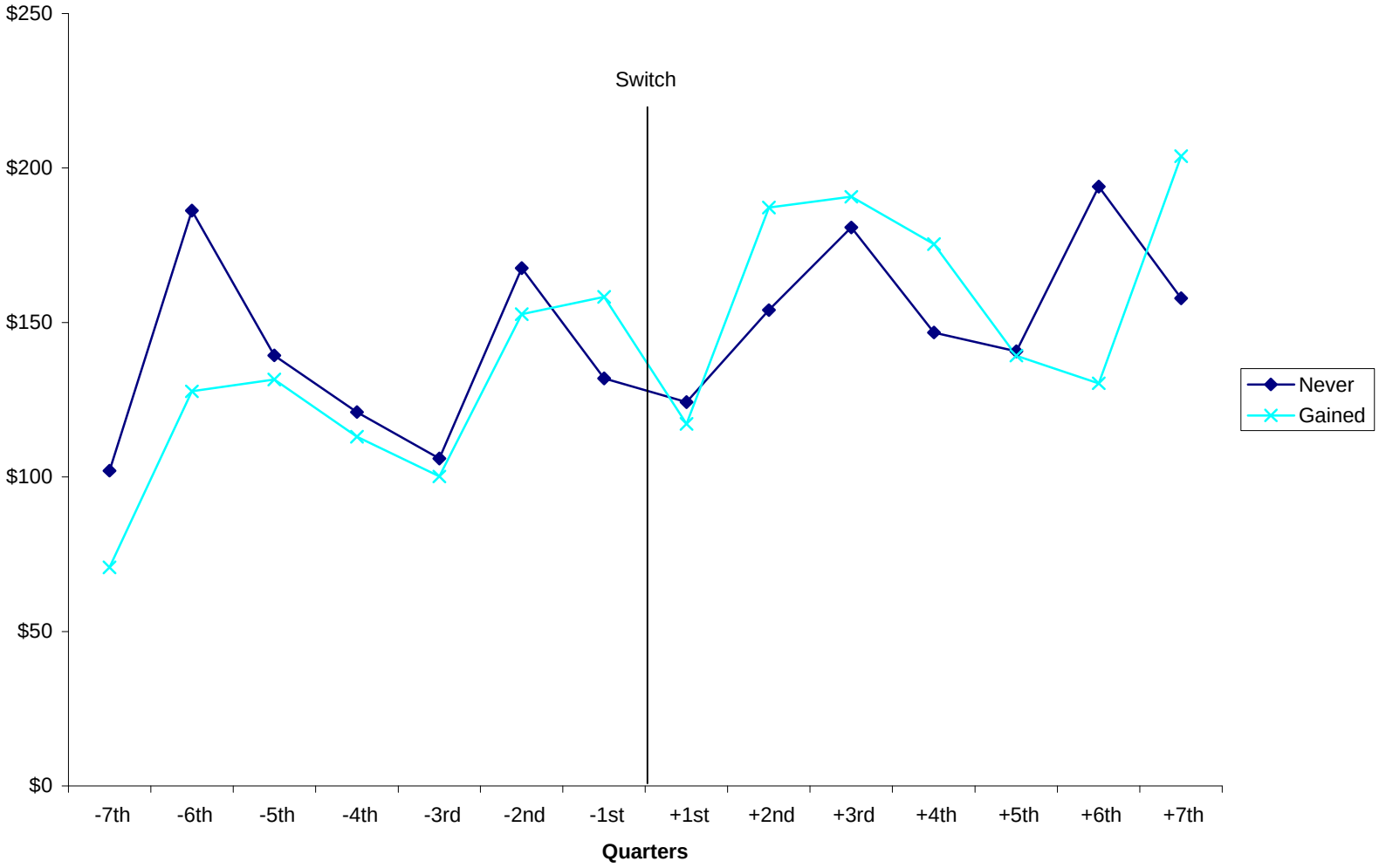
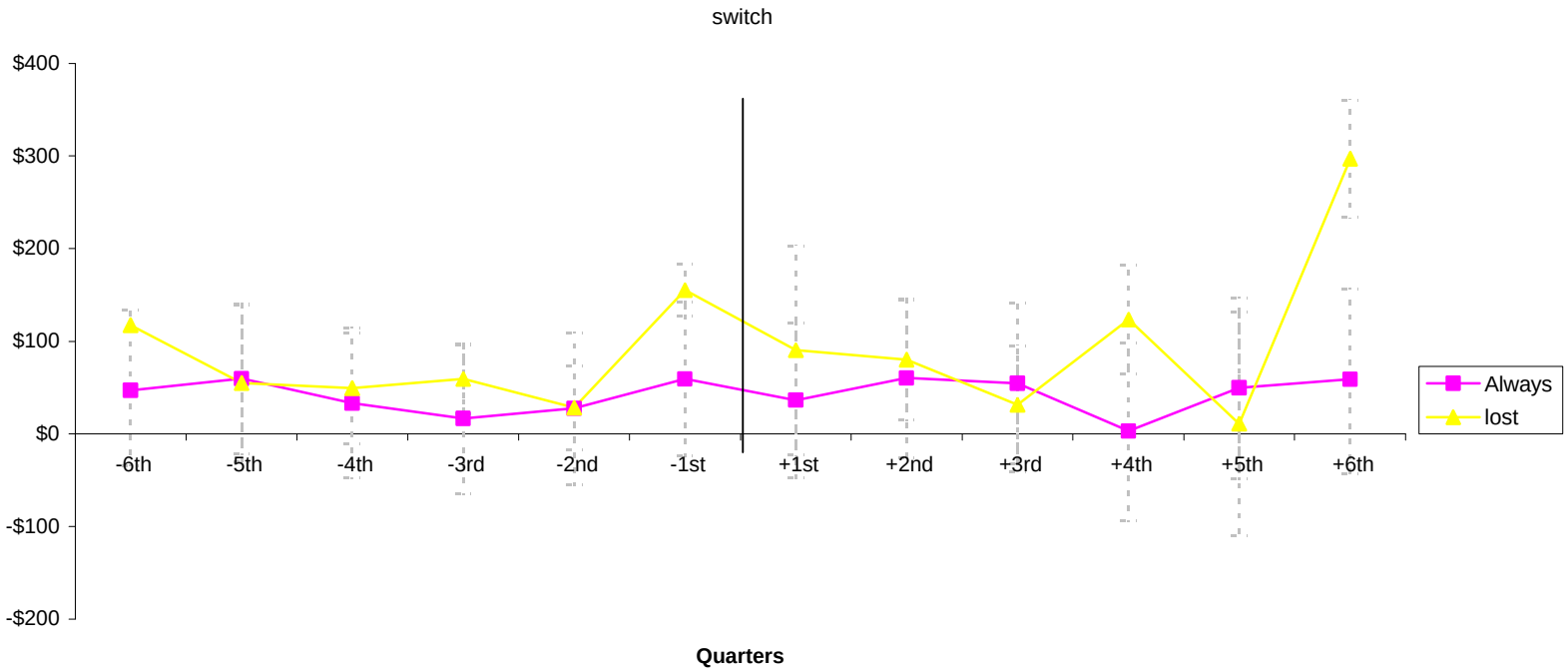


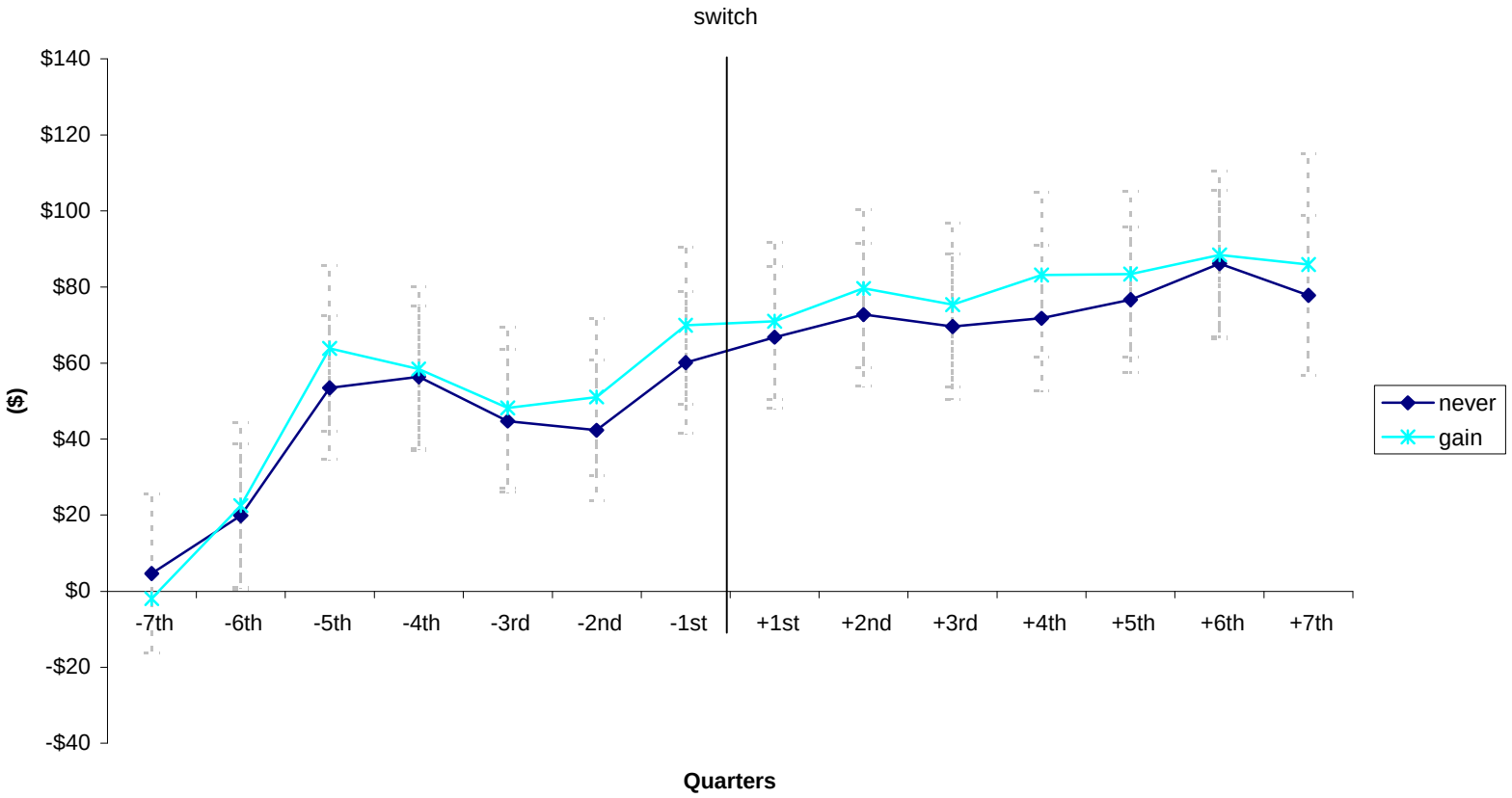
Exhibit 1.13
Adjusted* Average Monthly Changes in Inpatient Spending
Before and After Drug Coverage Switch for Losers vs. Always



*Adjusted for year, age, marital status, income urban residence, health status, and individual effects.

Dashed lines are 95% confidence intervals.

Exhibit 1.14
Adjusted* Average Monthly Changes in Physician/Supplier Spending Before and After Drug Coverage Switch for Gainers vs. Nevers



*Adjusted for year, age, marital status, income, urban residence, health status, and fixed effects.

Dashed lines are 95% confidence intervals.

Exhibit 1.15
Unadjusted Average Monthly Physician/Supplier Spending
Before and After Drug Coverage Switch for Losers vs. Always Covered

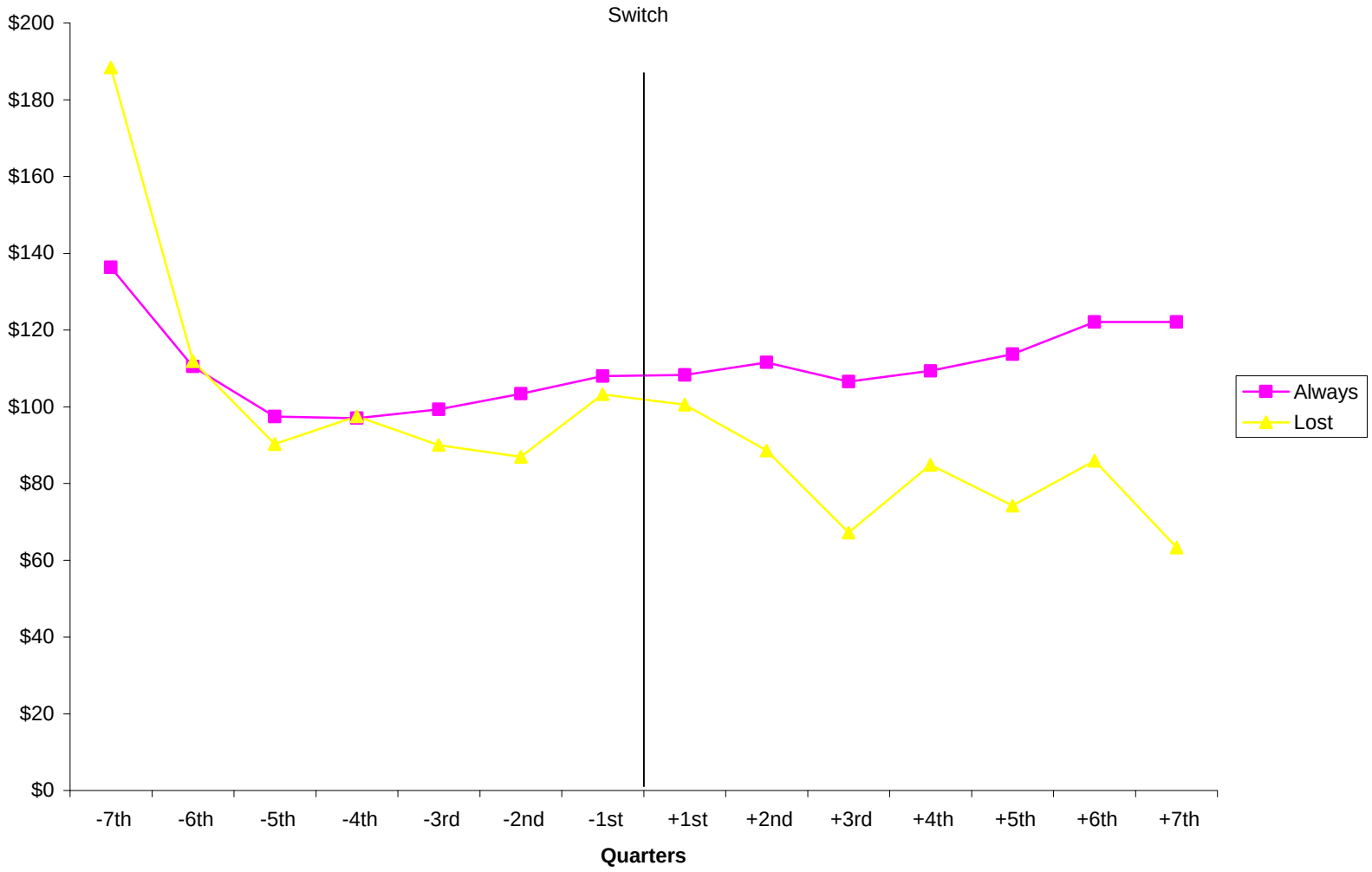


Exhibit 1.16
Unadjusted Average Monthly Physician/Supplier Spending
Before and After Drug Coverage Switch for Gainers vs. Never Covered

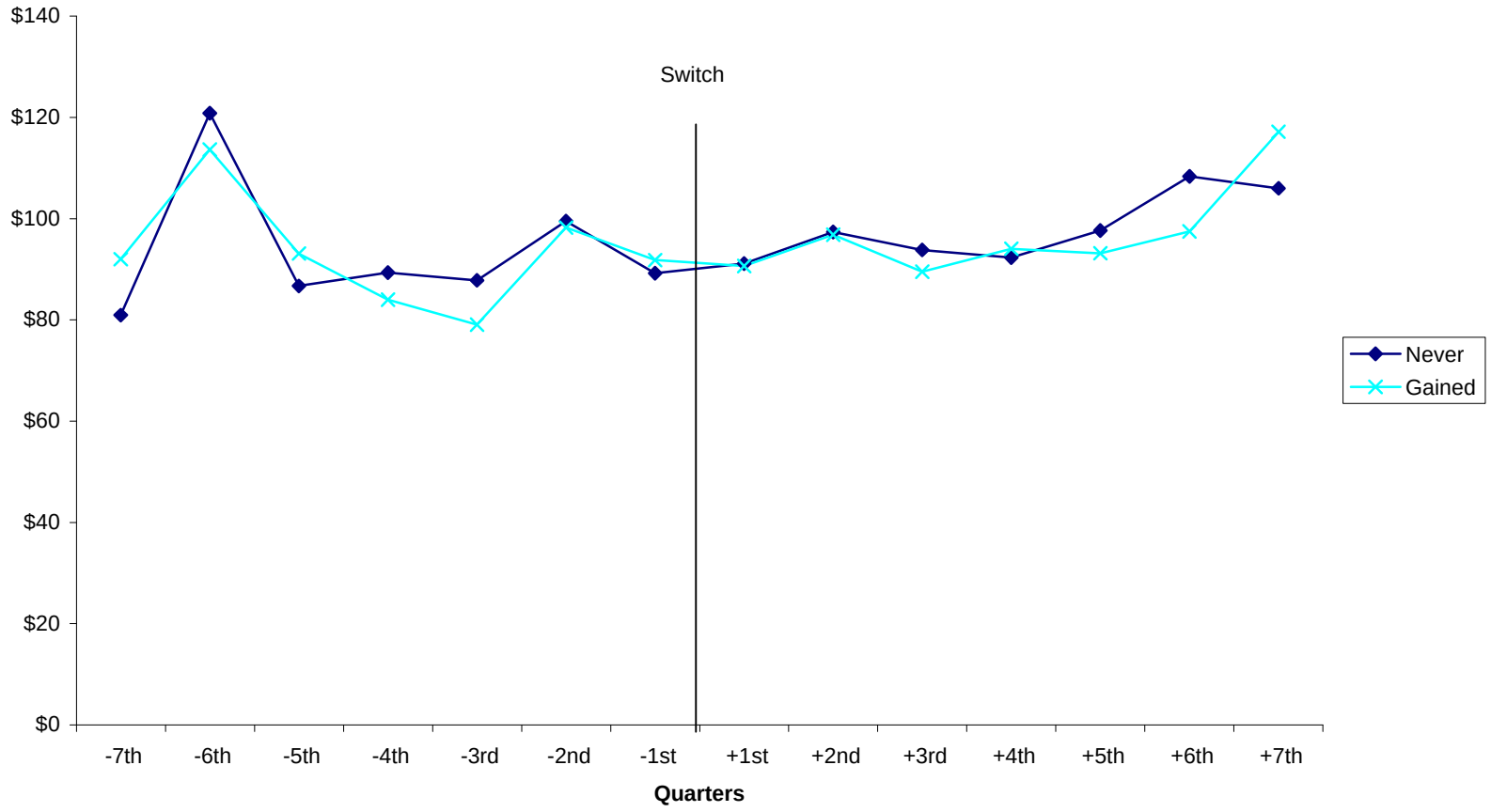
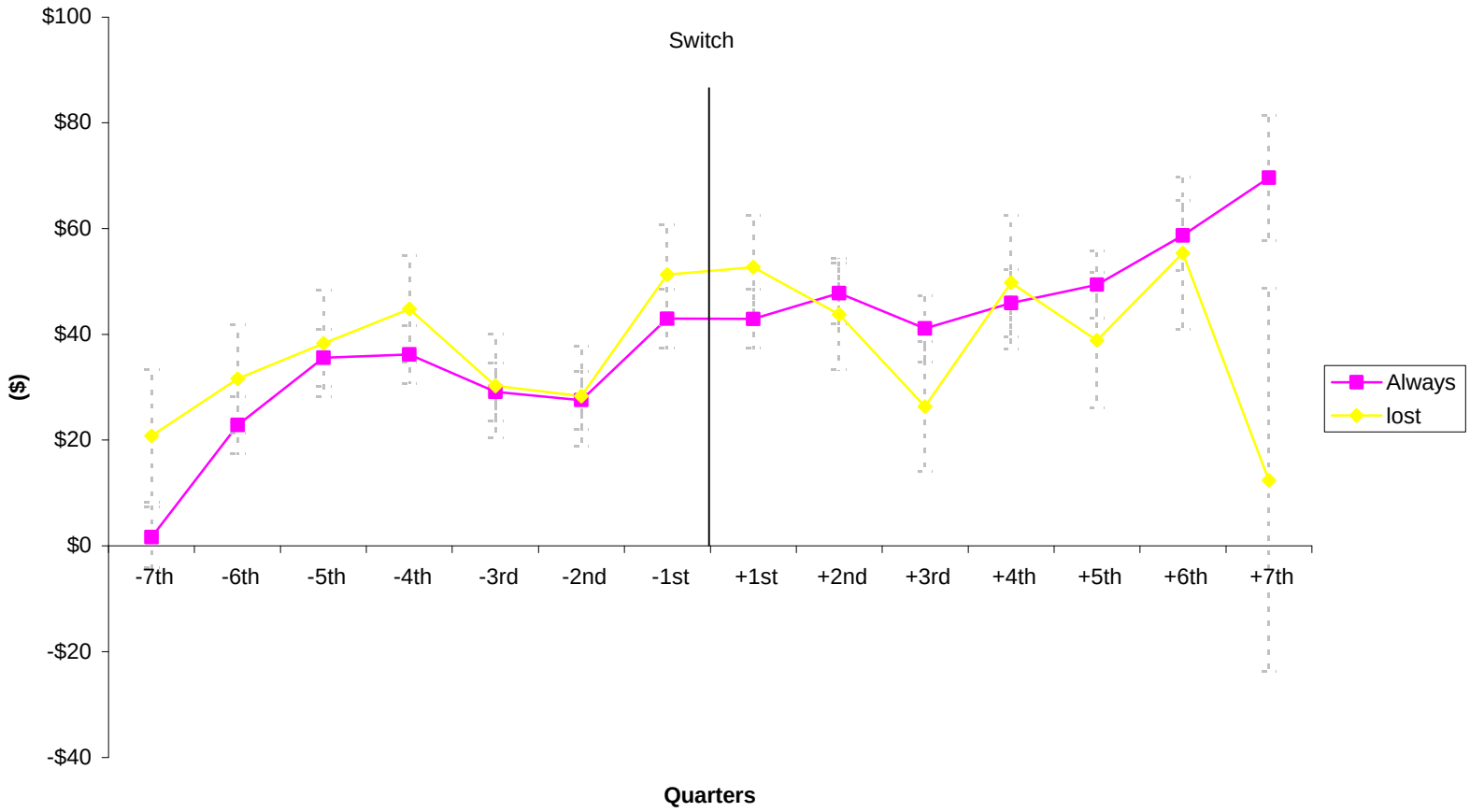


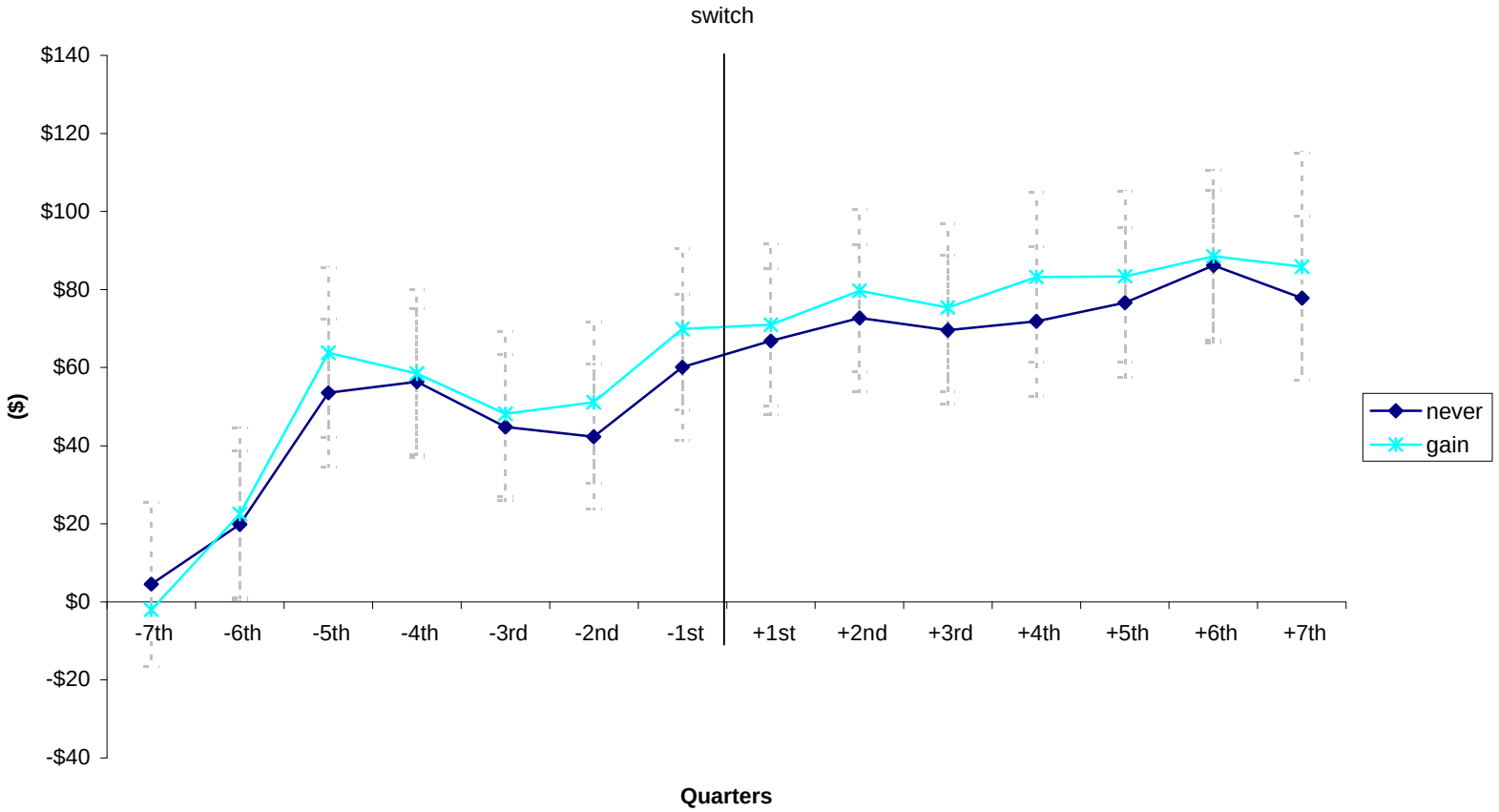
Exhibit 1.17
Adjusted* Average Monthly Changes in Physician/Supplier Spending Before and After Drug Coverage Switch for Losers vs. Always



*Adjusted for year, age, marital status, income urban residence, health status, and fixed effects.

Dashed lines are 95% confidence intervals.

Exhibit 1.18
Adjusted* Average Monthly Changes in Physician/Supplier Spending Before and After Drug Coverage Switch for Gainers vs. Nevers



*Adjusted for year, age, marital status, income urban residence, health status, and fixed effects.

Dashed lines are 95% confidence intervals.

Exhibit 1.19

Differences in Annual Drug and Medicare Expenditures Among MCBS Beneficiaries in the Longitudinal Sample by Switching Status

	Difference in Expenditures (Always Had Coverage vs. Lost it)		Difference in Expenditures (Gained Drug Coverage vs. Never Had)	
Expenditures	**Unadjusted Difference***	**Fixed Effects Adjusted Difference****	**Unadjusted Difference**	**Fixed Effects Adjusted Difference**
All Beneficiaries				
Drug	+$91	----	+$391	----
Inpatient hospital	+$711	+95	+$215	-$176
Physician	+$370	+$77	+$18	-$32

* Estimate calculated as pre-post difference in spending for persons with drug coverage minus per-post difference in spending for persons without drug coverage.

** Adjusted for year, age, marital status, income, urban residence, health status

Source: Medicare Current Beneficiary Survey, 1995–2000

2.0 Aim 2: Design Issues

2.1 Background and Aims

This study addresses design issues for the evaluation of prescription drug programs, specifically for the evaluation of the United Mineworkers of America (UMWA) demonstration. This demonstration, funded by CMS, provides partial funding for a drug benefit for the UMWA retirees, and the Congress has mandated an evaluation. In this study, the authors present and assess two procedures that could be used to select comparison groups for this evaluation.

2.1.1 The United Mineworkers of America Demonstration and Evaluation

The UMWA Health and Retirement Funds cover about 73,000 people, 90 percent of whom are Medicare beneficiaries. The Health Care Financing Administration (now CMS) awarded a demonstration to the UMWA Health and Retirement Funds to provide 27 percent of the Funds' prescription drug costs for the period July 1, 2001 to June 30, 2004. This demonstration, entitled "An Integrated Care Coordination/Management Program for an Elderly, Chronically, Ill Population," supplemented an existing demonstration of Part A risk sharing and Part B capitation involving the Funds.

The UMWA evaluation would examine whether providing, structuring, and managing an outpatient prescription drug benefit would contribute to more effective utilization and more economic provision of services covered under Parts A and B of Medicare. The evaluation would not address the related issue of the effect of the drug benefit on prescription drug expenditures because the source of data for the evaluation, Medicare enrollment and claims data, does not contain information on these expenditures.

For the current study, the authors assume that the evaluation of the UMWA demonstration would proceed in four steps:

1) Identify a comparison group and draw the comparison sample using data available in the Medicare drug claims (and possibly from the UMWA demonstration). Create an analytic data set using claims data that includes Medicare expenditures, basic demographic characteristics, and measures of disease burden.

2) Use the difference in expenditures between the UMWA beneficiaries and the comparison group to estimate the impact on per capita medical expenditures of universal coverage with the UMWA benefit package relative to the (unmeasured) level of drug coverage and other supplemental coverage in the comparison group;

3) Use a survey to establish the levels of drug coverage and other supplemental coverage in the comparison group; and

4) Use the results of steps 2 and 3 to infer the effects of the UMWA benefit package relative to either A) no drug coverage and no other supplemental coverage, i.e. Medicare only, or B) supplemental coverage but no drug coverage.

There are several necessary conditions for these methods to provide unbiased and well-measured parameter estimates. First, in order to attribute differences in spending to differences in coverage, the comparison group for the evaluation must have different levels of drug and supplemental coverage from the UMWA beneficiaries but be otherwise similar in terms of factors that affect spending. This comparison group must be identified and the study conducted using the Medicare claims and enrollment files because these are the data available.

There are significant concerns surrounding the credibility of the comparison group because the UMWA membership is quite distinct from the rest of the Medicare population. They are geographically concentrated. Most (78%) reside in five states: West Virginia, Pennsylvania, Kentucky, Virginia and Ohio.[15] Their health status is poor and their health services utilization is high. On average in 1997, UMWA beneficiaries used 47.2 prescriptions and had drug costs of $1,335. These levels are nearly double the national rates for community-dwelling Medicare beneficiaries with any prescription coverage: 23.4 prescriptions and $835 total prescription spending in 1997. In addition, the miners themselves have high rates of occupationally-related disease such as black lung; this problem is presumably less acute for miners' spouses. While some of these characteristics can be measured and matched using the Medicare claims; the concern is that there are other important characteristics that can not be measured and matched but may differ between the two groups and bias estimates of the demonstration effect.

Second, in order to separately identify the effects of prescription drug coverage and other supplemental coverage, the evaluation potentially needs two comparison groups. Estimating the marginal effect of drug coverage when supplemental coverage is present calls for a comparison group with no drug coverage but with supplemental coverage similar to that provided by the UMWA. Presumably, this would be employer-provided supplemental coverage because "source of coverage" is normally the best available proxy for generosity. Estimating the effect of drug and supplemental coverage together would require a comparison group with neither drug nor supplemental coverage. As a result, expected coverage rates in the comparison group become critical.

Third, the evaluation must address selection bias. Adverse selection is the tendency of individuals with higher expected need for health care services to also have rates of insurance coverage due to voluntary purchase. If one attempts to estimate the effect of insurance by comparing rates of service utilization between the insured and the uninsured, the estimate is biased because it combines the insurance effect with the selection effect (an "effect" that stems not from insurance but from underlying differences in the population.)

For comparison A) above (UMWA coverage relative to neither supplemental nor drug coverage), these issues are clearly significant and highly challenging. The options are either to use measured covariates, including measures of disease burden, to control for selection as the authors did in previous work (Stuart et al. 2003) or to treat UMWA coverage as an instrumental variable. The former option is questionable because of concerns regarding bias due to unmeasured variables. The latter option is questionable because the ideal instrumental variable, in this case, would affect coverage but not expenditures, and "being a UMWA beneficiary" does not appear to meet the latter

[15] See CMS, 2002 for additional information concerning the UWMA beneficiaries. The current study is based on the Medicare Current Beneficiary Survey which has only a very limited number of UMWA beneficiaries.

criterion. Moreover, equations predicting whether an individual is a UMWA beneficiary are likely to have low predictive power leading to poorly measured parameter estimates.

For comparison B), (UMWA coverage relative to employer-provided supplemental coverage but not employer-provided drug coverage) selection issues seem more manageable. It seems reasonable to individual choice is less of an issue with employer-provided supplemental coverage than with supplemental coverage as a whole and hence adverse selection is relatively mild. Moreover, this selection should be similar between UMWA beneficiaries and others with employer-provided coverage so that it should not bias comparisons. Given the paucity of stand-alone drug coverage, it also seems reasonable to assume that, within a population with employer-provided supplemental coverage, selection into drug coverage is low. Either individuals also have access to drug coverage and enroll, or they do not have access into drug coverage and go without. In this setting, matching on covariates and including covariates in estimation equations should be an adequate approach to selection. For the remainder of the study, the authors assume that the UMWA evaluation will focus on comparison B).

2.2 Analytic Approach

This study uses MCBS data to develop two possible procedures for comparison group selection and to assess these procedures. The advantage of using the MCBS (rather than Medicare data) is the presence of data regarding drug and supplemental coverage and drug utilization. The disadvantage is the relatively small sample size and the resulting need to use a broader base group than the UMWA beneficiaries to develop the procedure. The authors use these data to develop procedures for comparison group selection that could be used in Medicare claims and enrollment data and then to assess those procedures using the wider set of variables that are present in the MCBS but not the Medicare files. In particular, we analyze whether base and comparison groups have similar drug and Medicare expenditures when drug and supplemental coverage are held constant. We also assess the rates of drug and supplemental coverage in comparison groups selected in this way.

In the UMWA evaluation, it may be more feasible to select a comparison group for female beneficiaries of the Funds than for male beneficiaries. The disease profile of the predominantly male miners may be very difficult to capture and match using claims data, while the disease profile of their predominantly female spouses may be closer to national norms. For this reason, males and females were treated as two separate samples and all analyses were conducted separately for each.

The analytic approach consisted of the following steps:

Choose base group: The first step was to define a base group – this was the group for which a comparison group was created. Initially, the authors identified 64 UMWA beneficiaries in the MCBS. [16] (Appendix A.) This group was deemed unsuitable for the analyses because the sample size was too small for statistical assessment and only a small minority had Medicare claims in the MCBS.[17] (The MCBS treats UMWA members as managed care enrollees). Instead, we elected to

[16] This calculation was based on an extended study sample which included individuals enrolled in managed care organizations.

[17] Medicare claims could have been available via the UMWA Health and Retirement Funds; however the authors did not pursue them, given the small number of observations.

create a comparable base group for the analysis using the following criteria: 1) evidence of employment in mining and 2) no Medicare+Choice enrollment. (The MCBS provides standard industry codes for current or former employers who provide supplemental coverage to sample members.) This approach identified 158 sample persons. The authors determined that this group was still too small for valid statistical assessment so the industry selection criterion was broadened to include jobs either in mining or involving physically demanding outdoor work. This decision expanded the base group to 652 sample persons. This base group was dubbed the "miner-plus" group and used in the study.

Identify leading statistical approaches to comparison group selection: Drawing on a literature review, the authors defined two general methodologies for comparison group selection. The first of these was based on matching according to estimated propensity scores. A propensity score is the estimated probability of being a member of treatment base group, given a vector of predictor variables X_i. If observations with characteristics X_i. are assigned to treatment and comparison groups with the probabilities represented by the propensity scores, then sets of treatment and comparison observations with the same propensity scores will, in expectation, have the same distribution of X_is. Hence, any differences in outcomes between the treatment and comparison samples cannot be due to differences in these observed covariates. Propensity methods enable the analyst to reconcile variation across a very large number of independent variables still establish probabilistically equivalent groups. The use of the propensity score in constructing comparison groups in observational studies is widely accepted in literature.[18] The approach has two limitations: the potential for bias due to unobserved variables, and the potential likelihood of not finding an adequate match for each subject in treatment group.

The second approach to comparison group selection was a matched pair design. Often, propensity-match methods are used in settings in which exact match comparison groups are impossible (or require limiting the number of independent variables) because the number of independent variables is large relative to the size of the population that can be sampled. In the UMWA evaluation, a matched pairs design may be appropriate because the number of independent variables is relatively small (depending on how medical conditions are measured) and the population of Medicare beneficiaries that can be sampled is large. This approach shares the limitations described above but requires fewer assumptions regarding functional form than does the propensity-matching approach.

Select key variables for matching or propensity score algorithms: The key issue here was to identify variables that both differed between the miner-plus group and the Medicare population as a whole and were predictive of drug and Medicare expenditures. This work drew on the authors' prior experience estimating Medicare expenditure equations. (Briesacher et al., 2003). The set was limited to variables that were included in Medicare enrollment and claims files because that was the set of variables that would be available to the ultimate evaluation.

In this setting, measures of disease burden were essential yet problematic. The UMWA beneficiaries are known to have a high burden of disease and known to have a very high prevalence of specific conditions, such as black lung. However, such measures are potentially endogenous. If a drug

[18] See Rubin, 2001; Rubin and Thomas, 2000; Dehejia & Wahba, 1998; Rosenbaum, 1995; and Rosenbaum & Rubin, 1983, 1985 for additional discussion of the implementation and advantages of propensity-score matching.

benefit (or supplemental benefit) has been in place for some time, lagged measures of disease may actually reflect its impact so that expenditure equations might show no impact even though one was present. The ideal was to find measures of disease burden that incorporated differences due to natural or occupational causes but not due to differential access to care, notably differential insurance coverage.

The measure selected, YBASE, stems from the Diagnostic Cost Group Hierarchical Condition Category (DCG/HCC) risk adjuster, developed by Health Economics Research Inc. under contract with CMS. The DCG/HCC is the current CMS methodology for predicting Medicare expenditures and is the basis for the "selected significant disease model" that will be used to reimburse the Medicare+Choice plans starting in January, 2004. In the current application, the HCC software created indicators for the presence of 189 medical conditions based on the diagnoses recorded on a patient's Medicare claims (physician, outpatient, and inpatient).[19] It then applied previously calibrated weights (based on regression coefficients) to approximately 100 of these conditions to create a single risk score (denoted YBASE) that is proportional to the patient's expected Medicare expenditure in the study year, given the medical conditions observed in that same year.

The DCG/HCC risk adjustment measure effectively controls for the prevalence of disease but not its severity or the intensity of its treatment. In the authors' opinion, this risk adjuster offers the best feasible balance between controlling for differences in disease burden due to natural and occupational causes and not controlling away any effect of insurance coverage. It is also a reasonable control for selection because it captures the diagnoses that influence expenditures but may also influence individuals' decisions to enroll in insurance. In the UMWA evaluation, it would potentially allow for a full and unbiased estimate of the effect of drug coverage on expenditures if one accepted the assumptions that coverage affects the use of services conditional on diagnoses but does not affect the diagnoses themselves.

Use leading methodology to select trial comparison groups: We then created two comparison groups for the miner-plus group, one using propensity score matching and one using the exact match technique. We note that this was an imperfect replication of the process using the Medicare claims because the potential for geographic matching would be much greater in the claims.

Take advantage of MCBS variables to evaluate trial comparison groups: Once the trial comparison groups were selected, the authors took advantage of the rich data on the MCBS (relative to the claims) to evaluate whether the trial comparison groups did indeed provide a good match for the base group. One set of analyses (relevant primarily for the propensity-score approach) concerned the quality of the match between the miner-plus and comparison groups on predictor variables.

The second set of analyses concerned prescription drug expenditures and expenditures covered by Part A and B of Medicare. An evaluation of the UMWA benefit that used a comparison group would require an assumption that, absent differences in drug coverage, Medicare expenditures for the UMWA members and the comparison group would be similar. For the miner-plus group and the trial comparison groups in the MCBS, it is possible to test this assumption directly by comparing the members of each comparison group with drug and supplemental coverage to the corresponding subset of members of the miner-plus group. If one observes differences in Medicare-covered

[19] See Ash, Ellis, and Pope, 2002 for a more thorough discussion of these models.

expenditures between these two groups, controlling for insurance coverage, then this is *prima facie* evidence that the matching procedure did not provide an appropriate comparison group. Note that this comparison is only valid if one assumes that the levels of adverse selection and the generosity of the drug and supplemental coverage are identical in the base and comparison groups.

The study examined drug expenditures in addition to Medicare-covered expenditures. While the UMWA evaluation would probably not be able to compare drug expenditures in the UMWA and comparison groups due to a lack of data on drug expenditures for the comparison group, any hypothesis concerning an impact of drug coverage on Medicare expenditures necessarily breaks down into a hypothesis concerning an impact of drug coverage on drug utilization (and expenditures) and one concerning an impact of drug utilization on other Medicare-covered utilization (and expenditures). Again, if one observes differences in drug expenditures between the miner-plus and comparison groups, conditional on drug coverage and reasonable adjustments for selection, then this is suggestive evidence against the validity of the matching procedure.

The third analysis concerned the level of benefits in the trial comparison groups selected by each methodology. If all members of the trial comparison group have drug and supplemental coverage and if this coverage is roughly comparable to the UMWA coverage, this suggests that it would not be possible to estimate the impact of the UMWA benefits using a parallel comparison group, even if the comparison group were free of the problem of bias. Moreover rates of drug and supplemental coverage provide a guide to sample sizes needed for the evaluation.

2.3 Methods

2.3.1 Data Source

The Medicare Current Beneficiary Survey (MCBS) Cost and Use files served as the primary dataset for these analyses. This study used data from 1995-2000.

The MCBS is a longitudinal panel survey of a representative national sample of the Medicare population conducted under the auspices of CMS. Begun in the fall of 1991, over 12,000 Medicare beneficiaries, both aged and disabled, living in the community or in institutions are sampled from Medicare enrollment files and surveyed three times a year using computer assisted personal interviewing. MCBS interviewers collect extensive information on each individual's use of and expenditures for health services, including source of payment, as well as information on health insurance, health and functional status, socioeconomic status, and demographic characteristics. The MCBS files link Medicare claims to survey-reported events and provide complete expenditure and source of payment data on all health care services, including those not covered by Medicare, namely prescription drugs and long term care.

This analysis drew on the MCBS survey data for all measures of drug coverage and individual characteristics except the HCC risk adjustment, which came from the diagnostic variables in the appended Medicare claims files. Expenditure data for total Medicare Part A and B spending and prescription spending were taken from the MCBS annual summary files.

2.3.2 Sample Selection Criteria

Study Sample

The following selection criteria were used to create the study sample:

- *Full-year Medicare entitled for both Parts A and B.* A full year of Medicare A and B claims was necessary to establish annual drug and Medicare expenditures and to assign HCC scores. The sample excluded persons who were newly Medicare entitled, persons with Part A but no Part B coverage, and decedents in the study period.
- *Community-dwelling entire year*. Because MCBS does not collect drug expenditure data on institutionalized beneficiaries, the sample excluded all MCBS respondents who were in a long-term care facility for all or part of the year.
- *In fee-for-service Medicare entire year*. There were no Medicare claims data for Medicare+Choice (M+C) enrollees, thus making it impossible to specify the dependent variable or to derive HCC scores. The sample excluded all respondents with any M+C enrollment in the observation year. This requirement was relaxed in order to determine the number of Funds' beneficiaries in the MCBS.
- *Unduplicated observations.* Although an individual may remain in the MCBS for up to four years, the data set only included one observation for each person, based on the most recent year available. This simplified the econometric issues considerably.

The Miner-plus Sample

The miner-plus sample was composed of individuals who received supplemental and drug coverage from a former employer or from a spouse's former employer in one of the following industries: mining (B), construction (C), oil and gas extraction (13), heavy construction excluding building (16), petroleum and coal products (29), railroad transport (40), electric gas and sanitary (49). This resulted in a sample size of 652 observations, 310 males and 352 females. (In the UMWA sample, men tend to receive the coverage via an employer and women via a spouse's former employer. The miner-plus sample may be more balanced.) [20]

The Propensity Match Sample

The study then used two different procedures to create trial comparison groups for the miner-plus group. As discussed above, males and females were analyzed separately. The first of these was matching on propensity scores. When propensity scores are used to create comparison groups, the propensity equation should include variables that both affect expenditures and are thought to differ between the study group and the general population. Based on the authors' prior research regarding determinants of Medicare expenditures and on descriptive statistics for the miner-plus group relative to the full study sample, the authors selected the following equation:

[20] Unfortunately, the project team did not examine this issue.

$$MP_i = a + b_1 X_i + b_2 H_i + e_i$$

with:

MP = an indicator for membership in the miner-plus group

X = basic demographic characteristics including year (6 indicators), age (4 indicator variables), current disability (one indicator), metropolitan status (one indicator), census region (8 indicators)

H = health status/disease burden, measured using the DCG/HCC risk adjustment score (YBASE)[21].

The authors also estimated an alternative version of the propensity score equation that replaced YBASE, the single risk adjustment measure, with indicators for individual conditions. This did not result in significant gains in the fit of the equation so the more parsimonious option was selected.

Once the propensity score equation had been estimated, each individual in the miner-plus sample was matched to three observations with similar propensity scores. These observations comprise the propensity match sample.

The Exact Match Sample

The authors also created an exact match sample. This match was based on six characteristics: MCBS dataset year, age within 5-year increments, disabled Medicare eligibility status, metropolitan residence, geographic residence (8 census regions), and YBASE. These were the same variables that were used to create the propensity scores. In the first stage of the match, each observation received a match code summarizing the first five characteristics. For example, Observation 1 received a match code of 19952790Y05, which shows the person appeared in MCBS year 1995, was female and between the ages of 75 and 79, was not disabled, and lived in a metropolitan area of the south U.S. Atlantic region. These codes were used to sort members of the miner-plus group and members of the remaining sample and to identify pairs with identical match codes. In the second stage, the matching algorithm calculated differences in the YBASE for each pair and selected the miner-plus / non-miner-plus pair with the smallest difference. Based on the number of matches in the first stage, the authors concluded that there were not sufficient exact matches to create a three-to-one comparison sample and opted to use a one-to-one match to ensure the quality of the comparison samples.

Pairs in Which Match has Drug Coverage or Employer-Provided Drug Coverage

The central argument of this study is that if the matching procedure is valid, then, controlling for drug and supplemental coverage, the miner-plus and trial comparison samples will have comparable expenditures. In order to test this hypothesis, it was necessary to create subsamples within each set of matched pairs than held insurance coverage constant. The first subsample consisted of pairs in which the match-member had drug coverage, regardless of the source. The second subsample consisted of pairs in which the match-member has employer-provided drug coverage. Note that for pairs from the propensity match sample, members of the miner-plus group may match to one, two, or three observations with drug coverage or employer-provided drug coverage.

[21] See Chapter 1.0 of this report for the analysis of Medicare expenditures.

2.3.3 Study Variables

The study analyzed three key variables: prescription drug expenditures, expenditures covered by Medicare, and the nature of drug and supplemental coverage. Prescription drug expenditures were measured according to the MCBS' estimated annual drug spending variable. Covered expenditures were drawn from the Medicare claims. Insurance coverage was determined according to beneficiaries' responses to survey questions.

2.3.4 Statistical Methods

Pooled t tests were used to compare mean expenditures between the miner-plus group and the trial comparison groups. Other percentiles of the expenditure distribution were also examined in order to establish the sensitivity of results to outliers. For subsamples of the propensity match group defined according to the insurance coverage in the match group, means and t tests were weighted to reflect the fact that one member of the miner-plus group could be associated with one, two, or three members of the propensity match group.[22]

2.4 Results and Discussion

Sample Sizes and Demographic Characteristics: UMWA Beneficiaries, "Miner" Sample, and "Miner-Plus" Sample

There were 64 observations in the MCBS in which the individual reported receiving supplemental and drug coverage via the UMWA Health and Retirement Funds. (See Appendix 2.A.1.) This number is from the extended study sample that included MCO enrollees. These individuals were geographically concentrated with 53 percent dwelling in the Mid-Atlantic states and 16 percent dwelling in the Mountain states opposed to 16 and 6 percent of the relevant full sample. (Appendix 2.A.2.) Thirty-six percent lived in rural areas.

There were 158 individuals in the MCBS who reported receiving drug and supplemental coverage from a past employer in the mining industry (the miner group). This number was based on the main study sample that required enrollment in fee-for-service Medicare. These observation were also geographically concentrated but in slightly different regions than the UMWA beneficiaries. As Appendix 2.A.3 indicates, 53 percent resided in the West South Central states and 11 percent in the Mountain states as opposed to 11 and 5 percent of the general population and 2 and 16 percent of the miner group. Eleven percent resided in the Mid-Atlantic states - compare to 11 percent of the general population and 53 percent of the UMWA beneficiaries. This group was disproportionately likely to live in rural areas (55 percent as opposed to 33 percent of the general population and 36 percent of the UMWA beneficiaries). The mean of ybase for this group was $5,722.

The sample used as the base group for this study was the miner-plus group, composed of 652 individuals. Like this miner group (which it subsumed), this group tended to be concentrated in the West South Central and Mountain regions, although this concentration was less extreme than for the miner group. Unlike the miner group, this group manifested average rates of living in rural areas. The mean of ybase for this group was $5,803, close to the mean for the miner group.

[22] The authors examined the potential efficiency gains from optimal weighting schemes and determined they were minimal.

These results suggest that the miner group was different from the UMWA group and that the miner-plus group was different from the miner group. Nevertheless, the miner-plus group was used as a base group for this study due to the need for adequate sample size and the reasoning that the core issue was an occupational history that had the potential to bring with it a unique burden of disease.

Analysis of Matching Algorithm

Propensity Match

Standard approaches indicated that the distributions of the individual predictor variables and other key variables were similar between the miner-plus and propensity match samples as desired. The success of propensity matching was assessed by comparing the groups for balance on selected characteristics used for estimating the propensity score equation (Exhibit 2.A.4). Chi-square tests were used for comparing distributions while t-tests were used for means.

Appendix 2.A.4 presents the comparison of characteristics of the male miner-plus group, non-miner-plus group, and propensity match group. The characteristics of the male miner-plus group (N=310) varied widely from those of the non-miner-plus group (N=9,862) on age, disability status, and census region of residence. On the other hand, after a 1:3 propensity score matching, the male miner-plus group and the male propensity match group (N=930) had very similar characteristics.

Similarly, comparing the female miner-plus group (N=342) with the remainder of the female population i.e. non-miner-plus group (N=12,696), indicated significant differences in their characteristics such as age, disability status, census region of residence, and mean Medicare risk score (YBASE). Next, when 3 propensity-score-based female matches were selected (from the non-miner-plus group) for every miner-plus female, complete balance was obtained on all characteristics. Comparison of the female propensity match group (N=1,026) with the female miner-plus group indicated no significant differences across all characteristics. These comparisons indicate that propensity score matching was successful in obtaining balance on key characteristics of the base and comparison groups, for both males and females.

Exact Match

The exact match procedure was successful in the MCBS. In the first stage of the match, 650 of the 652 observations in the miner-plus sample (males and females) matched exactly on all five characteristics.[23] In the second stage of the match, the median absolute difference in the risk adjustment measure between the miner-plus observation and the match observation was $561 (just over one tenth of the associated standard deviation). This indicates that the algorithm was able to match closely but not perfectly on health status. In this stage, the mean absolute difference in the risk adjustment measure, ybase, was $2,344 (just under one half of the associated standard deviation.) This indicates that there were some outlier pairs with large differences in health status.

Drug and Medicare-Covered Expenditures

Among males, when the miner-plus sample was compared to the propensity-match sample, there was a statistically significant gap in mean prescription drug expenditures for all pairs, for pairs in which

[23] Because this was an exact match, all demographic characteristics are identical between miner-plus and comparison groups and no appendix table is provided.

the match member had supplemental and drug coverage (SC/DC pairs), and pairs in which the match member had employer-provided supplemental and drug coverage (employer-provided SC/DC pairs). (See Exhibit 2.1.) In every case, drug expenditures were higher for the miner-plus sample than for the match sample Drug expenditures were also higher for the miner-plus sample (all pairs, SC/DC pairs, and employer-provided SC/DC pairs) at the 99th, 95th, 90th, 75th, 50th, 25th, and 10th percentiles of the drug expenditure distribution. (See Appendix 2.A.5). This indicates that the differences in means do indeed reflect an overall difference in the expenditure distribution rather than a set of large positive outliers among the miner-plus sample.

The magnitude of this gap in means was quite large. In the sample containing all pairs it was $316, 28 percent of the mean for the miner-plus sample. Note that in this case, the gap reflects differences in utilization caused by both differences in the underlying population and differential insurance coverage. In the samples based on employer-provided SC/DC pairs, the gap was still large, $294, 25 percent of the miner-plus mean of $1186.

Similarly, Medicare-covered expenditures were higher for the male miner-plus sample than for the propensity match samples for samples defined by all pairs, SC/DC pairs, and employer-provided SC/SC pairs. The differences in means were not statistically significant but the differences were observed at many but not all points of the expenditure distribution. Specifically they were observed at all listed percentiles except the 75th for all pairs, the 90th and 75th for SC/CD pairs, and the 75th and 50th for employer-provided SC/DC pairs. Again, magnitudes were not trivial: $984 for all pairs, almost 20 percent of the mean for the miner-plus sample; and $737 for pairs in which the match member had employer-provided SC/DC, 15 percent of the miner-plus mean.

Among females, when the miner-plus and propensity-matched samples were compared, there were still statistically significant gaps in prescription drug expenditures for samples defined by all pairs and by SC/DC pairs with the miner-plus sample spending more. This gap persisted but was not statistically significant when the samples were restricted to employer-provided SC/DC pairs. Again, based on a comparison of multiple percentiles of the expenditure distribution, the observed discrepancies seemed to reflect a systematic difference in expenditures rather than the influence of positive outliers. Furthermore, the magnitude was not trivial, $215 for pairs in which the match-member provided-provided coverage, 14 percent of the mean for the miner-plus sample. (This gap was smaller than the corresponding male gap of $294 but the difference is not statistically significant.)

Mean expenditures for Medicare-covered services for females in the miner-plus group were consistently higher than for propensity-matched females, even when the match-member had employer-provided supplemental and drug coverage. Following the precedent in the male case, these differences were not statistically significant but persisted at many (but not all) percentiles of the distribution.

When the miner-plus sample was contrasted with comparison samples created using exact match techniques, results were broadly similar to those described above. (See Exhibit 2.1. Additional Detail in Appendix 2.A.6). For males, the discrepancies in drug expenditures were smaller in magnitude and never statistically significant. In fact, the discrepancy for samples in which the match member had employer-provided SC and DC was only $9. Discrepancies in Medicare expenditures were roughly comparable to those observed in the propensity-matched case.

For females, the discrepancies in drug expenditures were essentially similar between propensity-match comparisons and exact-match comparisons in the all-pairs and SC/DC pairs comparisons. This difference became negative and close to zero (-$13) for samples in which the match member had employer-provided SC and DC. Difference in Medicare expenditures were smaller in the "all pairs" case, similar but much larger in the "SC/DC" and "employer-provided SC/DC" case. Unfortunately, large standard errors make it difficult to draw conclusions regarding these comparisons and regarding the merits of the exact match procedure relative to propensity-matching.

Rates of Drug and Supplemental Coverage

For the UMWA evaluation to provide an estimate of the impact of drug coverage, the ideal would be to compare the Funds' beneficiaries to a matched set of individuals with employer-provided supplemental coverage but with no drug coverage. In the MCBS propensity-matched samples, six percent of males and five percent of females meet this criterion. (Exhibit 2.2.)[24] Rates were identical in the exact-match sample. Note that this implies that very large samples would be needed for the UMWA evaluation because the sample size needed to detect an effect is roughly proportional to the square of the inverse of the proportion of the sample in the sub-population of interest.

2.5 Conclusion

This study defined two procedures that could be used to create comparison groups for the UMWA Health and Retirement Funds' beneficiaries in an evaluation of the UMWA drug benefit. This evaluation would presumably be based on Medicare claims data. The study then used these procedures to create comparison groups for a base group – the miner-plus group, defined as individuals receiving drug and supplemental coverage via previous employers in a range of industries requiring physically demanding outdoor work- using data from the MCBS. (The broader base group was needed because of sample size restrictions in the MCBS.) Finally, the study assessed these two procedures, taking particular advantage of the fact that the MCBS contains data concerning individuals' prescription drug expenditures supplemental and drug coverage (data that are not present in Medicare claims and would not be available to the UMWA evaluation.)

The first of the procedures involved creating propensity scores and matching the comparison group to the miner-plus group using these scores. This is the approach favored by many recent non-experimental evaluations. In brief, this procedure was successful in terms of metrics that compared the base and comparison samples on observable characteristics that would be present in the Medicare claims and would serve as independent variables in predicting Medicare expenditures. However, it was less successful in that, even when supplemental and drug coverage were held constant between the base and comparison samples, the miner-plus group appeared to have higher expenditures that the propensity –matched comparison group. The difference in drug expenditures for males was statistically significant. The differences in drug expenditures for females and in Medicare-covered expenditures for both genders were not statistically significant but the pattern of higher expenditures for the miner-plus group was consistent.

[24] Technically, Exhibit 2.2 captures the percentage of observations with employer-provided supplemental coverage who do not have drug coverage **from an employer**. Because free-standing drug coverage is very rare, it is reasonable to assume that the vast majority of these do not have drug coverage at all.

The second of the procedures involved an exact match. This may be an attractive option for the UMWA evaluation because of the large sample of Medicare beneficiaries and the manageable number of independent variables. Unfortunately, MCBS sample sizes forced the authors to use a one-to-one (rather than a three-to-one match) and the results were too poorly measured to effectively analyze discrepancies in expenditures or to compare this procedure with the propensity match procedure.

In addition, this study established the rates of drug and supplemental coverage within comparison groups created in these ways. Approximately, six percent of males and five percent of females have employer-provided supplemental coverage but not employer-provided drug coverage. This is the group that would be used to estimate the impact of Funds' drug coverage.

This study had several important limitations. First, the base group for this study (the miner-plus group) was not the base group for the ultimate evaluation (the Funds' beneficiaries) and appeared different on several key dimensions. Second, the match procedures used in the MCBS were not as precise as the procedures that could ultimately be used in the Medicare claims. Both geographical matching and the matching on measures of disease burden were not as precise as they might be in work with Medicare claims. Moreover, if desired, the UMWA evaluation could match on specific conditions, such as black lung. Some of the differences currently observed between base and comparison group might be narrowed through the use of more precise matching.

The third limitation is a higher level concern: it is not obvious how best to evaluate the quality of a comparison group. The authors used a combination of established methods related to the match of predictor variables and a unique approach of comparing the dependent variable in a subsamples of observations that held the treatment variable (drug and supplemental coverage) constant between base and comparison groups. Nevertheless, many of the real concerns regarding comparability pertain to variables that are unobserved in both the claims and the MCBS.

At a more practical level, the comparisons that were made, particularly the most important comparison: expenditures for females with supplemental and drug coverage, suffered from low power and large confidence intervals. Finally, while it is hypothesized that when coverage status is held constant, remaining differences in expenditures result from underlying differences in the populations, it is still possible that they result from unmeasured differences in the nature of the insurance coverage (or from differences in the nature of the health system which might be corrected via a more precise geographic match).

Despite its limitations this study makes three important contributions to those interested in the UMWA evaluation. First, it spells out procedures that could be used. Second, it offers a preliminary response to the concern that it may be difficult to find a credible comparison group for the Funds' beneficiaries. Subject to the four limitations mentioned above, results presented here tend to support that concern. Finally, the study analyzed rates of insurance coverage. The rates observed here suggest that there would be a core group of observations in a comparison group that would have employer-provided supplemental coverage but not drug coverage. The rates reported could also be used to establish sample sizes for the ultimate UMWA evaluation.

Exhibits

Exhibit 2.1

Expenditures for Miner-plus and Trial Comparison Groups

	All pairs				Pairs in which match-member has SC& DC				Pairs in which match-member has employer-provided SC&DC			
	Miner-plus	Match	Diff	Stat sig?	Miner-plus	Match	Diff	Stat sig?	Miner-plus	Match	Diff	Stat sig?
Propensity Match, Males												
Mn Drug Exp	$1141	$825	$316	***	$1148	$935	$213	***	$1186	$891	$294	***
Mn Medicare Exp	$5567	$4583	$984	NS	$5562	$4764	$798	NS	$4943	$4205	$737	NS
N	310	930			303	628			228	343		
Propensity Match, Females												
Mn Drug Exp	$1530	$1087	$443	***	$1562	$1270	$292	**	$1582	$1367	$215	NS
Mn Medicare Exp	$4151	$3819	$332	NS	$4184	$4029	$155	NS	$3935	$3419	$516	NS
N	342	1026			320	674			293	218		
Exact Match, Males												
Mn Drug Exp	$1141	$971	$179	NS	$1138	$1191	-$53	NS	$1082	$1073	$9	NS
Mn Medicare Exp	$5567	$4433	$1134	NS	$6101	$5463	$638	NS	$5070	$4644	$426	NS
N	310	309			217	217			120	120		
Exact Match, Females												
Mn Drug Exp	$1530	$1126	$404	***	$1545	$1303	$242	*	$1550	$1563	-$13	NS
Mn Medicare Exp	$4151	$3895	$256	NS	$4277	$3490	$787	NS	$4979	$2902	$2077	NS
N	342	341			226	226			108	108		

Miner-plus– Individuals who receive supplemental and drug coverage via a previous employer in the mining industry (includes spouses). These industries were: mining (MCBS industry code B), construction (C), oil and gas extraction (13), heavy construction excluding building (16), petroleum and coal products (29), railroad transport (40), electric gas and sanitary (49).

SC refers to supplemental coverage, DC to drug coverage.

In subsamples of propensity-matched pairs defined by supplemental and drug coverage or employer-provided supplemental and drug coverage, the N for the miner-plus group represents the number of unduplicated observations. However, mean expenditures are weighted according to the number of times the miner-plus observation matches to an observation with drug coverage or employer-provided drug coverage.

Sources: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare, dwelling in the community, and in fee-for-service Medicare for the full year. See text for additional detail.

Exhibit 2.2

Extent of Supplemental and Drug Coverage in the Trial Comparison Groups

		Any Coverage?			Employer-Provided Coverage?		
	N	No SC / no DC	SC / no DC	SC&DC	No SC / no DC	SC / no DC	SC & DC
Propensity Match, Males	930	8%	25%	68%	58%	6%	37%
Propensity Match, Females	1026	8%	27%	66%	66%	5%	29%
Exact Match, Males	309	6%	24%	70%	56%	6%	39%
Exact Match, Females	341	8%	26%	66%	63%	5%	32%

SC refers to supplemental coverage, DC to drug coverage.

Sources: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare, dwelling in the community, and in fee-for-service Medicare for the full year. See text for additional detail.

3.0 Aim 3: Predictability of Drug Expenditures

3.1 Background and Aims

Approximately one-quarter of Medicare beneficiaries lack prescription drug insurance. Both the general public and health policy experts consider improving Medicare beneficiaries' access to affordable and comprehensive drug insurance to be a key domestic priority, and there is an ongoing debate concerning federal policy in this area. Many options under consideration allow private carriers to offer drug insurance either alone or as a component of a more comprehensive health plan. Such options generally involve a regulatory role for CMS in areas such as premium guidelines, quality standards, the level and structure of public subsidies, and underwriting guidelines.

Public subsidies may well be per capita subsidies, in which case CMS might wish to consider risk-adjustment, i.e., adjusting the total per capita payment a plan receives (subsidy plus premium) according to the individual senior's expected drug utilization. Such a system reduces insurance carriers' incentives to avoid high cost individuals and hence reduces distortions in the market that result from plans either altering their products or engaging in other activities to attract good risks and avoid bad ones. It also reduces the financial risk for the carriers, especially small or new carriers, and reduces losses for those that end up with a high-expenditure caseload.

As a precursor to a focused research program to develop a risk-adjustment methodology, CMS requires basic research on the determinants of drug expenditures. This report addresses the following research questions:

- To what extent is a person's annual drug expenditure unpredictable and to what extent can it be predicted?
- What individual characteristics are important predictors of drug expenditures?
- Given that health status is an important predictor of drug expenditure, how well does CMS's existing methodology for predicting Medicare expenditures, the Hierarchical Conditions Categories (HCC) methodology, perform in this setting?

We note that the answers to these questions are relevant even if drug coverage were provided directly by the public sector, as they improve the ability to forecast the total cost of the program and its sensitivity to various assumptions and market changes.

3.2 Methods

3.2.1 Data Source

The 1999-2000 Medicare Current Beneficiary Survey (MCBS) Cost and Use files were used for the analyses. The MCBS is a longitudinal panel survey of a representative national sample of the Medicare population conducted under the auspices of CMS. Begun in the fall of 1991, over 12,000 Medicare beneficiaries, both aged and disabled, living in the community or in institutions are sampled from Medicare enrollment files and surveyed three times a year using computer assisted personal interviewing. MCBS interviewers collect extensive information on individuals' use and expenditures for health services including source of payment, as well as information on health insurance, health and functional status, socioeconomic status, and demographic characteristics. The MCBS files link Medicare claims to survey-reported events and provide complete expenditure and

source of payment data on all health care services, including those not covered by Medicare, namely prescription drugs and long term care.
This analysis drew on both the survey data (for drug expenditures and individual characteristics) and the outpatient and physician claims (for claims-based measures of health status).

3.2.2 Study Samples

Because our objective was to model drug expenditures for the entire Medicare population, we include both the aged and the disabled and include those with end-stage renal disease.[25] There are two types of study samples: (1) cross-sectional samples for 1999 and 2000, used for concurrent models in which current year drug expenditures are modeled as a function of current year characteristics and (2) a rectangular longitudinal panel sample based on both years, used for prospective models in which current year drug expenditures are modeled as a function of characteristics in the previous year. Inclusion and exclusion criteria for each of these samples are listed below with accompanying notes describing the rationale for each criterion.

Cross-Sectional Samples

- Full-year Medicare entitled for both Parts A and B
  - Our measure of annual drug expenditures takes advantage of MCBS imputations that that allocate drug use across years when necessary (e.g. late December prescriptions) and that impute apparently missing data (e.g. gaps in ongoing drug utilization for chronic conditions.) These imputations are designed for use in annual measures and cannot be practically re-created or altered for part-year observations.
  - A full year of Medicare A and B claims is required to accurately assign HCC scores. Since the concurrent models use only a single year of data, it follows that every sample member be Medicare entitled for both Parts A and B the entire year. For these models we thus exclude decedents, persons newly Medicare entitled during the year, and persons with Part A but no Part B coverage.
- Community-dwelling entire year
  - Because MCBS does not collect drug expenditure data on institutionalized beneficiaries we exclude all MCBS respondents who were in a LTC facility for all or part of the year (i.e., persons with any facility "interview" during the year. Facility interviews are only conducted for long-term care residents. Persons with Medicare-qualified SNF stays are considered to be community dwelling unless their stays extend beyond Medicare stay limits.)
- In fee-for-service Medicare entire year
  - It is impossible to determine HCC scores for beneficiaries in M+C plans because there are no Medicare claims generated during the M+C enrollment periods. We thus exclude all respondents with any M+C enrollment in the year.

[25] Key results are shown for the aged and disabled separately and are not sensitive to the exclusion of beneficiaries with end-stage renal disease.

- Completed all 3 survey rounds in the year
  - Prescription medication events (PMEs) included in the MCBS files are based on recorded use and are not imputed. Thus persons with missed interviews during the year will have incomplete prescription records. We thus exclude all respondents with one or more missed interviews in the year.

- Are "regular" sample beneficiaries and not "ghosts"
  - The MCBS includes limited data for new program accretes and replacement respondents (these persons are referred to as "ghosts"). Because there are no PME records for ghosts we must exclude them from the sample.

Two-year Panel Sample

Beneficiary present in both the 1999 and 2000 Cost and Use samples

- Given the rotating panel design of the MCBS approximately 25 percent of beneficiaries surveyed in 1999 are dropped from the 2000 sample. Because the prospective model derives HCC scores from 1999 claims and drug expenditures from 2000 self-reports, persons must be represented in both years to be included in the panel.

- Same inclusion/exclusion criteria as for the cross-sectional samples described above
  - The rationale for each criterion is the same for both the panel and cross-sectional samples. These criteria assure that the panel will be fully balanced (rectangular) with each sample member having 3 completed survey rounds in both years.

Sensitivity of Results to These Exclusion Criteria

Our results may be biased to the extent that observations eliminated due to our sample selection criteria differ from other observations along key dimensions. Appendix 3.A describes the methodology and results of an analysis intended to explore this issue. In short, we found that while mean drug expenditures are notably higher for individuals in the months before death and lower for individuals in the months before nursing home admission, the numbers of these cases and therefore the magnitude of the bias is small.

3.2.3 Study Variables

The dependent variable was annual drug expenditures (including expenditures for drugs that are currently covered by Medicare) measured in terms of the average wholesale price (AWP) rather than the retail price for the drugs.[26] Prices for the same drug may vary across different insurance groups based on the negotiated discounts and rebates. The AWP offers the solution of a standardized price for each drug so that measured expenditures do not represent variation in price but do represent variation in utilization (including variation that results from different types of insurance either moral hazard on the part of the patient or utilization management on the part of the insurer).
The independent variables of greatest interest were the summary measure of predicted Medicare expenditure for physician and inpatient care and the indicators for individual medical conditions, both produced by the HCC methodology. This methodology, created by Health Economics Research Inc., is CMS's existing methodology for predicting Medicare expenditures and is the basis for the

[26] A pharmacy follow-back survey indicated that the annual numbers of prescriptions are under-reported by 17.5 percent in the MCBS. (John Poisal, "Mis-reporting of prescription drugs in the MCBS," Unpublished, October, 2002.)

"selected significant disease model" that will be used to reimburse the Medicare + Choice plans starting in January, 2004. In our application, this model created indicators for the presence of 189 medical conditions based on the diagnoses recorded on a patient's Medicare claims (physician, outpatient, and inpatient). It then applied previously calibrated weights (based on regression coefficients) to approximately 100 of these conditions to create a single risk score (denoted "ybase") that is proportional to the patients expected Medicare expenditure. Our models examined the predictive performance of both the summary measure and the individual condition indicators. In addition, we examined the performance of the self-reported indicators for health conditions, that are part of the MCBS health status survey.

Our models also include basic demographic characteristics: age, gender, and geographic region of residence (metro status and 10 detailed census regions). We included another two measures on whether the beneficiary had a current "disabled" Medicare entitlement status and if the beneficiary was previously entitled to Medicare as "disabled" but currently has an "aged" Medicare entitlement status.

For many analyses, we stratified the analyses on whether or not the Medicare beneficiary had any drug coverage in 1999. Although risk-adjustment would pertain to insured individuals only, many of the beneficiaries who would be covered under a Medicare drug benefit are those without drug coverage today. We further stratified the analysis by basis of Medicare entitlement (aged or disabled) to test whether results were generally similar between the two groups.

3.2.4 Drug Expenditure Models

Models were estimated by unweighted, ordinary least squares (OLS) using both the level and the natural logarithm of drug expenditures as the dependent variable.[27] The unit of observation was the individual. To ensure reliable estimates, we dropped all HCC categories that had a sample size of less than 30. This resulted in a total of 128 HCC categories that were used in this analysis.

Concurrent Models

Four sets of concurrent models were estimated using data from current year to predict costs in the same year.

1. DE_t = f (basic characteristics$_t$)
2. DE_t = f (basic characteristics$_t$, ln Ybase$_t$)
3. DE_t = f (basic characteristics$_t$, indicators for self-reported health conditions$_t$)

[27] We chose unweighted OLS in order to maximize the efficiency of parameter estimates. Our sample is small relative to the number of condition indicators. While the MCBS contains survey weights so that it can be used to create nationally representative estimates, even with these weights, our sample cannot produce nationally representative estimates because of the observations excluded according to the sample selection criteria. We chose log linear models to adjust for skewness in the data and set (ln 0) = 0 in the 8.7 percent of cases with no recorded drug expenditures. We acknowledge that there are problems with log linear models: first the sensitivity of the results to observations with zero expenditures and to the way these observations are handled, second the difficulty of obtaining unbiased parameter estimates for the effect on the level of the dependent variable if errors are heteroskedastic. Future work should certainly consider alternate functional forms and estimation methodologies.

4. DE_t = f (basic characteristics$_{t,}$ 128 HCC indicators$_t$)

Where

DE_t is the level or natural logarithm of annual drug expenditures.

Basic characteristics include age, currently disabled, previously disabled, gender, metro status, and detailed census regions.

Ybase is the level or logarithm of predicted Medicare Part A & B payments from DCG-HCC risk-adjuster

These models were estimated with the 1999 and 2000 cross-sectional samples.

Prospective Models

Eight sets of prospective models were estimated using data from prior year to predict costs in the current year. The first four were the prospective analogues of the 4 concurrent models.

1. DE_t = f (basic characteristics$_{t-1}$)
2. DE_t = f (basic characteristics$_{t-1,}$ ln$Ybase_{t-1}$)
3. DE_t = f (basic characteristics$_{t-1}$, indicators for self-reported health conditions$_{t-1}$)
4. DE_t = f (basic characteristics$_{t-1,}$ 128 HCC indicators$_{t-1}$)

The next four models were identical to the four models listed above, except that each included a lagged drug-spending variable.

5. DE_t = f (basic characteristics$_{t-1,}$ DE_{t-1})
6. DE_t = f (basic characteristics$_{t-1,}$ ln$Ybase_{t-1,}$ DE_{t-1})
7. DE_t = f (basic characteristics$_{t-1}$, indicators for self-reported health conditions$_{t-1,}$ DE_{t-1})
8. DE_t = f (basic characteristics$_{t-1,}$ 128 HCC indicators$_{t-1,}$ DE_{t-1})

These models were estimated with the two-year panel samples.

Measure of Predictive Accuracy

The adjusted R-square was used as a measure to compare the predictive accuracy of the various models including different risk-adjustment measures. R-square captures the percentage of the variation in the annual drug expenditures explained by the risk-adjuster model.[28]

3.3 Results – Concurrent Models

Exhibit 3.1 presents descriptive characteristics of the 1999 cross-sectional sample of 8,067 Medicare beneficiaries. More than half the beneficiaries were female (55 percent). About 16 percent of the sample was Medicare disabled under the age of 65. Another 6 percent of the beneficiaries above the age of 65 years were previously entitled to Medicare through the "disabled" status. The mean age of the sample was 71.9 years with over a quarter of the beneficiaries aged 80 years or older. About two-

[28] Further work might consider additional approaches to model assessment such as predictive ratios, measures of forecast bias, and other measures of forecast error, including forecast mean squared error.

thirds of the beneficiaries lived in the urban setting and the largest proportion resided in the Southern region of the country.

Approximately 28 percent of the beneficiaries did not have any source of drug coverage during 1999. Appendix Exhibit 3.B.1 presents the study sample characteristics stratified by drug coverage. Medicare beneficiaries with drug coverage were disproportionately disabled, disproportionately urban, and there were regional differences.[29]

The distributions of the three different sets of health status measures: Ybase (predicted Medicare Part A & B payments using the HCC/DCG risk-adjuster model), the self-reported health conditions, and the HCCs are provided in Appendix Exhibits 3.B.2, 3.B.3, and 3.B.4, respectively for the entire sample and for the sample stratified by the presence of drug coverage. Beneficiaries with drug coverage (both with drug coverage via Medicaid and with coverage via another source) had disproportionately high disease burden, proxied by expected spending under Parts A and B. The mean predicted spending measure was $6,368 for individuals with drug insurance ($7,766 Medicaid, $5,959 other source) and $5,229 for individuals without drug insurance.

Exhibit 3.2 presents univariate statistics on the actual annual drug expenditures in 1999. The mean total drug expenditures calculated using 1999 AWP were $1,354 (SD=$1727). Roughly 8.7 percent of the sample reported no drug expenditures, and 10.5 percent of the sample reported expenditures in excess of $3,000. Drug expenditures were notably higher for those with drug insurance ($1,566) than for those without insurance ($804). This was true both for those insured via the Medicaid program ($1,849) and for those with drug insurance from a different source ($1,428).[30] (See Appendix 3.B.2.)

Exhibit 3.3 compares the R-squares associated with the concurrent models of drug expenditures using the three different risk-adjustment measures. The R-squares are presented for the models estimated in the entire sample of 8,067 beneficiaries.

Model 1 only used the age, gender, disability and geographic variables included in the base model. In the sample of all beneficiaries, the level model resulted in an adjusted R-Square of .035 and the log model in an adjusted R-square of 0.015. This indicates that the demographic variables explained very little of the variation in the annual drug expenditures of the Medicare beneficiaries. Addition of Ybase, the predicted Medicare Part A & B payment from the HCC/DCG risk-adjuster within Model 2 increased the adjusted R-square to .10 (level model) and .16 (log model). A $1000 increase in expected Medicare expenditure was associated with an $89 increase in predicted drug expenditures. Model 3 used binary measures of health conditions in the last one year as reported by the beneficiary. This model's performance was similar to Model 2's with a comparable adjusted R-square of .09 (levels) and 0.15 (logs). Model 4 included the variables in the base model plus 128 indicators for the

[29] Recall that low income and disabled Medicare beneficiaries are often also eligible for Medicaid, which offers drug coverage.

[30] This difference may actually be understated. The pharmacy follow-back survey suggested that individuals with drug coverage were more likely to under-report drug utilization that those without, and that conditional on under-reporting, those with Medicaid made errors of especially large magnitude. (John Poisal, op cit.)

individual medical problems that form the building blocks for the HCC/DCG model.[31] This model yielded an adjusted R-square of .22 (levels) and 0.30 (logs); the individual HCCs significantly outperformed the single summary measure (Ybase) suggesting that, the relative importance of the conditions differed between drug expenditures and expenditures covered by Parts A and B. Said another way, the conditions that predict high Medicare expenditures are not necessarily conditions that predict high drug expenditures and vice versa.

When the same models (Models 1 to 4) were estimated separately for beneficiaries with and without any drug coverage, major differences in the predictive performance of the models were observed (Appendix Exhibit 3.B.5). The models resulted in a consistently higher adjusted R-square among the group of beneficiaries with no drug coverage during 1999. For Model 4, the best predictive model in terms of R-square, the difference in the adjusted-R-square between the "no drug coverage" group (adjusted R-square =.39) and the "some drug coverage" group (adjusted R-square =.26) amounted to half the total amount of variation predicted for the "some coverage group. (If the insured are further divided into those with Medicaid drug insurance and those with other drug insurance, the adjusted R-square is .26 for the former group and .27 for the latter, so the difference is indeed an insurance difference and not a Medicaid difference.[32])

The final row of Exhibit 3.3 shows results based on 2000 data. Results were virtually identical to those observed in 1999. (This impression is confirmed in Exhibit 3.B.7).

Exhibit 3.4 presents the regression output for the log version of Model 4 (base model + 128 HCC categories) in the entire sample of 8,067 beneficiaries. The HCC variables in bold text in the Exhibit are those that were found to be statistically significant predictors of total drug expenditures. These are arranged in descending order of the value of the regression co-efficient. In general, the HCC categories predicting higher drug costs appear to be reasonable in context of the need for chronic use and/or high cost medications for those diagnoses. As seen in the model the HCC categories predicting higher drug expenditures (i.e. high positive coefficients) included conditions such as kidney transplant status (HCC128), schizophrenia (HCC54), hypertension (HCC115), congestive heart failure (HCC80) and major depressive disorder (HCC55).[33,34] Appendix 3.B.8 allows the reader

[31] Recall that we only included conditions for which we observed 30 or more cases in the 1999 cross-sectional sample.

[32] Nor is the discrepancy a "disabled" difference. Roughly speaking, the predictive power of Models 1-4 was comparable between the aged and disabled subpopulations (Appendix 3.B.6). Further work should investigate these differences and differences in drug utilization between those with and without insurance more generally.

[33] A risk-adjustment methodology would further refine the set of conditions to include only those that had a statistically significant, clinically justifiable, and positive impact on expenditures. Moreover, it would re-examine the HCC categories in the context of drug expenditures as they were created for the physician and hospital settings, potentially dividing some categories and combining others. The project team deemed that to eliminate statistically insignificant conditions at this point would be arbitrary, and we consider Model 4 to be our preferred model.

[34] Because these are unweighted regression, the disabled are over-represented in the sample population relative to the Medicare population as a whole. As a result, these regressions may overstate the relative statistical significance (but not necessarily the coefficients) of the psychiatric conditions, which are highly prevalent in the disabled population.

to compare the individual regression coefficients. Again, results were very similar between the two years.[35]

3.4 Results – Prospective Models

The next set of models are models are analogous to the models in Exhibit 3.3 except that drug expenditures in 2000 were modeled as a function of 1999 independent from a two-year panel sample. The striking result is that the fit of the prospective models is every bit as good as the fit of the concurrent models. For example, the adjusted R-square of the log version of concurrent model with HCC indicators is .30 and the adjusted R-square of the corresponding prospective model is .29. (Compare Exhibit 3.3 and rows 1-4 of Exhibit 3.5.)[36] Apparently, the majority of the explanatory power in these models comes from chronic conditions that persist from one year to the next and presumably require ongoing use of medication, rather than acute conditions that are relevant for one year only.[37] Appendix 3.B.8 also shows remarkable consistency between the regression coefficients estimated for individual conditions in concurrent and prospective models.[38]

Via the prospective models, we also explored the persistence of drug expenditures by including 1999 drug expenditures among the variables used to predict 2000 expenditures. Consistent with our prior research, we found that drug expenditures were highly persistent. The coefficient on lagged drug expenditures in the log version of the base model was .825 suggesting that a 10 percent elevation in drug expenditures in 1999 was associated with an 8.25 percent elevation in 2000. (See Appendix 3.B.9.) While the logarithmic, prospective version of the base model only explained 1.5 percent of the variation in drug expenditures, the same model with lagged expenditures added explained 70 percent of the variation in drug expenditures. (Exhibit 3.5.) It is also noteworthy that when lagged drug expenditures were included in the model, lagged health status indicators made no additional contribution to explanatory power, and the majority of condition indicators became insignificant. (Appendix 3.B.8.)

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[35] Of the 43 HCC conditions that were statistically significant predictors of drug expenditures in 1999, 40 were also statistically significant in 2000. Of the 87 HCC conditions that were not statistically significant in 1999, six were statistically significant in 2000. One would expect approximately seven of the 130 included conditions to be statistically significant by chance in any given year.

[36] These results are very similar to Chris Hogan's finding of an R-square of .21 in a prospective model of the level of drug expenditure that included 172 diagnostic clusters that make up the PIP-DCG model. (Hogan, C, "MCBS-based study of prescription drug coverage linked to Medicare claims," memorandum to Joan Sokolovsky, DHHS/OS/ASPE, October 25, 2000, delivered pursuant to RFP-5-00-HHS-OS, purchase order BPA-OS-00-0203-A, October 25, 2000.)

[37] Again, in prospective models, fit is better in samples lacking drug coverage than in samples with this coverage (3B7).

[38] Among the 43 conditions that were statistically significant in 1999, the value of the coefficient in the prospective model was within 25 percent of the value of the coefficient in the concurrent model in 30 cases. For nine conditions, the positive coefficient fell by more than 25 percent, for three conditions, the positive coefficient increased by more than 25 percent; for one, a negative coefficient lost approximately one-third of its absolute value.

3.5 Conclusions/Policy Implications

This report can be summarized in terms of two broad sets of findings. First, the concurrent models showed that health conditions were key predictors of drug expenditures and that, while many of the same conditions that predict physician and hospital expenditures were also important predictors of drug expenditures, the relative weights of the conditions differed notably between drug expenditures and the expenditures currently covered by Medicare. Said another way, the conditions that predict high drug expenditures are not necessarily the same conditions that predict physician and hospital expenditures and vice versa. In logarithmic models, demographic variables alone explained less than two percent of drug expenditures (adjusted R-square); adding a single summary measure of expected hospital and physician cost raised this figure to 16 percent; replacing that single measure with 128 indicators for specific conditions further increased the share of expenditures predicted to 30 percent.

Second, the prospective models showed that the predictable component of drug expenditures was a function of chronic conditions that persisted from year to year (rather than short-lived acute conditions) and that the previous year's drug expenditures were a notably more powerful predictor of the current year's drug expenditures than the medical condition indicators.[39] Indicators for conditions observed in 1999 proved just as effective in predicting 2000 drug expenditures as did indicators for conditions observed in 2000. Moreover, adding a measure of lagged drug expenditures caused the adjusted R-square of the prospective model including HCCs to more than double from .29 to .70.

The findings have several implications. First, it appears possible to develop a case-mix methodology for drug benefits given the relatively high R-square of these models combined with the fact that the predictive power of prospective models is virtually equal to the predictive power of concurrent models. In addition, the fact that the individual HCC indicators outperform the HCC summary measure suggest that even if drug benefits were to be provided in conjunction with Part A and Part B services, Ybase (or another risk adjustment methodology developed for Parts A and B only) would not be the optimal risk adjustment methodology for this package of services. Clearly, freestanding drug benefits would require their own risk adjustment methodology, although the HCC categories might be used as a starting point.

Third, the persistence of drug expenditures combined with the variation among individuals suggest the potential for powerful adverse selection if individuals are free to decide whether or not to purchase drug insurance at a single market price. In addition, the fact that lagged drug expenditures appear to add significant explanatory power to the expenditure equation suggest that insurers in competitive markets may retain strong incentives for risk selection even if their rates are case-mix adjusted. (Risk adjustment methodologies typically avoid lagged expenditure measures in order to preserve incentives for cost-containment.) Policy makers should give these issues careful consideration as they select policy options, and these issues argue for strong underwriting guidelines if drug benefits are either purchased voluntarily or provided competitively.

These findings suggest several avenues for further research. A recent literature has developed alternative approaches to modeling health care expenditures that are more sophisticated than using OLS to estimate linear and log-linear models. Such approaches should be explored. A wider range of metrics could be used to evaluate fit, including out-of-sample performance, predictive ratios for key

[39] Of course, the HCCs could be refined to improve their performance in predicting drug expenditures.

subpopulations, mean squared and mean absolute deviation, percentiles of the error distribution etc. Moreover, models could be estimated and analyzed separately for the disabled, the dual eligible, and other Medicare sub-populations of interest.

Second, we have observed that the insured tend to have higher levels of prescription drug use than the uninsured and that their drug use is less predictable. It would be interesting to analyze the patterns that underlie these trends, especially given the potential for policy change that would raise coverage rates among the Medicare population. Ideally such work would incorporate both the clinical and the statistical perspective.

Third, it would be valuable to validate the essential results using actual drug claims data. Such results would have the potential to be more current and more precise (due to large sample size) than the MCBS results and to avoid measurement error due to under-reporting and imputation. These results would complement the MCBS results, which have the advantages of representing the entire Medicare population and a direct link to Medicare claims.

Terminology

UMWA – United Mine Workers of America

Miner Group/Miners – Individuals who receive supplemental and drug coverage via a previous employer in the mining industry (includes former miners and their spouses).

Miner-plus group/Miner-plus – Individuals who receive supplemental and drug coverage via a previous employer in the mining industry (includes spouses). These industries were: mining (MCBS industry code B), construction (C), oil and gas extraction (13), heavy construction excluding building (16), petroleum and coal products (29), railroad transport (40), electric gas and sanitary (49).

Base group –- the group for which a matching procedure selects a match.

Trial Comparison group / comparison group – Used to describe comparison groups selected by both propensity and exact match methods.

DC – Drug coverage

SC – Supplemental coverage

Pairs in Which Match Member has SC & DC – Comparison sample contains observations with supplemental and drug coverage. Miner-plus sample is restricted to the subset of observations that matched to those pairs

Pairs in Which Match Member has employer-provided SC & DC – Comparison sample contains observations with employer-provided supplemental and drug coverage. Miner-plus sample is restricted to the subset of observations that matched to those pairs

Exhibits

Exhibit 3.1

1999 Cross-sectional Sample Characteristics

Characteristic	Percent Beneficiaries
Total, N	8,067
Gender	
Female	55.7%
Male	44.3
Medicare Entitlement status	
Disabled	16.1%
Aged but previously disabled	5.9
Age, (years)	
< 65	16.1%
65-69	14.1
70-74	22.2
75-79	18.6
80+	28.9
Metropolitan Status	
Rural	34.0%
Urban	66.0
Detailed Census Regions	
New England	2.9%
Middle Atlantic	15.9
East North Central	17.9
West North Central	7.3
South Atlantic	21.9
East South Central	6.6
West South Central	11.2
Mountain	5.4
Pacific	9.5
Puerto Rico	1.5
Drug coverage	
Any drug coverage	72.2%
No drug coverage	27.8

Source: 1999 Cross-Sectional Sample, Medicare Current Beneficiary Survey. (N = 8067)

Exhibit 3.2

Univariate Statistics on Actual Total (AWP) Drug Expenditures, 1999

Measure	Dollar Amounts
Mean	$1,354 (SD=$1,727)
Median	$ 907
Minimum	$0
Maximum	$40,532
Frequency Distribution	
$0	8.7%
>$0 to ≤ $250	14.7%
> $250 to ≤ $500	10.9%
> $500 to ≤ $1,000	18.9%
>$1,000 to ≤ $2,000	25.1%
>$2,000 to ≤ $3,000	11.2%
>$3,000	10.5%

Source: 1999 Cross-Sectional Sample, Medicare Current Beneficiary Survey. (N = 8067)

Exhibit 3.3

R-squares Associated with Concurrent Models of Drug Expenditures using Different Risk-adjusters

Model and Year		Adj R-square (Level Model)	Adj R-square (Log Model)
Model 1 (1999)	.035	.035	0.015
Model 2 (1999)	.10	.10	0.16
Model 3 (1999)	.09	.09	0.15
Model 4 (1999)	.20	.20	0.30
Model 4 (2000)	.22	.22	0.31

* Base model: Y = f (age, currently disabled, previously disabled, gender, metro status, detailed census regions).

* Predicted Medicare Part A & B payment from DCG-HCC risk adjuster.

*** Self-reported conditions include heart disease, cancer, arthritis, lung disease, mental illness, Alzheimer's, diabetes, hypertension, osteoporosis, stroke, benign prostatic hypertrophy, paralysis, Parkinson's, hip fracture.

Source: 1999 Cross-Sectional Sample (N=8,067) and 2000 Cross-Sectional Sample (N=7,992), Medicare Current Beneficiary Survey.

Exhibit 3.4

Estimated Effects on Drug Expenditures
Model 4 (1999) (Dependent Variables is Ln Drug Expenditures)

Independent Variable Name	Variable Code	Regression Coefficient	P>|t|	[95% Conf. Interval]	
Aged but previously Medicare disabled	disaged	0.35	0.000	0.17	0.54
Disabled	disabled	0.54	0.000	0.37	0.71
Age 70-74 years	age74	-0.06	0.409	-0.20	0.08
Age 75-79 years	age79	-0.06	0.459	-0.21	0.09
Age 80 years or older	age80plus	-0.16	0.030	-0.30	-0.02
Female	female99	0.09	0.085	-0.01	0.20
Rural	rural99	-0.08	0.096	-0.18	0.01
New England	neweng	-0.21	0.112	-0.47	0.05
Middle Atlantic	Midatl	-0.22	0.003	-0.36	-0.08
East North Central	encentral	-0.05	0.475	-0.18	0.09
West North Central	wncentral	-0.21	0.025	-0.39	-0.03
East South Central	escentral	-0.02	0.840	-0.21	0.17
West South Central	wscentral	0.10	0.185	-0.05	0.26
Mountain	mountain	-0.12	0.251	-0.32	0.08
Pacific	Pacific	0.05	0.562	-0.12	0.21
Puerto Rico	puertorico	-0.16	0.397	-0.52	0.21
Kidney Transplant Status	hcc128	**1.62**	**0.000**	0.97	2.27
Schizophrenia	hcc54	**1.53**	**0.000**	1.21	1.85
Hypertensive Heart Disease	hcc90	**1.09**	**0.000**	0.84	1.33
Hypertension	hcc91	**1.05**	**0.000**	0.95	1.15
Congestive Heart Failure	hcc80	**0.99**	**0.000**	0.83	1.15
Inflammatory Bowel Disease	hcc33	**0.72**	**0.009**	0.18	1.27
Major Depressive, Bipolar, and Paranoid Disorder	hcc55	**0.72**	**0.000**	0.48	0.96
Parkinson's and Huntington's Diseases	hcc73	**0.65**	**0.001**	0.25	1.06
Diabetes with Ophthalmologic Manifestation	hcc18	**0.62**	**0.001**	0.26	0.98
Seizure Disorders and Convulsions	hcc74	**0.62**	**0.000**	0.36	0.88
Hypertensive Heart and Renal Disease	hcc89	**0.57**	**0.018**	0.10	1.05
Glaucoma	hcc122	**0.54**	**0.000**	0.40	0.68
Other Endocrine/Metabolic/Nutritional Disorders	hcc24	**0.49**	**0.000**	0.39	0.59
Reactive and Unspecified Psychosis	hcc56	**0.48**	**0.036**	0.03	0.93
Angina Pectoris/Old Myocardial Infarction	hcc83	**0.47**	**0.000**	0.28	0.66
Asthma	hcc110	**0.46**	**0.001**	0.19	0.73
Coronary Atherosclerosis/Other Chronic Ischemia	hcc84	**0.45**	**0.000**	0.31	0.58
Diabetes with No or Unspecified Complications	hcc19	**0.44**	**0.000**	0.30	0.57
Screening/Observation/Special Exams	hcc183	**0.43**	**0.000**	0.33	0.52
Osteoporosis and Other Bone/Cartilage Disorder	hcc41	**0.40**	**0.000**	0.25	0.54

Exhibit 3.4

Estimated Effects on Drug Expenditures
Model 4 (1999) (Dependent Variables is Ln Drug Expenditures)

Independent Variable Name	Variable Code	Regression Coefficient	P>|t|	[95% Conf. Interval]	
Diabetes with Neurologic or Peripheral Complication	hcc16	**0.39**	**0.015**	0.08	0.71
Rheumatoid Arthritis and Inflammatory Co	hcc38	**0.38**	**0.000**	0.18	0.58
Chronic Obstructive Pulmonary Disease	hcc108	**0.38**	**0.000**	0.24	0.51
Minor Symptoms, Signs, Findings	hcc167	**0.36**	**0.000**	0.24	0.48
Depression	hcc58	**0.36**	**0.001**	0.14	0.58
Major Symptoms, Abnormalities	hcc166	**0.35**	**0.000**	0.24	0.47
Post-Surgical States/Aftercare/Elective	hcc179	**0.29**	**0.000**	0.18	0.40
Peptic Ulcer, Hemorrhage, Other Specified	hcc34	**0.28**	**0.003**	0.10	0.47
Diabetic and Other Vascular Retinopathies	hcc120	**0.27**	**0.022**	0.04	0.50
Incontinence	hcc134	**0.26**	**0.033**	0.02	0.49
Urinary Obstruction and Retention	hcc133	**0.24**	**0.021**	0.04	0.44
Other Musculoskeletal and Connective Tissue Disorder	hcc43	**0.22**	**0.000**	0.12	0.33
Osteoarthritis of Hip or Knee	hcc40	**0.21**	**0.018**	0.04	0.38
Specified Heart Arrhythmias	hcc92	**0.21**	**0.006**	0.06	0.36
Other Gastrointestinal Disorders	hcc36	**0.20**	**0.000**	0.09	0.31
Disorders of the Vertebrae and Spinal Disorder	hcc39	**0.20**	**0.012**	0.04	0.35
Other Injuries	hcc162	**0.19**	**0.002**	0.07	0.30
Other Ear, Nose, Throat, and Mouth Disorder	hcc127	**0.18**	**0.000**	0.08	0.28
Other Female Genital Disorders	hcc139	**0.16**	**0.036**	0.01	0.32
Vascular Disease	hcc105	**0.15**	**0.046**	0.00	0.31
Other Lung Disorders	hcc115	**0.15**	**0.045**	0.00	0.30
Other Dermatological Disorders	hcc153	**0.15**	**0.006**	0.04	0.26
Gallbladder and Biliary Tract Disorders	hcc30	**-0.37**	**0.043**	-0.73	-0.01
Diabetes with Renal Manifestation	hcc15	0.45	0.072	-0.04	0.94
Cerebral Atherosclerosis and Aneurysm	hcc98	0.45	0.124	-0.12	1.02
Chemotherapy	hcc181	0.31	0.241	-0.21	0.83
Other Respiratory and Heart Neoplasms	hcc11	0.26	0.437	-0.39	0.91
Fibrosis of Lung and Other Chronic Lung	hcc109	0.26	0.142	-0.09	0.60
Disorders of Immunity	hcc45	0.23	0.399	-0.30	0.75
Pancreatic Disease	hcc32	0.22	0.380	-0.27	0.70
Unstable Angina and Other Acute Ischemic	hcc82	0.21	0.095	-0.04	0.46
Lung, Upper Digestive Tract, and Other Specified	hcc8	0.21	0.316	-0.20	0.61
Other Psychiatric Disorders	hcc60	0.20	0.113	-0.05	0.46
Acute Myocardial Infarction	hcc81	0.20	0.320	-0.19	0.59
Cerebral Hemorrhage	hcc95	0.20	0.575	-0.49	0.88
Speech, Language, Cognitive, Perceptual	hcc102	0.18	0.518	-0.37	0.74
Benign Neoplasms of Skin, Breast, Eye	hcc14	0.16	0.061	-0.01	0.33
Vertebral Fractures	hcc157	0.16	0.490	-0.29	0.60

Exhibit 3.4

Estimated Effects on Drug Expenditures
Model 4 (1999) (Dependent Variables is Ln Drug Expenditures)

Independent Variable Name	Variable Code	Regression Coefficient	P>|t|	[95% Conf. Interval]	
Retinal Detachment	hcc118	0.15	0.610	-0.42	0.72
Rehabilitation	hcc182	0.13	0.316	-0.13	0.39
Other Neoplasms	hcc13	0.13	0.153	-0.05	0.30
Spinal Cord Disorders/Injuries	hcc69	0.12	0.608	-0.35	0.59
Disorders of Fluid/Electrolyte/Acid-Base	hcc23	0.12	0.177	-0.05	0.30
Metastatic Cancer and Acute Leukemia	hcc7	0.12	0.558	-0.28	0.52
Poisonings and Allergic Reactions	hcc163	0.12	0.226	-0.07	0.31
Chronic Ulcer of Skin, Except Decubitus	hcc149	0.12	0.456	-0.19	0.43
Anxiety Disorders	hcc59	0.11	0.672	-0.39	0.61
Diabetes with Acute Complications	hcc17	0.10	0.683	-0.40	0.60
Aspiration and Specified Bacterial Pneumonia	hcc111	0.10	0.693	-0.41	0.62
Artificial Openings for Feeding or Elimination	hcc176	0.10	0.731	-0.46	0.66
Severe Hematological Disorders	hcc44	0.10	0.654	-0.33	0.52
Retinal Disorders, Except Detachment	hcc121	0.09	0.251	-0.07	0.26
Coagulation Defects and Other Specified	hcc46	0.09	0.438	-0.14	0.32
Other Circulatory Disease	hcc106	0.09	0.277	-0.07	0.25
Hearing Loss	hcc126	0.08	0.504	-0.15	0.31
Other Infectious Diseases	hcc6	0.08	0.217	-0.05	0.20
Breast, Prostate, Colorectal and Other Cancers	hcc10	0.08	0.378	-0.09	0.24
Intestinal Obstruction/Perforation	hcc31	0.07	0.682	-0.26	0.40
Type I Diabetes Mellitus	hcc20	0.07	0.577	-0.17	0.30
Viral and Unspecified Pneumonia, Pleurisy	hcc113	0.06	0.518	-0.12	0.25
Protein-Calorie Malnutrition	hcc21	0.06	0.808	-0.43	0.55
Cellulitis, Local Skin Infection	hcc152	0.06	0.515	-0.12	0.24
Other Significant Endocrine and Metabolic Disorder	hcc22	0.04	0.791	-0.27	0.36
Renal Failure	hcc131	0.04	0.806	-0.26	0.33
Mononeuropathy, Other Neurological Conditions	hcc76	0.04	0.716	-0.16	0.23
Polyneuropathy	hcc71	0.03	0.794	-0.22	0.29
Dementia	hcc49	0.03	0.792	-0.20	0.26
Cataract	hcc123	0.03	0.551	-0.07	0.13
Precerebral Arterial Occlusion	hcc97	0.03	0.805	-0.18	0.23
History of Disease	hcc184	0.03	0.706	-0.11	0.16
Significant Ear, Nose, and Throat Disorder	hcc125	0.02	0.926	-0.46	0.50
Pelvic Inflammatory Disease and Other Specified	hcc138	0.02	0.879	-0.25	0.29
Other Heart Rhythm and Conduction Disorder	hcc93	0.01	0.913	-0.18	0.20
Iron Deficiency and Other/Unspecified	hcc47	0.01	0.886	-0.12	0.14
Proliferative Diabetic Retinopathy	hcc119	0.01	0.973	-0.52	0.54
Pneumococcal Pneumonia, Emphysema, Lung	hcc112	0.00	0.988	-0.52	0.53
Valvular and Rheumatic Heart Disease	hcc86	0.00	0.971	-0.15	0.16

Exhibit 3.4

Estimated Effects on Drug Expenditures
Model 4 (1999) (Dependent Variables is Ln Drug Expenditures)

Independent Variable Name	Variable Code	Regression Coefficient	P>|t|	[95% Conf. Interval]	
Other Eye Disorders	hcc124	0.00	0.996	-0.16	0.16
Vascular Disease with Complications	hcc104	-0.01	0.969	-0.33	0.32
Ischemic or Unspecified Stroke	hcc96	-0.01	0.955	-0.24	0.22
Decubitus Ulcer of Skin	hcc148	-0.01	0.962	-0.53	0.51
Male Genital Disorders	hcc140	-0.02	0.824	-0.16	0.13
Cerebrovascular Disease Late Effects, Unspecified	hcc103	-0.03	0.907	-0.55	0.49
Cardio-Respiratory Failure and Shock	hcc79	-0.03	0.817	-0.31	0.25
Other Urinary Tract Disorders	hcc136	-0.03	0.697	-0.21	0.14
Urinary Tract Infection	hcc135	-0.04	0.591	-0.17	0.09
Mild/Unspecified Mental Retardation	hcc64	-0.05	0.843	-0.52	0.42
Delirium and Encephalopathy	hcc48	-0.06	0.755	-0.45	0.32
Senility, Non-psychotic Organic Brain Syndrome	hcc50	-0.08	0.771	-0.62	0.46
Major Fracture, Except of Skull, Vertebrae	hcc159	-0.09	0.666	-0.47	0.30
Major Complications of Medical Care	hcc164	-0.09	0.502	-0.36	0.18
Other Hepatitis and Liver Disease	hcc29	-0.10	0.515	-0.42	0.21
Other and Unspecified Heart Disease	hcc94	-0.13	0.493	-0.51	0.25
Other Complications of Medical Care	hcc165	-0.13	0.479	-0.50	0.23
Drug/Alcohol Psychosis	hcc51	-0.14	0.690	-0.81	0.54
Major Head Injury	hcc155	-0.14	0.556	-0.62	0.33
Lymphatic, Head and Neck, Brain, and Other Cancer	hcc9	-0.15	0.409	-0.52	0.21
Bone/Joint/Muscle Infections/Necrosis	hcc37	-0.17	0.443	-0.59	0.26
Drug/Alcohol Dependence	hcc52	-0.17	0.457	-0.61	0.28
Other Digestive and Urinary Neoplasms	hcc12	-0.17	0.156	-0.41	0.07
Pleural Effusion/Pneumothorax	hcc114	-0.22	0.150	-0.51	0.08
Drug/Alcohol Abuse, Without Dependence	hcc53	-0.22	0.118	-0.50	0.06
Hemiplegia/Hemiparesis	hcc100	-0.22	0.357	-0.70	0.25
Radiation Therapy	hcc180	-0.24	0.445	-0.87	0.38
Hip Fracture/Dislocation	hcc158	-0.26	0.203	-0.65	0.14
Traumatic Amputation	hcc161	-0.26	0.660	-1.43	0.90
Septicemia/Shock	hcc2	-0.29	0.167	-0.71	0.12
Central Nervous System Infection	hcc3	-0.36	0.310	-1.05	0.33
Concussion or Unspecified Head Injury	hcc156	-0.41	0.112	-0.92	0.10
Internal Injuries	hcc160	-0.57	0.199	-1.44	0.30
Regression Constant	_cons	3.85	0.000	3.68	4.03

Based on an OLS regression of ln (drug expenditures) on the variables shown. All variables measured in 1999. Includes observations with no drug expenditures 8.7 percent of total.

Omitted categories: Age 65-69 years, Male, Urban, South Atlantic.

Source: 1999 Cross-Sectional Sample, Medicare Current Beneficiary Survey. (N = 8067)

Exhibit 3.5

R-squares Associated with Prospective Models of 2000 Drug Expenditures using Different Risk-adjusters

	Model	Adj R-square (Level Model)	Adj R-square (Log Model)
Model 1P	Base Model*	.05	.015
Model 2P	Base model + log (Ybase)**	.13	.15
Model 3P	Base model + self-reports of health conditions in the last one year***	.10	.14
Model 4P	Base model + claims-based indicators for 128 conditions	.23	.29
Model 5P	Base Model + lagged drug expenditures	.53	.70
Model 6P	Model 2 + lagged drug expenditures	.54	.70
Model 7P	Model 3 + lagged drug expenditures	.53	.70
Model 8P	Model 4 + lagged drug expenditures	.55	.70

* Base model: Y = f (age, currently disabled, previously disabled, gender, metro status, detailed census regions).

** Predicted Medicare Part A & B payment from DCG-HCC risk adjuster.

*** Self-reported conditions include heart disease, cancer, arthritis, lung disease, mental illness, Alzheimer's, diabetes, hypertension, osteoporosis, stroke, benign prostatic hypertrophy, paralysis, Parkinson's, hip fracture.

Source: 1999/2000 Longitudinal Sample, Medicare Current Beneficiary Survey, N = 4978

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APPENDICES

Appendix 1.A: Aim 1: Additional Exhibits

Exhibit 1.A.1

Sample Sizes of 2-Year Panels Used in the Longitudinal Models

	Persons Month Observed Before Drug Coverage Switch																						
	-23	-22	-21	-20	-19	-18	-17	-16	-15	-14	-13	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Never	.	29	70	109	147	267	575	1006	1441	1491	1537	1587	1678	1714	1784	1857	1963	2174	2676	3354	3990	4078	4216
Always	.	672	1221	1514	2120	3549	5328	6852	6927	7069	7268	7372	7457	7505	7542	7647	7949	8934	10391	11669	11744	11858	11981
Lost	.	71	129	160	224	375	563	724	732	747	768	779	788	793	797	808	840	944	1098	1233	1241	1253	1266
Gained	.	10	24	37	50	91	196	343	491	508	524	541	572	584	608	633	669	741	912	1143	1360	1390	1437

	Persons Month Observed After Drug Coverage Switch																						
	+1	+2	+3	+4	+5	+6	+7	+8	+9	+10	+11	+12	+13	+14	+15	+16	+17	+18	+19	+20	+21	+22	+23
Never	4366	4337	4296	4257	4219	4099	3791	3360	2925	2875	2829	2779	2688	2652	2582	2509	2403	2192	1690	1012	376	288	156
Always	12066	11394	10845	10552	9946	8517	6738	5214	5139	4997	4798	4694	4609	4561	4524	4419	4117	3132	1675	397	322	208	102
Lost	1275	1204	1146	1115	1051	900	712	551	543	528	507	496	487	482	478	467	435	331	177	42	34	22	12
Gained	1488	1478	1464	1451	1438	1397	1292	1145	997	980	964	947	916	904	880	855	819	747	576	345	128	98	51

Source: Medicare Current Beneficiary Survey, 1995-2000

Exhibit 1.A.2

GLM-Regression Output for Total Drug Expenditures (AWP), 1999-2000

```
Generalized linear models                         No. of obs      =      3365
Optimization     : ML: Newton-Raphson             Residual df     =      3346
                                                  Scale param     =  .9330359
Deviance         =  2933.208178                   (1/df) Deviance =  .8766313
Pearson          =  3121.938258                   (1/df) Pearson  =  .9330359

Variance function: V(u) = u^2                     [Gamma]
Link function    : g(u) = ln(u)                   [Log]
Standard errors  : OIM

Log likelihood   = -28313.29289                   AIC             =   16.8394
BIC              =  2778.905696
```

Total Drug Exp(AWP)	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Drug Coverage	.4881861	.042391	11.52	0.000	.4051012	.571271
Prior disabled*	.3316421	.0702562	4.72	0.000	.1939424	.4693418
Disabled(<65 y)	.4444348	.0698301	6.36	0.000	.3075703	.5812993
Age 69-74 y	-.0352762	.0599369	-0.59	0.556	-.1527504	.0821979
Age 75-79 y	-.0892017	.0630675	-1.41	0.157	-.2128116	.0344083
Age >= 80 y	-.171592	.0610865	-2.81	0.005	-.2913194	-.0518647
Female	.2093571	.0364593	5.74	0.000	.1378981	.280816
White race	.2025392	.052403	3.87	0.000	.0998311	.3052472
Married	.026311	.0409006	0.64	0.520	-.0538527	.1064748
High school grad.	-.0217243	.0389034	-0.56	0.577	-.0979736	.0545251
Income $10k-<$20k	.1196399	.0504018	2.37	0.018	.0208542	.2184256
Income $20k-<$30k	.113326	.0594344	1.91	0.057	-.0031633	.2298153
Income $≥30k	.1405525	.0588072	2.39	0.017	.0252924	.2558125
Rural	-.0934086	.0373613	-2.50	0.012	-.1666354	-.0201819
Midwest	.0970386	.0521907	1.86	0.063	-.0052533	.1993306
South	.0776734	.0480593	1.62	0.106	-.016521	.1718678
West	-.0853525	.0567688	-1.50	0.133	-.1966173	.0259123
HCC Index	.408084	.025872	15.77	0.000	.3573758	.4587921
_cons	6.212051	.1017613	61.05	0.000	6.012603	6.411499

Reference categories are: No drug coverage, not prior disabled, age 65-69 y, male, non-white race, single, not high school graduate, income <$10k, urban, Northeast.

* Currently aged but had prior Medicare disability status

Exhibit 1.A.3

GLM-Regression Output for Total Medicare Expenditures, 1999-2000

```
Generalized linear models                         No. of obs      =      3365
Optimization     : ML: Newton-Raphson             Residual df     =      3346
                                                  Scale param     =  4.402229
Deviance         =  7407.521471                   (1/df) Deviance =  2.213844
Pearson          =  14729.85844                   (1/df) Pearson  =  4.402229

Variance function: V(u) = u^2                     [Gamma]
Link function    : g(u) = ln(u)                   [Log]
Standard errors  : OIM

Log likelihood   = -31065.46187                   AIC             =  18.47516
BIC              =  7253.218989

------------------------------------------------------------------------------
Total Medicare Exp |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
 Drug Coverage     |   .0622991   .0913716     0.68   0.495    -.1167859    .2413841
 Prior disabled*   |   .2759468   .1559262     1.77   0.077     -.029663    .5815565
 Disabled(<65 y)   |  -.1304074   .1533781    -0.85   0.395    -.4310229    .1702081
 Age 69-74 y       |   .0591499    .132033     0.45   0.654    -.1996301    .3179299
 Age 75-79 y       |   .1621865   .1390597     1.17   0.243    -.1103655    .4347385
 Age >= 80 y       |    .123928   .1342137     0.92   0.356    -.1391261     .386982
 Female            |  -.0803946   .0793029    -1.01   0.311    -.2358256    .0750363
 White race        |    .156159   .1152882     1.35   0.176    -.0698017    .3821196
 Married           |   .0119424   .0921094     0.13   0.897    -.1685887    .1924736
 High school grad. |   .0098667   .0858611     0.11   0.909    -.1584179    .1781514
 Income $10k-<$20k |  -.0985597   .1127066    -0.87   0.382    -.3194606    .1223411
 Income $20k-<$30k |  -.1818505   .1363354    -1.33   0.182     -.449063     .085362
 Income $>=30k     |   .0546441   .1394278     0.39   0.695    -.2186294    .3279176
 Rural             |  -.1656752   .0819955    -2.02   0.043    -.3263834    -.004967
 Midwest           |   -.077655   .1140735    -0.68   0.496    -.3012349     .145925
 South             |  -.0462901   .1047947    -0.44   0.659    -.2516839    .1591036
 West              |   .0441002   .1244537     0.35   0.723    -.1998246     .288025
 HCC Index         |   .7727242   .0559294    13.82   0.000     .6631046    .8823437
 _cons             |   7.363962   .2160794    34.08   0.000     6.940455     7.78747
------------------------------------------------------------------------------
Reference categories are:  No drug coverage, not prior disabled, age 65-69 y, male,
non-white race, single, not high school graduate, income <$10k, urban, Northeast.

* Currently aged but had prior Medicare disability status
------------------------------------------------------------------------------
```

Exhibit 1.A.4

GLM-Regression Output for Total Inpatient Expenditures, 1999-2000

```
Generalized linear models                         No. of obs      =      3365
Optimization     : ML: Newton-Raphson             Residual df     =      3346
                                                  Scale param     =  11.66635
Deviance         =  3993.402575                   (1/df) Deviance =  1.193486
Pearson          =   39035.5974                   (1/df) Pearson  =  11.66635

Variance function: V(u) = u^2                     [Gamma]
Link function    : g(u) = ln(u)                   [Log]
Standard errors  : OIM

Log likelihood   = -28160.18907                   AIC             =   16.7484
BIC              =  3839.100093
```

Total Inpatient	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Drug Coverage	-.0167537	.1509006	-0.11	0.912	-.3125135	.2790061
Prior disabled*	.382991	.2567624	1.49	0.136	-.1202541	.8862361
Disabled(<65 y)	-.1484268	.2558176	-0.58	0.562	-.64982	.3529665
Age 69-74 y	.2458026	.2162201	1.14	0.256	-.177981	.6695862
Age 75-79 y	.3323765	.2303078	1.44	0.149	-.1190185	.7837715
Age >= 80 y	.2101798	.2220423	0.95	0.344	-.2250152	.6453748
Female	-.1984978	.1332077	-1.49	0.136	-.45958	.0625845
White race	.2512992	.1881308	1.34	0.182	-.1174305	.6200289
Married	-.004855	.1595461	-0.03	0.976	-.3175597	.3078496
High school grad.	.0049032	.1394587	0.04	0.972	-.2684308	.2782372
Income $10k-<$20k	-.2822193	.1853639	-1.52	0.128	-.6455259	.0810872
Income $20k-<$30k	-.3928027	.2267971	-1.73	0.083	-.8373169	.0517115
Income $≥30k	-.0280306	.2344209	-0.12	0.905	-.4874871	.4314259
Rural	-.2428088	.1355068	-1.79	0.073	-.5083974	.0227797
Midwest	-.0723543	.1876276	-0.39	0.700	-.4400976	.2953891
South	-.1001263	.1727448	-0.58	0.562	-.4386999	.2384473
West	.1010248	.2045377	0.49	0.621	-.2998617	.5019113
HCC Index	.8131625	.0949344	8.57	0.000	.6270946	.9992304
_cons	6.560021	.3546577	18.50	0.000	5.864905	7.255138

Reference categories are: No drug coverage, not prior disabled, age 65-69 y, male, non-white race, single, not high school graduate, income <$10k, urban, Northeast.

* Currently aged but had prior Medicare disability status

Exhibit 1.A.5

GLM-Regression Output for Total Physician Expenditures, 1999-2000

```
Generalized linear models                         No. of obs      =      3365
Optimization     : ML: Newton-Raphson             Residual df     =      3346
                                                  Scale param     =  2.037746
Deviance         =  4533.150652                   (1/df) Deviance =  1.354797
Pearson          =  6818.299303                   (1/df) Pearson  =  2.037746

Variance function: V(u) = u^2                     [Gamma]
Link function    : g(u) = ln(u)                   [Log]
Standard errors  : OIM

Log likelihood   =  -27441.8743                   AIC             =  16.32147
BIC              =   4378.84817
```

Total Physician	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Drug Coverage	.1250644	.0617996	2.02	0.043	.0039394	.2461893
Prior disabled*	.0978703	.105157	0.93	0.352	-.1082336	.3039742
Disabled(<65 y)	-.4046205	.10408	-3.89	0.000	-.6086136	-.2006274
Age 69-74 y	-.0189477	.0890014	-0.21	0.831	-.1933872	.1554918
Age 75-79 y	.1115858	.0940005	1.19	0.235	-.0726518	.2958235
Age >= 80 y	.0579394	.0895561	0.65	0.518	-.1175874	.2334661
Female	-.0221732	.0530751	-0.42	0.676	-.1261984	.081852
White race	.1938822	.0778402	2.49	0.013	.0413182	.3464462
Married	.0342312	.0606714	0.56	0.573	-.0846825	.1531449
High school grad.	.0715882	.0582075	1.23	0.219	-.0424964	.1856729
Income $10k-<$20k	.006553	.0769158	0.09	0.932	-.1441991	.1573052
Income $20k-<$30k	-.0227282	.0899516	-0.25	0.801	-.1990302	.1535737
Income $>=30k	.1767579	.0918544	1.92	0.054	-.0032734	.3567891
Rural	-.2430069	.0558483	-4.35	0.000	-.3524676	-.1335462
Midwest	-.0406608	.0776321	-0.52	0.600	-.1928168	.1114953
South	-.0121636	.0710169	-0.17	0.864	-.1513541	.127027
West	.048377	.0840022	0.58	0.565	-.1162643	.2130182
HCC Index	.5983107	.0375606	15.93	0.000	.5246933	.6719282
_cons	6.310711	.1463971	43.11	0.000	6.023778	6.597644

Reference categories are: No drug coverage, not prior disabled, age 65-69 y, male, non-white race, single, not high school graduate, income <$10k, urban, Northeast.

* Currently aged but had prior Medicare disability status

Exhibit 1.A.6

Fixed Effects Model of Inpatient Spending for Gainers and Nevers

```
Fixed-effects (within) regression               Number of obs      =     13680
Group variable (i): baseid                      Number of groups   =      1401

R-sq:  within  = 0.0064                         Obs per group: min =         8
       between = 0.0005                                        avg =       9.8
       overall = 0.0007                                        max =        16

                                                F(39,12240)        =      2.01
corr(u_i, Xb)  = -0.6606                        Prob > F           =    0.0002
-------------+----------------------------------------------------------------
Total Inpatient|    Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       y1996 |   95.67099   65.94314     1.45   0.147    -33.58797    224.9299
       y1997 |    16.0444   108.0562     0.15   0.882    -195.7628    227.8516
       y1998 |   5.674696    151.177     0.04   0.970    -290.6562    302.0056
       y1999 |   19.42882   195.6302     0.10   0.921    -364.0372    402.8948
       y2000 |  -15.86792   239.7097    -0.07   0.947    -485.7368     454.001
         Age |  -273.3299   435.1404    -0.63   0.530    -1126.274     579.614
        Age2 |   1.967984   2.724608     0.72   0.470    -3.372678    7.308646
     Married |    35.7559   241.7554     0.15   0.882    -438.1227    509.6345
      Income |   .0469359   1.455766     0.03   0.974    -2.806596    2.900468
       Metro |  -139.7878   715.8657    -0.20   0.845    -1542.998    1263.422
   HCC index |   122.3378   35.77586     3.42   0.001     52.21142    192.4641
         Q-7 |   246.0855   331.1968     0.74   0.457    -403.1125    895.2835
         Q-6 |    131.018   294.1277     0.45   0.656    -445.5187    707.5546
         Q-5 |   345.1391   293.3794     1.18   0.239    -229.9309     920.209
         Q-4 |   289.4415   292.4946     0.99   0.322    -283.8942    862.7771
         Q-3 |   222.3661   291.5066     0.76   0.446    -349.0329    793.7651
         Q-2 |   333.6983   291.1203     1.15   0.252    -236.9435      904.34
         Q-1 |   365.9546   291.1448     1.26   0.209    -204.7351    936.6444
         Q+1 |   329.0116   291.9651     1.13   0.260    -243.2861    901.3093
         Q+2 |      408.05   292.7354     1.39   0.163    -165.7576    981.8575
         Q+3 |   519.7541    299.032     1.74   0.082    -66.39576    1105.904
         Q+4 |   469.3507   301.0732     1.56   0.119    -120.8004    1059.502
         Q+5 |   377.1528   301.8031     1.25   0.211    -214.4288    968.7344
         Q+6 |   577.1065   303.2152     1.90   0.057    -17.24323    1171.456
         Q+7 |    374.519   330.1981     1.13   0.257    -272.7213    1021.759
  Switch Q-7 |   16.59545   358.1003     0.05   0.963    -685.3376    718.5285
  Switch Q-6 |  -18.96706   189.1396    -0.10   0.920    -389.7106    351.7764
  Switch Q-5 |   17.22748   183.7791     0.09   0.925    -343.0086    377.4635
  Switch Q-4 |  -4.581376   177.1013    -0.03   0.979    -351.7278    342.5651
  Switch Q-3 |   29.15178   170.1627     0.17   0.864     -304.394    362.6976
  Switch Q-2 |    -.44538   156.2894    -0.00   0.998    -306.7973    305.9065
  Switch Q-1 |   100.7159   155.0487     0.65   0.516     -203.204    404.6357
  Switch Q+1 |    9.26083   155.9816     0.06   0.953    -296.4877    315.0094
  Switch Q+2 |   59.22103    157.305     0.38   0.707    -249.1217    367.5637
  Switch Q+3 |   84.26272   171.0874     0.49   0.622    -251.0956     419.621
  Switch Q+4 |   67.90675   173.4245     0.39   0.695    -272.0326    407.8461
  Switch Q+5 |   58.96286   177.3198     0.33   0.740     -288.612    406.5377
  Switch Q+6 |  -116.8152   183.6975    -0.64   0.525    -476.8912    243.2609
  Switch Q+7 |  -109.4708   311.3909    -0.35   0.725     -719.846    500.9044
       _cons |    9072.05   17543.54     0.52   0.605    -25316.05    43460.15
-------------+----------------------------------------------------------------
     sigma_u |   652.6796
     sigma_e |   1419.784
         rho |  .17445926   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.7

Fixed Effects Model of Inpatient Spending for Losers and Always

```
Fixed-effects (within) regression               Number of obs      =     33352
Group variable (i): baseid                      Number of groups   =      3219

R-sq:  within  = 0.0036                         Obs per group: min =         8
       between = 0.0058                                        avg =      10.4
       overall = 0.0010                                        max =        16

                                                F(39,30094)        =      2.76
corr(u_i, Xb)  = -0.9638                        Prob > F           =    0.0000

------------------------------------------------------------------------------
Inpatient  $ |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       y1996 |   73.98024   42.35033     1.75   0.081    -9.028214    156.9887
       y1997 |   179.5843   66.03843     2.72   0.007     50.14616    309.0225
       y1998 |   256.6517   90.42752     2.84   0.005     79.40992    433.8935
       y1999 |   413.1767   115.6765     3.57   0.000     186.4458    639.9075
       y2000 |   474.8591   139.4593     3.41   0.001      201.513    748.2053
         Age |  -180.4723   119.6541    -1.51   0.131    -414.9995    54.05484
        Age2 |   .4505222   .8008532     0.56   0.574    -1.119184    2.020229
     Married |  -68.43764   145.1778    -0.47   0.637    -352.9924    216.1171
      Income |  -.6399003   1.020604    -0.63   0.531    -2.640328    1.360528
       Metro |   282.1479   415.5947     0.68   0.497    -532.4354    1096.731
   HCC Index |   116.5292    20.7482     5.62   0.000     75.86185    157.1966
         Q-7 |  -103.7826   86.24291    -1.20   0.229    -272.8224    65.25718
         Q-6 |   46.87563   80.96678     0.58   0.563    -111.8227     205.574
         Q-5 |   59.61942   80.64105     0.74   0.460    -98.44048    217.6793
         Q-4 |   33.11292   80.84736     0.41   0.682    -125.3514    191.5772
         Q-3 |   16.75828    81.3142     0.21   0.837     -142.621    176.1376
         Q-2 |   27.41813   82.78218     0.33   0.740    -134.8385    189.6747
         Q-1 |   59.36698   83.01879     0.72   0.475    -103.3534    222.0873
         Q+1 |    36.3196   84.16666     0.43   0.666    -128.6506    201.2898
         Q+2 |   60.28961   86.50536     0.70   0.486    -109.2646    229.8438
         Q+3 |   54.46408   95.30498     0.57   0.568    -132.3378    241.2659
         Q+4 |   2.890381   97.29603     0.03   0.976     -187.814    193.5948
         Q+5 |   49.65212   97.73895     0.51   0.611    -141.9204    241.2246
         Q+6 |   58.92309   101.9712     0.58   0.563    -140.9447    258.7909
         Q+7 |   236.2091   172.3098     1.37   0.170    -101.5255    573.9436
  Switch Q-7 |   288.5567   176.7698     1.63   0.103    -57.91969     635.033
  Switch Q-6 |   70.40452   142.2773     0.49   0.621     -208.465     349.274
  Switch Q-5 |  -4.726777   139.3178    -0.03   0.973    -277.7956    268.3421
  Switch Q-4 |   16.35145    138.119     0.12   0.906    -254.3677    287.0706
  Switch Q-3 |   42.37733   132.8516     0.32   0.750    -218.0175    302.7722
  Switch Q-2 |   .8363971   127.1002     0.01   0.995    -248.2853    249.9581
  Switch Q-1 |    95.8204    126.899     0.76   0.450    -152.9071    344.5479
  Switch Q+1 |    54.0189   132.2351     0.41   0.683    -205.1676    313.2054
  Switch Q+2 |   19.90986   143.0151     0.14   0.889    -260.4058    300.2255
  Switch Q+3 |  -23.05108   168.3351    -0.14   0.891    -352.9951     306.893
  Switch Q+4 |   120.4921   174.4024     0.69   0.490     -221.344    462.3282
  Switch Q+5 |  -38.92015   177.7049    -0.22   0.827    -387.2293     309.389
  Switch Q+6 |   237.9712   203.5358     1.17   0.242    -160.9677    636.9101
  Switch Q+7 |  -597.5416   780.1405    -0.77   0.444     -2126.65     931.567
       _cons |   10463.48   4713.783     2.22   0.026     1224.265     19702.7
-------------+----------------------------------------------------------------
     sigma_u |  1834.7518
     sigma_e |  1429.3967
         rho |  .62229799   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.8

Fixed Effects Model of Physician/Supplier Spending for Gainers and Never

```
Fixed-effects (within) regression               Number of obs      =     45384
Group variable (i): baseid                      Number of groups   =      4054

R-sq:  within  = 0.0100                         Obs per group: min =         8
       between = 0.0511                                        avg =      11.2
       overall = 0.0167                                        max =        16

                                                F(39,41291)        =     10.75
corr(u_i, Xb)  = -0.3217                        Prob > F           =    0.0000

------------------------------------------------------------------------------
Total Physician|      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
        y1996 |    1.769563    3.99966     0.44   0.658    -6.069857    9.608983
        y1997 |   -.3698462   6.433038    -0.06   0.954    -12.97874    12.23905
        y1998 |    .5950762   8.973856     0.07   0.947    -16.99387    18.18403
        y1999 |    .4695174   11.59554     0.04   0.968    -22.25799    23.19702
        y2000 |    -3.01079   14.19326    -0.21   0.832    -30.82987     24.8083
          Age |   -13.24289   20.95015    -0.63   0.527    -54.30563    27.81985
         Age2 |    .1145161   .1325959     0.86   0.388    -.1453746    .3744069
      Married |     -18.135   12.08829    -1.50   0.134    -41.82831    5.558312
       Income |    .0004296   .0547241     0.01   0.994    -.1068308    .1076901
        Metro |   -21.39455   37.69287    -0.57   0.570    -95.27338    52.48429
    HCC Index |    29.87082   3.309814     9.02   0.000     23.38351    36.35812
          Q-7 |    4.579995   20.97395     0.22   0.827    -36.52939    45.68938
          Q-6 |     19.8889   18.88936     1.05   0.292    -17.13465    56.91246
          Q-5 |    53.50206   18.84451     2.84   0.005     16.56641    90.43771
          Q-4 |     56.3745   18.79285     3.00   0.003      19.5401    93.20889
          Q-3 |    44.76665   18.72701     2.39   0.017     8.061307      81.472
          Q-2 |    42.33336   18.64959     2.27   0.023     5.779761    78.88696
          Q-1 |    60.12183   18.64203     3.23   0.001     23.58305    96.66061
          Q+1 |    66.81161   18.68121     3.58   0.000     30.19604    103.4272
          Q+2 |    72.71694   18.71909     3.88   0.000     36.02713    109.4068
          Q+3 |    69.59066   19.03547     3.66   0.000     32.28074    106.9006
          Q+4 |     71.8269   19.13328     3.75   0.000     34.32525    109.3285
          Q+5 |    76.65644    19.1686     4.00   0.000     39.08558    114.2273
          Q+6 |    86.19003   19.23982     4.48   0.000     48.47958    123.9005
          Q+7 |    77.77779   21.02986     3.70   0.000     36.55881    118.9968
  Switch Q-7 |    -6.56832   22.43183    -0.29   0.770     -50.5352    37.39856
  Switch Q-6 |    2.646746   11.14534     0.24   0.812    -19.19836    24.49185
  Switch Q-5 |    10.34302    10.7895     0.96   0.338    -10.80463    31.49068
  Switch Q-4 |    2.122972   10.43932     0.20   0.839    -18.33833    22.58427
  Switch Q-3 |     3.43205   9.961074     0.34   0.730    -16.09187    22.95597
  Switch Q-2 |     8.76266   8.968058     0.98   0.329    -8.814926    26.34024
  Switch Q-1 |    9.790342   8.872852     1.10   0.270    -7.600638    27.18132
  Switch Q+1 |    4.163768   8.920421     0.47   0.641    -13.32045    21.64798
  Switch Q+2 |    6.959398   9.045293     0.77   0.442    -10.76957    24.68837
  Switch Q+3 |    5.793644   10.08805     0.57   0.566    -13.97915    25.56644
  Switch Q+4 |    11.37292   10.26325     1.11   0.268    -8.743265     31.4891
  Switch Q+5 |    6.732112   10.48031     0.64   0.521    -13.80951    27.27374
  Switch Q+6 |    2.268495   10.93034     0.21   0.836    -19.15521     23.6922
  Switch Q+7 |    8.104849   20.10596     0.40   0.687    -31.30327    47.51296
       _cons |    343.9378   837.8682     0.41   0.681    -1298.302    1986.177
---------------+--------------------------------------------------------------
     sigma_u |   91.668221
     sigma_e |   167.97532
         rho |    .2294742   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.9

Fixed Effects Model of Inpatient Spending for Losers and Always

```
Fixed-effects (within) regression               Number of obs      =    102264
Group variable (i): baseid                      Number of groups   =      8509

R-sq:  within  = 0.0091                         Obs per group: min =         8
       between = 0.2048                                        avg =      12.0
       overall = 0.0557                                        max =        16

                                                F(39,93716)        =     22.01
corr(u_i, Xb)  = 0.1503                         Prob > F           =    0.0000

------------------------------------------------------------------------------
Total physician |   Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
         y1996 |  -.4033776   2.778417    -0.15   0.885    -5.849044    5.042289
         y1997 |   7.639544   4.266561     1.79   0.073    -.7228703    16.00196
         y1998 |   11.42513   5.827387     1.96   0.050     .0035152    22.84675
         y1999 |   21.60302   7.433399     2.91   0.004     7.033636     36.1724
         y2000 |    36.7982   8.929997     4.12   0.000      19.2955    54.30089
           Age |  -3.213372   6.987209    -0.46   0.646    -16.90823    10.48148
          Age2 |   .0304898   .0464429     0.66   0.512    -.0605378    .1215174
       Married |  -.0325078   8.701902    -0.00   0.997    -17.08814    17.02313
        Income |  -.0033292   .0359715    -0.09   0.926    -.0738329    .0671745
         Metro |   12.68564   16.34624     0.78   0.438    -19.35282     44.7241
     HCC Index |   27.66425   1.997037    13.85   0.000     23.75008    31.57842
           Q-7 |    1.63591   5.773562     0.28   0.777    -9.680211    12.95203
           Q-6 |   22.85414   5.428322     4.21   0.000     12.21469    33.49359
           Q-5 |   35.56065   5.406265     6.58   0.000     24.96443    46.15688
           Q-4 |   36.16995   5.416743     6.68   0.000     25.55319    46.78671
           Q-3 |   29.10654   5.434433     5.36   0.000     18.45511    39.75797
           Q-2 |   27.58295    5.48702     5.03   0.000     16.82845    38.33745
           Q-1 |   42.95053   5.496922     7.81   0.000     32.17663    53.72444
           Q+1 |   42.89088   5.567405     7.70   0.000     31.97883    53.80294
           Q+2 |   47.77405   5.711246     8.36   0.000     36.58007    58.96803
           Q+3 |   41.08682   6.233765     6.59   0.000     28.86871    53.30493
           Q+4 |   45.90341    6.34993     7.23   0.000     33.45761     58.3492
           Q+5 |   49.37439   6.377632     7.74   0.000      36.8743    61.87448
           Q+6 |   58.70116   6.664922     8.81   0.000     45.63799    71.76434
           Q+7 |   69.62369   11.84443     5.88   0.000     46.40872    92.83865
  Switch Q-7 |   19.17476   11.13211     1.72   0.085    -2.644056    40.99357
  Switch Q-6 |   8.726339   8.678594     1.01   0.315    -8.283612    25.73629
  Switch Q-5 |   2.738537   8.521421     0.32   0.748    -13.96336    19.44043
  Switch Q-4 |   8.646572   8.464215     1.02   0.307    -7.943198    25.23634
  Switch Q-3 |   1.166268   8.129773     0.14   0.886      -14.768    17.10053
  Switch Q-2 |   .7610758   7.739849     0.10   0.922    -14.40894     15.9311
  Switch Q-1 |   8.364703   7.710269     1.08   0.278    -6.747341    23.47675
  Switch Q+1 |   9.829929   8.032642     1.22   0.221    -5.913963    25.57382
  Switch Q+2 |  -3.963427   8.746776    -0.45   0.650    -21.10701    13.18016
  Switch Q+3 |  -14.72559   10.64974    -1.38   0.167    -35.59897    6.147782
  Switch Q+4 |   3.912246    11.0037     0.36   0.722    -17.65488    25.47937
  Switch Q+5 |  -10.49454   11.15685    -0.94   0.347    -32.36184    11.37275
  Switch Q+6 |  -3.342451   12.74943    -0.26   0.793     -28.3312     21.6463
  Switch Q+7 |  -57.20318   34.18439    -1.67   0.094    -124.2042    9.797862
       _cons |   70.93254   276.6681     0.26   0.798     -471.334    613.1991
----------------+-------------------------------------------------------------
     sigma_u |  87.138263
     sigma_e |   172.7879
         rho |  .20275924   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.10

Fixed Effects Model of Inpatient Spending for Gainers and Nevers with Employer-sponsored Drug Coverage

```
Fixed-effects (within) regression               Number of obs      =     11024
Group variable (i): baseid                      Number of groups   =      1119

R-sq:  within  = 0.0067                         Obs per group: min =         8
       between = 0.0014                                        avg =       9.9
       overall = 0.0009                                        max =        16

                                                F(35,9870)         =      1.89
corr(u_i, Xb)  = -0.6407                        Prob > F           =    0.0011

------------------------------------------------------------------------------
Total inpatient |   Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
       y1996 |   67.48976   72.44858     0.93   0.352    -74.52427    209.5038
       y1997 |  -36.99729   120.0072    -0.31   0.758    -272.2359    198.2413
       y1998 |  -51.00009     169.03    -0.30   0.763    -382.3334    280.3332
       y1999 |  -18.35924   218.8824    -0.08   0.933    -447.4135     410.695
       y2000 |  -41.52345   269.5139    -0.15   0.878    -569.8258    486.7789
         Age |  -138.6304   488.4324    -0.28   0.777    -1096.058     818.797
        Age2 |   1.168392   3.041908     0.38   0.701    -4.794368    7.131153
     Married |  -137.4818   324.1043    -0.42   0.671    -772.7924    497.8289
      Income |   .1503987   1.500295     0.10   0.920    -2.790487    3.091284
       Metro |  -133.5253   718.7007    -0.19   0.853    -1542.325    1275.275
   HCC Index |   124.5209   38.11514     3.27   0.001     49.80747    199.2344
         Q-7 |   301.5833     380.68     0.79   0.428    -444.6272    1047.794
         Q-6 |    183.372   351.7604     0.52   0.602    -506.1502    872.8943
         Q-5 |   397.7364   351.1904     1.13   0.257    -290.6686    1086.141
         Q-4 |   342.5289   350.6933     0.98   0.329    -344.9015    1029.959
         Q-3 |   275.5219   350.2025     0.79   0.431    -410.9465    961.9902
         Q-2 |   389.6041    351.176     1.11   0.267    -298.7727    1077.981
         Q-1 |   422.0454   351.3184     1.20   0.230    -266.6104    1110.701
         Q+1 |   385.4501   352.3252     1.09   0.274    -305.1793    1076.079
         Q+2 |   464.4835     353.24     1.31   0.189    -227.9391    1156.906
         Q+3 |   579.4019   360.3618     1.61   0.108    -126.9809    1285.785
         Q+4 |   529.6862   362.6678     1.46   0.144    -181.2169    1240.589
         Q+5 |   437.6107    363.362     1.20   0.228    -274.6531    1149.874
         Q+6 |   638.5248   364.6741     1.75   0.080    -76.31087     1353.36
         Q+7 |   435.4914   387.7112     1.12   0.261    -324.5017    1195.484
  Switch Q-7 |  (dropped)
  Switch Q-6 |  (dropped)
  Switch Q-5 |  (dropped)
  Switch Q-4 |   109.3529    1593.42     0.07   0.945    -3014.076    3232.782
  Switch Q-3 |  -26.65792   641.1782    -0.04   0.967    -1283.498    1230.182
  Switch Q-2 |  -24.23909   488.6554    -0.05   0.960    -982.1036    933.6254
  Switch Q-1 |   86.83534   480.0351     0.18   0.856    -854.1316    1027.802
  Switch Q+1 |   92.31075   480.1104     0.19   0.848    -848.8038    1033.425
  Switch Q+2 |   27.33332   480.1741     0.06   0.955     -913.906    968.5727
  Switch Q+3 |   226.9293    480.645     0.47   0.637     -715.233    1169.092
  Switch Q+4 |   152.4162   480.7296     0.32   0.751     -789.912    1094.744
  Switch Q+5 |   163.7276   481.0805     0.34   0.734    -779.2885    1106.744
 Switch Q+6 |  -173.3218   483.3061    -0.36   0.720      -1120.7    774.0569
  Switch Q+7 |  (dropped)
       _cons |   3549.418   19860.47     0.18   0.858    -35381.16       42480
----------------+-------------------------------------------------------------
     sigma_u |  616.50624
     sigma_e |  1423.3481
         rho |  .15797174   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.11

Fixed Effects Model of Inpatient Spending for Losers and Always with Employer-sponsored Drug Coverage

```
Fixed-effects (within) regression               Number of obs      =     16728
Group variable (i): baseid                      Number of groups   =      1615

R-sq:  within  = 0.0051                         Obs per group: min =         8
       between = 0.0002                                        avg =      10.4
       overall = 0.0002                                        max =        16

                                                F(39,15074)        =      1.98
corr(u_i, Xb)  = -0.8908                        Prob > F           =    0.0003

------------------------------------------------------------------------------
Total inpatient |   Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
       y1996 |   25.58055   62.87648     0.41   0.684    -97.66499    148.8261
       y1997 |   223.8798   97.87522     2.29   0.022     32.03248    415.7271
       y1998 |   266.6857   133.1014     2.00   0.045     5.790844    527.5805
       y1999 |   448.5481   169.2231     2.65   0.008     116.8503     780.246
       y2000 |   454.8177   204.4378     2.22   0.026      54.0947    855.5406
         Age |    136.804   264.4133     0.52   0.605    -381.4781     655.086
        Age2 |  -1.674415   1.747934    -0.96   0.338    -5.100577    1.751746
     Married |  -106.0348   243.8725    -0.43   0.664    -584.0546    371.9849
      Income |  -1.525946   1.767288    -0.86   0.388    -4.990045    1.938154
       Metro |   385.6498   538.1024     0.72   0.474    -669.0962    1440.396
   HCC Index |    92.7033   30.85578     3.00   0.003     32.22223    153.1844
         Q-7 |   -276.182   123.5391    -2.24   0.025    -518.3337   -34.03037
         Q-6 |  -143.3898   116.0777    -1.24   0.217    -370.9162    84.13663
         Q-5 |  -73.57684   115.6065    -0.64   0.524    -300.1796    153.0259
         Q-4 |  -116.2681   115.8885    -1.00   0.316    -343.4236    110.8873
         Q-3 |  -165.4698   116.6242    -1.42   0.156    -394.0674    63.12788
         Q-2 |  -146.7453   118.8778    -1.23   0.217    -379.7602    86.26955
         Q-1 |  -70.15464   119.2495    -0.59   0.556    -303.8982    163.5889
         Q+1 |  -91.45471   120.9798    -0.76   0.450    -328.5898    145.6803
         Q+2 |  -125.0945   124.5413    -1.00   0.315    -369.2105    119.0215
         Q+3 |  -60.86403   137.4515    -0.44   0.658    -330.2857    208.5577
         Q+4 |  -56.41657   140.5496    -0.40   0.688    -331.9108    219.0777
         Q+5 |  -59.69685   141.3083    -0.42   0.673    -336.6782    217.2845
         Q+6 |   -61.6594   148.0929    -0.42   0.677    -351.9395    228.6207
         Q+7 |   331.4164   246.1756     1.35   0.178    -151.1177    813.9505
  Switch Q-7 |   464.5531   237.2466     1.96   0.050    -.4789384    929.5852
  Switch Q-6 |   132.9879   190.4103     0.70   0.485    -240.2394    506.2152
  Switch Q-5 |   27.66388   188.2476     0.15   0.883    -341.3243    396.6521
  Switch Q-4 |   9.600032    187.846     0.05   0.959    -358.6009    377.8009
  Switch Q-3 |   73.00812    183.022     0.40   0.690    -285.7372    431.7534
  Switch Q-2 |   96.33474     178.07     0.54   0.589    -252.7041    445.3735
  Switch Q-1 |   57.30104   177.7155     0.32   0.747    -291.0428    405.6449
  Switch Q+1 |   86.22715    190.447     0.45   0.651     -287.072    459.5263
  Switch Q+2 |   235.5462   211.6144     1.11   0.266    -179.2437     650.336
  Switch Q+3 |   342.5951   292.7282     1.17   0.242    -231.1876    916.3779
  Switch Q+4 |   200.9438   305.9032     0.66   0.511    -398.6636    800.5513
  Switch Q+5 |   140.6111   309.2316     0.45   0.649    -465.5204    746.7425
  Switch Q+6 |   327.7404    373.053     0.88   0.380    -403.4888     1058.97
  Switch Q+7 |  -400.8099   1152.347    -0.35   0.728    -2659.549    1857.929
       _cons |  -661.9112   10275.15    -0.06   0.949    -20802.46    19478.63
----------------+-------------------------------------------------------------
     sigma_u |  1063.0024
     sigma_e |  1480.5311
         rho |  .34015424   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.12

Fixed Effects Model of Physician/Supplier Spending for Gainers and Nevers-with Employer-sponsored Drug Coverage

```
Fixed-effects (within) regression               Number of obs      =     36936
Group variable (i): baseid                      Number of groups   =      3250

R-sq:  within  = 0.0102                         Obs per group: min =         8
       between = 0.0403                                        avg =      11.4
       overall = 0.0128                                        max =        16

                                                F(35,33651)        =      9.90
corr(u_i, Xb)  = -0.4116                        Prob > F           =    0.0000

------------------------------------------------------------------------------
Total physician |   Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
       y1996 |  -.6202609   4.395067    -0.14   0.888    -9.234743    7.994221
       y1997 |   -3.02629   7.096852    -0.43   0.670    -16.93636    10.88378
       y1998 |   -1.97195   9.914359    -0.20   0.842    -21.40443    17.46054
       y1999 |   .7030787   12.81234     0.05   0.956    -24.40955    25.81571
       y2000 |  -1.529126   15.71956    -0.10   0.923       -32.34    29.28175
         Age |  -6.322626   22.93566    -0.28   0.783    -51.27731    38.63206
        Age2 |   .0785102   .1447781     0.54   0.588    -.2052599    .3622803
     Married |  -20.01151   13.93043    -1.44   0.151    -47.31564    7.292616
      Income |   .0119458   .0568985     0.21   0.834    -.0995772    .1234689
       Metro |   -14.0893   48.52473    -0.29   0.772    -109.1994    81.02085
   HCC Index |   27.21885   3.551334     7.66   0.000     20.25811    34.17958
         Q-7 |   7.842654   23.30188     0.34   0.736    -37.82983    53.51514
         Q-6 |   23.14001   21.54668     1.07   0.283    -19.09223    65.37226
         Q-5 |   56.80784   21.51006     2.64   0.008     14.64737     98.9683
         Q-4 |   59.58384   21.47024     2.78   0.006     17.50143    101.6663
         Q-3 |   48.04616   21.42593     2.24   0.025     6.050599    90.04173
         Q-2 |   45.29612   21.40577     2.12   0.034     3.340068    87.25217
         Q-1 |   63.06529   21.40394     2.95   0.003     21.11284    105.0177
         Q+1 |   69.76347   21.44998     3.25   0.001     27.72077    111.8062
         Q+2 |   75.61143   21.49322     3.52   0.000     33.48397    117.7389
         Q+3 |   72.38981   21.84469     3.31   0.001     29.57347    115.2062
         Q+4 |   74.55771   21.95388     3.40   0.001     31.52734    117.5881
         Q+5 |   79.42451   21.98889     3.61   0.000     36.32552    122.5235
         Q+6 |   88.84624   22.05575     4.03   0.000     45.61621    132.0763
         Q+7 |   80.41825   23.65365     3.40   0.001     34.05629    126.7802
  Switch Q-7 |  (dropped)
  Switch Q-6 |  (dropped)
  Switch Q-5 |  (dropped)
  Switch Q-4 |  (dropped)
  Switch Q-3 |  -26.81636   106.3989    -0.25   0.801    -235.3618    181.7291
  Switch Q-2 |   7.380418   104.2012     0.07   0.944    -196.8576    211.6184
  Switch Q-1 |   29.68326   104.1764     0.28   0.776     -174.506    233.8725
  Switch Q+1 |    17.9026   104.1781     0.17   0.864    -186.2902    222.0954
  Switch Q+2 |   12.40201     104.18     0.12   0.905    -191.7943    216.5983
  Switch Q+3 |   25.58082   104.1956     0.25   0.806    -178.6461    229.8077
  Switch Q+4 |   30.64564   104.1994     0.29   0.769    -173.5887      234.88
  Switch Q+5 |   23.49323   104.3113     0.23   0.822    -180.9605    227.9469
  Switch Q+6 |   16.51395   104.3863     0.16   0.874    -188.0869    221.1148
  Switch Q+7 |   28.41012   109.4839     0.26   0.795    -186.1822    243.0024
       _cons |   23.09128    922.102     0.03   0.980     -1784.26    1830.443
----------------+-------------------------------------------------------------
     sigma_u |  96.046802
     sigma_e |  167.98573
         rho |  .24636632   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.13

Fixed Effects Model of Physician/Supplier Spending for Losers and Always with Employer-sponsored Drug Coverage

```
Fixed-effects (within) regression               Number of obs      =     55688
Group variable (i): baseid                      Number of groups   =      4620

R-sq:  within  = 0.0097                         Obs per group: min =         8
       between = 0.1434                                        avg =      12.1
       overall = 0.0404                                        max =        16

                                                F(39,51029)        =     12.87
corr(u_i, Xb)  = 0.0467                         Prob > F           =    0.0000

------------------------------------------------------------------------------
Total physician |   Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
       y1996 |  -3.246562   3.952087    -0.82   0.411    -10.99269    4.499568
       y1997 |   10.38438   6.034215     1.72   0.085     -1.44274    22.21151
       y1998 |   12.34634   8.184213     1.51   0.131    -3.694798    28.38749
       y1999 |   23.95615   10.39087     2.31   0.021     3.589935    44.32236
       y2000 |   38.68835   12.48424     3.10   0.002     14.21911    63.15759
         Age |  -11.50006   15.73347    -0.73   0.465    -42.33782    19.33771
        Age2 |   .0865264   .1040056     0.83   0.405    -.1173257    .2903785
     Married |   3.860336   12.72042     0.30   0.762    -21.07183     28.7925
      Income |  -.0033799   .0400416    -0.08   0.933    -.0818619    .0751022
       Metro |   20.58423   23.01369     0.89   0.371    -24.52285     65.6913
   HCC Index |   26.51784   3.025157     8.77   0.000      20.5885    32.44718
         Q-7 |  -11.67503   7.922038    -1.47   0.141    -27.20231    3.852244
         Q-6 |   12.27637   7.452481     1.65   0.100    -2.330568    26.88331
         Q-5 |   24.28283   7.420739     3.27   0.001     9.738103    38.82756
         Q-4 |   25.85842   7.435314     3.48   0.001     11.28512    40.43171
         Q-3 |   15.60246   7.463549     2.09   0.037     .9738264    30.23109
         Q-2 |   14.72815   7.539439     1.95   0.051    -.0492336    29.50552
         Q-1 |   32.25081   7.554859     4.27   0.000     17.44321    47.05841
         Q+1 |   33.12333   7.651755     4.33   0.000     18.12581    48.12085
         Q+2 |   36.87849   7.855479     4.69   0.000     21.48167    52.27531
         Q+3 |    31.2732   8.586952     3.64   0.000     14.44268    48.10371
         Q+4 |    38.5603    8.75563     4.40   0.000     21.39917    55.72142
         Q+5 |   42.75525   8.792908     4.86   0.000     25.52106    59.98945
         Q+6 |   57.68304   9.194368     6.27   0.000     39.66198     75.7041
         Q+7 |    60.6877   16.28694     3.73   0.000     28.76514    92.61027
  Switch Q-7 |   23.39742   14.72267     1.59   0.112    -5.459171    52.25402
  Switch Q-6 |   6.490388   11.62033     0.56   0.576    -16.28557    29.26635
  Switch Q-5 |   8.291404    11.4959     0.72   0.471    -14.24067    30.82348
  Switch Q-4 |   9.355002   11.48533     0.81   0.415    -13.15637    31.86638
  Switch Q-3 |   4.082169   11.19492     0.36   0.715    -17.85999    26.02433
  Switch Q-2 |  -4.509592   10.86696    -0.41   0.678    -25.80895    16.78976
  Switch Q-1 |  -5.512156   10.83543    -0.51   0.611    -26.74971     15.7254
  Switch Q+1 |   7.496847   11.51314     0.65   0.515    -15.06903    30.06272
  Switch Q+2 |  -3.353072    13.1012    -0.26   0.798    -29.03156    22.32542
  Switch Q+3 |  -2.121427   19.05492    -0.11   0.911    -39.46927    35.22641
  Switch Q+4 |   1.974507   19.89632     0.10   0.921    -37.02248     40.9715
  Switch Q+5 |   1.925744   19.97224     0.10   0.923    -37.22006    41.07155
  Switch Q+6 |  -15.84827   23.89973    -0.66   0.507    -62.69198    30.99544
  Switch Q+7 |  -109.2784   68.15987    -1.60   0.109    -242.8725    24.31561
       _cons |   377.0582   608.3807     0.62   0.535    -815.3743    1569.491
-------------+-------------------------------------------------------------
     sigma_u |  88.297747
     sigma_e |  177.52204
         rho |   .1983307   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.14

Difference-in-Difference Model of Total Inpatient Spending for Gainers and Nevers

```
Fixed-effects (within) regression               Number of obs      =     13680
Group variable (i): baseid                      Number of groups   =      1401

R-sq:  within  = 0.0036                         Obs per group: min =         8
       between = 0.0035                                        avg =       9.8
       overall = 0.0007                                        max =        16

                                                F(14,12265)        =      3.19
corr(u_i, Xb)  = -0.8453                        Prob > F           =    0.0000

------------------------------------------------------------------------------
 Total inpatient |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
        y1996 |    187.791   54.95742     3.42   0.001     80.06581    295.5162
        y1997 |   197.1407   79.44047     2.48   0.013     41.42485    352.8565
        y1998 |   278.7367   103.0436     2.71   0.007     76.75515    480.7183
        y1999 |   384.1231   127.8534     3.00   0.003     133.5104    634.7359
        y2000 |   441.7032   150.1892     2.94   0.003     147.3087    736.0976
          Age |  -336.8673   434.3684    -0.78   0.438    -1188.298    514.5632
         Age2 |   1.850741    2.72236     0.68   0.497    -3.485513    7.186995
      Married |   10.11199   241.6825     0.04   0.967    -463.6238    483.8478
       Income |   .1033875    1.45629     0.07   0.943    -2.751171    2.957946
        metro |  -145.9165   716.1161    -0.20   0.839    -1549.617    1257.784
    HCC Index |   121.5006    35.7935     3.39   0.001     51.33974    191.6615
  Post period |   44.89839   37.38742     1.20   0.230    -28.38683    118.1836
       Switch |  -22.63968   135.5702    -0.17   0.867    -288.3786    243.0992
 Post*Switch |  -14.70328   63.81229    -0.23   0.818    -139.7854    110.3789
        _cons |   14946.69   17388.75     0.86   0.390       -19138    49031.38
-----------------+------------------------------------------------------------
      sigma_u |  931.39804
      sigma_e |  1420.2969
          rho |  .30072056   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.15

Difference-in-Difference Model of Total Inpatient Spending for Losers and Always

```
Fixed-effects (within) regression               Number of obs      =     33352
Group variable (i): baseid                      Number of groups   =      3219

R-sq:  within  = 0.0029                         Obs per group: min =         8
       between = 0.0055                                        avg =      10.4
       overall = 0.0009                                        max =        16

                                                F(14,30119)        =      6.25
corr(u_i, Xb)  = -0.9692                        Prob > F           =    0.0000

------------------------------------------------------------------------------
Total inpatient |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
       y1996 |   82.23101    36.9463     2.23   0.026     9.814679    154.6473
       y1997 |   197.6232   51.38304     3.85   0.000     96.91025    298.3361
       y1998 |   284.3737   65.66735     4.33   0.000     155.6629    413.0846
       y1999 |   451.3691   80.29332     5.62   0.000     293.9907    608.7474
       y2000 |   522.3211   92.45346     5.65   0.000     341.1084    703.5339
         Age |   -189.698   118.4332    -1.60   0.109     -421.832    42.43607
        Age2 |   .4404386   .8004246     0.55   0.582    -1.128428    2.009305
     Married |  -66.61721   145.1768    -0.46   0.646      -351.17    217.9356
      Income |  -.5998574   1.020279    -0.59   0.557    -2.599648    1.399933
       Metro |   281.5672   415.5639     0.68   0.498    -532.9559     1096.09
   HCC Index |    116.802   20.74375     5.63   0.000     76.14339    157.4607
 Post period |   3.390005   22.42457     0.15   0.880     -40.5631    47.34311
      Switch |   65.21728   105.9976     0.62   0.538    -142.5425    272.9771
 Post*Switch |  -7.956975   69.50833    -0.11   0.909    -144.1963    128.2823
       _cons |   11195.94   4519.648     2.48   0.013     2337.239    20054.65
----------------+-------------------------------------------------------------
     sigma_u |  1980.8321
     sigma_e |  1429.2829
         rho |    .657616   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.16

Difference-in-Difference Model of Physician/Supplier Spending for Gainers and Nevers

```
Fixed-effects (within) regression               Number of obs      =     45384
Group variable (i): baseid                      Number of groups   =      4054

R-sq:  within  = 0.0066                         Obs per group: min =         8
       between = 0.0242                                        avg =      11.2
       overall = 0.0098                                        max =        16

                                                F(14,41316)        =     19.68
corr(u_i, Xb)  = -0.3113                        Prob > F           =    0.0000

------------------------------------------------------------------------------
Total physician |   Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
       y1996 |   9.100585   3.430918     2.65   0.008     2.375913    15.82526
       y1997 |   14.25092   4.949754     2.88   0.004     4.549295    23.95254
       y1998 |   22.28622   6.533179     3.41   0.001     9.481051    35.09139
       y1999 |   29.73888   8.153666     3.65   0.000     13.75752    45.72024
       y2000 |    33.8768   9.628832     3.52   0.000     15.00408    52.74951
         Age |   -20.6048   20.90089    -0.99   0.324    -61.57099    20.36139
        Age2 |    .122362   .1327581     0.92   0.357    -.1378466    .3825706
     Married |  -17.61857   12.10421    -1.46   0.146    -41.34308    6.105949
      Income |  -.0014219   .0547972    -0.03   0.979    -.1088255    .1059817
       Metro |  -22.75821   37.74338    -0.60   0.547    -96.73604    51.21962
   HCC Index |   29.52116   3.312933     8.91   0.000     23.02774    36.01458
 Post period |   19.03616   2.345403     8.12   0.000     14.43912     23.6332
      Switch |   .8919971   7.274963     0.12   0.902    -13.36709    15.15108
 Post*Switch |  -2.738953   4.122824    -0.66   0.506    -10.81978    5.341871
       _cons |   900.9817   827.3328     1.09   0.276    -720.6082    2522.572
-------------+-----------------------------------------------------------------
     sigma_u |  94.073779
     sigma_e |  168.21478
         rho |  .23824516   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Exhibit 1.A.17

Difference-in-Difference Model of Physician/Supplier Spending for Losers and Always

```
Fixed-effects (within) regression               Number of obs      =    102264
Group variable (i): baseid                      Number of groups   =      8509

R-sq:  within  = 0.0064                         Obs per group: min =         8
       between = 0.0048                                        avg =      12.0
       overall = 0.0016                                        max =        16

                                                F(14,93741)        =     43.41
corr(u_i, Xb)  = -0.6318                        Prob > F           =    0.0000

------------------------------------------------------------------------------
 Total physician|   Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
       y1996 |   5.085904   2.481463     2.05   0.040     .2222632    9.949545
       y1997 |   18.79327   3.449583     5.45   0.000     12.03212    25.55441
       y1998 |   28.56961   4.435022     6.44   0.000     19.87701     37.2622
       y1999 |   44.67111   5.452914     8.19   0.000     33.98345    55.35876
       y2000 |   65.85788   6.304716    10.45   0.000      53.5007    78.21505
         Age |  -10.02485   6.869913    -1.46   0.145     -23.4898     3.44011
        Age2 |   .0362598   .0465002     0.78   0.436    -.0548801    .1273997
     Married |  -.1293651   8.711825    -0.01   0.988    -17.20445    16.94572
      Income |  -.0035213    .036013    -0.10   0.922    -.0741064    .0670639
       Metro |   12.26184   16.36563     0.75   0.454    -19.81463     44.3383
   HCC Index |   27.78329   1.999359    13.90   0.000     23.86457    31.70201
 Post period |   10.76284   1.511812     7.12   0.000     7.799704    13.72598
      Switch |   5.683806   6.106544     0.93   0.352    -6.284955    17.65257
 Post*Switch |  -6.481916   4.476283    -1.45   0.148    -15.25538    2.291552
       _cons |   545.3549    261.903     2.08   0.037     32.02788    1058.682
----------------+-------------------------------------------------------------
     sigma_u |  122.89876
     sigma_e |  172.99459
         rho |  .33541399   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 2.A: Aim 2: Sample Sizes

Exhibit 2.A.1

Sample Sizes

Sample	N
Extended Study Sample (includes M+C enrollees)	27,777
UMWA beneficiaries (majority are M+C enrollees)	64
Study Sample (excludes M+C enrollees)	23,210
Miners	158
Miner-plus	652
Miner-plus– Males	310
Miner-plus – Females	342
Propensity Match – Males	930
With SC & DC	628
With Employer-provided SC & DC[a]	343
Propensity Match – Females	1026
With SC & DC	674
With Employer-provided SC & DC	293
Exact Match – Males	309
With SC & DC	217
With Employer-provided SC & DC	120
Exact Match – Females	341
With SC & DC	226
With Employer-provided SC & DC	118

Miners – Individuals who receive supplemental and drug coverage via a previous employer in the mining industry (includes former miners and their spouses).

Miner-plus – Individuals who receive supplemental and drug coverage via a previous employer in the mining industry (includes spouses). These industries were: mining (MCBS industry code B), construction (C), oil and gas extraction (13), heavy construction excluding building (16), petroleum and coal products (29), railroad transport (40), electric gas and sanitary (49).

SC refers to supplemental coverage, DC to drug coverage.

Sources: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare, dwelling in the community, and in fee-for-service Medicare for the full year. See text for additional detail.

Exhibit 2.A.2

Demographic Characteristics: UMWA Beneficiaries, Extended Study Sample

	UMWA		Ext. Study Sample	
Year	**Number**	**Percent**	**Number**	**Percent**
1995	6	9	3,695	13
1996	11	17	3,196	12
1997	12	19	3,321	12
1998	10	16	3,619	13
1999	10	16	3,841	14
2000	15	23	9,883	36
Total	64	100	27,555	100
Sex				
MALE	24	38	12,100	44
FEMALE	40	63	15,455	56
Total	64	100	27,555	100
Age				
<65	3	5	4,083	15
65-69	2	3	3,448	13
70-74	10	16	5,944	22
75-79	10	16	4,987	18
80+	39	61	9,093	33
Total	64	100	27,555	100
Disabled				
Not disabled	61	95	23,519	85
Disabled	3	5	4,036	15
Total	64	100	27,555	100
Metro				
NON-METRO AREA	23	36	7,855	29
METRO AREA	41	64	19,700	71
Total	**64**	**100**	**27,555**	**100**

Exhibit 2.A.2

Demographic Characteristics: UMWA Beneficiaries, Extended Study Sample

	UMWA		Ext. Study Sample	
Census Region	**Number**	**Percent**	**Number**	**Percent**
UNKNOWN	0	0	2	0
NEW ENGLAND	0	0	807	3
MIDDLE ATLANTIC	34	53	4,471	16
EAST NORTH CENTRAL	4	6	4,635	17
WEST NORTH CENTRAL	0	0	1,803	7
SOUTH ATLANTIC	7	11	5,692	21
EAST SOUTH CENTRAL	8	13	1,612	6
WEST SOUTH CENTRAL	1	2	2,886	10
MOUNTAIN	10	16	1,750	6
PACIFIC	0	0	3,490	13
PUERTO RICO	0	0	407	1
Total	64	100	27,555	100
Ybase			**All**	**All**
Mean	$5,173			
Median	$3,936			

Sources: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare and dwelling in the community full year. See text for additional detail.

Exhibit 2.A.3

Demographic Characteristics: Miners, Miner-Plus, Study Sample

	Miner		Miner-Plus		Study Sample	
Year	**Number**	**Percent**	**Number**	**Percent**	**Number**	**Percent**
1995	11	7	81	12	3,290	14
1996	7	4	69	11	2,806	12
1997	10	6	73	11	2,880	12
1998	18	11	80	12	3,011	13
1999	41	26	105	16	3,116	13
2000	71	45	244	37	8,107	35
Total	158	100	652	100	23,210	100
UMWA member and miner by Gender (95-00)						
Sex						
MALE	72	46	310	48	10,172	44
FEMALE	86	54	342	52	13,038	56
Total	158	100	652	100	23,210	100
UMWA member and miner by Age Group (95-00)						
Age						
<65	8	5	37	6	3,711	16
65-69	25	16	100	15	2,735	12
70-74	45	28	188	29	4,877	21
75-79	33	21	142	22	4,140	18
80+	47	30	185	28	7,747	33
Total	158	100	652	100	23,210	100
UMWA member and miner by Disabled, Disaged (95-00)						
Disabled						
Not disabled	150	95	615	94	19,546	84
Disabled	8	5	37	6	3,664	16
Total	158	100	652	100	23,210	100
UMWA member and miner by Disabled, Disaged (95-00)						
UMWA member and miner by Metro (95-00)						
Metro						
NON-METRO AREA	87	55	221	34	7,633	33
METRO AREA	71	45	431	66	15,577	67
Total	**158**	**100**	**652**	**100**	**23,210**	**100**
UMWA member and miner by Census region (95-00)						

Exhibit 2.A.3

Demographic Characteristics: Miners, Miner-Plus, Study Sample

	Miner		Miner-Plus		Study Sample	
Census Region	**Number**	**Percent**	**Number**	**Percent**	**Number**	**Percent**
NEW ENGLAND						
MIDDLE ATLANTIC	17	11	97	15	3,816	16
EAST NORTH CENTRAL	17	11	121	19	4,227	18
WEST NORTH CENTRAL	2	1	27	4	1,674	7
SOUTH ATLANTIC	9	6	95	15	5,145	22
EAST SOUTH CENTRAL	5	3	40	6	1,571	7
WEST SOUTH CENTRAL	84	53	164	25	2,571	11
MOUNTAIN	18	11	58	9	1,245	5
PACIFIC	5	3	39	6	2,263	10
Total	158	100	652	100	23,210	100
Ybase						
Mean	$5,722		$5,803			
Median	$4,157		$4,157			

Miners – Individuals who receive supplemental and drug coverage via a previous employer in the mining industry (includes former miners and their spouses).

Miner-plus – Individuals who receive supplemental and drug coverage via a previous employer in the mining industry (includes spouses). These industries were: mining (MCBS industry code B), construction (C), oil and gas extraction (13), heavy construction excluding building (16), petroleum and coal products (29), railroad transport (40), electric gas and sanitary (49).

Sources: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare, dwelling in the community, and in fee-for-service Medicare full year. See text for additional detail.

Exhibit 2.A.4

Demographic Characteristics: Males and Females
Miner-Plus, Non-Miner-Plus, and Propensity Match

Characteristics (Males)	Miner-plus	Non-Miner-plus	Propensity Match
N	310	9862	930
Age (Years, %)			
<65	5.2	21.6*	4.8
65-69	15.5	12.6	15.7
70-74	29.4	21.7*	27.6
75-79	23.2	16.9*	25.4
80+	26.8	27.2	26.5
Disabled (%)			
Not disabled	94.8	78.7	95.2
Disabled	5.2	21.3*	4.8
Metropolitan Status (%)			
Non-Metro Area	33.2	34.1	32.5
Metro Area	66.8	65.9	67.5
Detailed Census Region (%)			
New England	1.9	3.2	2.8
Middle Atlantic	18.1	15.9	17.6
East North Central	20.6	18.2	21.8
West North Central	3.9	7.3*	3.1
South Atlantic	15.2	22.0*	15.6
East South Central	6.8	6.6	6.1
West South Central	20.0	11.2*	17.8
Mountain	9.0	5.5*	10.6
Pacific	4.5	10.2*	4.4
YBASE, Mean (SD)	6,194 (4957)	6,692 (6180)	6,171 (5472)
Characteristics (Females)	**Miner-plus**	**Non-Miner-plus**	**Propensity Match**
N	342	12,696	1,026
Age (Years, %)			
<65	6.1	12.2*	6.9
65-69	15.2	11.0*	14.7
70-74	28.4	20.1*	28.4
75-79	20.5	18.4	20.7
80+	29.8	38.4*	29.3

Exhibit 2.A.4

Demographic Characteristics: Males and Females
Miner-Plus, Non-Miner-Plus, and Propensity Match

Characteristics (Females)	Miner-plus	Non-Miner-plus	Propensity Match
Disabled (%)			
Not disabled	93.9	88.0	93.3
Disabled	6.1	12.0*	6.7
Metropolitan Status (%)			
Non-Metro Area	34.5	31.9	36.3
Metro Area	65.5	68.1	63.7
Detailed Census Region (%)			
New England	1.5	3.0	1.9
Middle Atlantic	12.0	17.0*	12.8
East North Central	16.7	18.2	15.1
West North Central	4.4	7.3*	5.9
South Atlantic	14.0	22.7*	13.3
East South Central	5.6	6.9	5.5
West South Central	29.8	10.3*	30.7
Mountain	8.8	5.1*	7.9
Pacific	7.3	9.6	7.0
YBASE, Mean (SD)	5,449 (4917)	6,193* (5518)	5,258 (4701)

Miners – Individuals who receive supplemental and drug coverage via a previous employer in the mining industry (includes former miners and their spouses).

Miner-plus– Individuals who receive supplemental and drug coverage via a previous employer in the mining industry (includes spouses). These industries were: mining (MCBS industry code B), construction (C), oil and gas extraction (13), heavy construction excluding building (16), petroleum and coal products (29), railroad transport (40), electric gas and sanitary (49).

* Significantly different from Miner-plus at $p<0.05$.

Note: Chi-square tests were used for comparing distributions and t-tests for means.

Sources: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare, dwelling in the community, and in fee-for-service Medicare for the full year. See text for additional detail.

Exhibit 2.A.5

Expenditures for Miner-plus and Propensity Match Groups: Additional Detail

Males, All Pairs

		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
Obs		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	930	310	930	310	930	310	930	310	930	310	930	310
2	Mean	825.46	1141.2	2793.39	3030.9	2312.65	2640.8	4583.09	5566.74	2266.9	2781.28	1409.53	1654.37
3	STD	917.66	1256.85	9617.68	10027.97	8936.28	9619.63	11641.45	13619.4	3481.31	3995.63	2406.37	2469.89
4	p_99	4110.31	5695.49	37083.12	36352.15	29947.84	33705.75	50187.32	68957.57	17379.31	16410.15	11821.83	11851.63
5	p_95	2620.87	3511.69	17390.94	19995.75	13496.92	17644.29	22862.54	31924.49	8423.58	11003.89	5605.17	7086.07
6	p_90	2034.71	2845.12	9015.12	9445.15	6269.19	7331.56	12951.07	13447.31	5716.92	7581.09	3640.74	4505.43
7	P_75	1129.81	1612.47	0	0	0	0	3448.4	3171.11	2626.42	3358.63	1673.26	1908.52
8	Median	537.84	735.09	0	0	0	0	769.89	997.72	1006.16	1321.23	562.08	695.19
9	p_25	150.22	267.3	0	0	0	0	165.98	235.21	367.65	462.31	123.7	205.7
10	p_10	0	53.83	0	0	0	0	0	34.29	112.5	180.87	0	20.05
11	p_5	0	0	0	0	0	0	0	0	23	65	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

Males, Pairs in Which Match Member has SC & DC

		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
Obs		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	628	303	628	303	628	303	628	303	628	303	628	303
2	Mean	934.6	1148.1	2967.6	2999.01	2394.62	2609.01	4763.69	5562.09	2434.3	2806.73	1508.34	1664.4
3	STD	956.12	1264.18	9958.76	10076.39	9250.91	9672.56	12103.82	13930.62	3573.92	4032.87	2442.9	2492.66
4	p_99	4741.59	5695.49	37083.12	36352.15	29479.88	33705.75	54030.23	68957.57	17379.31	16410.15	11821.83	11851.63
5	p_95	2791.19	3511.69	18685.1	19972.29	15642.39	15574.43	25260.04	31924.49	9166.38	11003.89	5941.1	7086.07
6	p_90	2247.68	2868.74	10106.05	9144.62	6875.65	7067.9	13426.48	13353.59	6089.47	7925.55	4139.32	4628.45
7	P_75	1275.14	1692.58	0	0	0	0	3454.56	3171.11	2854.69	3368.38	1852.93	1902.11
8	Median	635.38	740.85	0	0	0	0	878.9	978.98	1233.76	1319.31	629.86	690.67
9	p_25	239.32	251.25	0	0	0	0	194.05	229.32	445.57	462.31	142.33	205.7
10	p_10	27.73	53.9	0	0	0	0	7.38	35.04	166.06	182.88	0	20.1
11	p_5	0	0	0	0	0	0	0	0	66.37	70	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

Male, Pairs in Which Match Member has Employer-Provided SC & DC

		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
Obs		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	343	228	343	228	343	228	343	228	343	228	343	228
2	Mean	891.35	1185.66	2477.4	2250.78	2139.06	1939.16	4205.43	4943.06	2494.31	2709.5	1483.72	1605.39
3	STD	955.5	1325.72	7459.27	7041.61	6982.16	6629.68	9586.69	12193.02	3595.39	4053.15	2390.63	2491.09
4	p_99	4741.59	6696.28	29408.22	36352.15	28648.22	33705.75	50187.32	68957.57	19313.89	17921.79	10624.19	12267.46
5	p_95	2748.41	3919.89	17850.4	12102.86	14921.1	11396.86	19660.37	27643.1	8287.5	9507.98	4872.86	7086.07
6	p_90	2083.14	2996.07	9055.06	6937.25	6985.57	5423.76	10860.3	12551.42	6414.18	8485.31	3731.01	3971.02
7	P_75	1216.36	1828.48	0	0	0	0	3398.07	2810.65	3039.55	3248.76	1946.06	1784.83
8	Median	605.02	744.93	0	0	0	0	853.95	824.32	1235.32	1302.04	603.69	650.72
9	p_25	176.42	276.79	0	0	0	0	218.87	226.02	480.31	426.68	162.06	204.06
10	p_10	6.14	46	0	0	0	0	7.67	33.54	163.36	175.25	6.2	15.76
11	p_5	0	0	0	0	0	0	0	0	63.59	64.19	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

SC refers to supplemental coverage, DC to drug coverage. In subsamples of propensity-matched pairs defined by drug coverage or employer-provided drug coverage, the M-P for the miner-plus group represents the number of unduplicated observations. However, mean expenditures and percentiles are weighted according to the number of times the miner-plus observation matches to an observation with drug coverage or employer-provided drug coverage.

Source: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare, dwelling in the community, and in fee-for-service Medicare for the full year. See text for additional detail.

Exhibit 2.A.5

Expenditures for Miner-plus and Propensity Match Groups: Additional Detail

Female, All Pairs

		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
Obs		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	1026	342	1026	342	1026	342	1026	342	1026	342	1026	342
2	Mean	1087.49	1530.36	1803.88	1966.96	1578.9	1762.73	3818.65	4151.02	2032.66	2398.45	1212.09	1463.13
3	STD	1926.65	1594.03	6168.71	6028.11	5846.35	5746.25	9017.95	9439.42	3101.26	3242.65	1949.64	2179.37
4	p_99	5635.94	7374.21	28572.5	32727.79	27812.5	31112.44	46195.3	49271.07	14874.48	17448.66	8284.78	11324.02
5	p_95	3138.41	4472.4	11334.43	12009.13	10081.03	9784.71	20393.76	20072.18	7085.8	8158.09	4770.51	5090.74
6	p_90	2435.41	3505.58	5083.64	5576	4098.36	4571.71	9960.5	9894.54	4890.89	6072.93	3175.02	3653.75
7	P_75	1451.8	2156.73	0	0	0	0	2813.69	3708.36	2454.17	2993.59	1490	1794.92
8	Median	717.14	1040.08	0	0	0	0	790.31	964.79	983.81	1268.26	517.82	688.51
9	p_25	236.46	369.46	0	0	0	0	192.73	272.9	389.27	471.3	137.5	225.3
10	p_10	6.72	56.12	0	0	0	0	0	83.66	103.24	198.1	0	40.51
11	p_5	0	4.95	0	0	0	0	0	7.66	12	114.45	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

Female, Pairs in Which Match Member has SC & DC

Obs		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	674	320	674	320	674	320	674	320	674	320	674	320
2	Mean	1269.67	1562.13	1760.46	1969.69	1521.03	1781.1	4028.54	4184.23	2232.66	2379.58	1367.22	1485.17
3	STD	2032.68	1607.51	5524.92	6050	5135.68	5771.07	8743.4	9385.72	3271.14	3108.68	2116.43	2216.83
4	p_99	5883.99	7374.21	34405.98	32727.79	33689.98	31112.44	44233.85	47454.62	14874.48	15274.72	9108.88	11324.02
5	p_95	3592.51	4517.55	11334.43	12175.22	9773.06	10299.01	24866.36	20396.39	8105.37	8127.97	5378.45	5162.15
6	p_90	2651.28	3569.85	5083.64	5735.12	3970.88	4844.98	10557.04	10736	5407.03	6057.58	3503.33	3696.4
7	P_75	1673.46	2179.05	0	0	0	0	2950.83	3767.78	2818.02	2996.62	1638.83	1817.16
8	Median	893.75	1089.85	0	0	0	0	990.75	971.98	1132.54	1290.14	654.61	726.1
9	p_25	320.39	370.78	0	0	0	0	252.82	281.18	458.39	477.49	188.13	231.28
10	p_10	69.36	65.28	0	0	0	0	22.44	83.28	154	196.24	0	37
11	p_5	0	7.54	0	0	0	0	0	3.75	48.79	96.57	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

Female, Pairs in Which Match Member has Employer-Provided SC & DC

Obs		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	293	218	293	218	293	218	293	218	293	218	293	218
2	Mean	1367.3	1581.69	1643.29	1907.59	1409.64	1738.14	3419.25	3935.13	2173.02	2212.09	1273.95	1398.18
3	STD	1450.64	1632.41	4992.15	5618.75	4606.57	5326.34	7451.4	9262.64	2784.61	2895.86	1685.31	2093.88
4	p_99	6160.67	7374.21	25083.36	32727.79	23531.36	31112.44	44233.65	47454.62	13419.94	15274.72	6233.39	11324.02
5	p_95	4291.95	4824.89	11338.48	14474.42	9885.1	13042.42	17135.26	18754.73	7507.4	7580.59	5447.5	4772.97
6	p_90	2891.67	3803.99	6022.81	4913.54	4307.64	4352.2	8075.83	9441.63	4906.26	5183	3130.93	3335.28
7	P_75	1833.05	2167.25	0	0	0	0	2517.91	3810.26	2743.62	2833.92	1602.74	1739.41
8	Median	1027.21	1126.5	0	0	0	0	886.54	972.68	1163.36	1290.14	687.92	703
9	p_25	327.39	372.1	0	0	0	0	304.75	279.16	518.17	518.12	240.05	239.98
10	p_10	61.92	60	0	0	0	0	79.1	93.61	251.48	237.6	28.12	40.51
11	p_5	0	6.54	0	0	0	0	0	15.25	95	96.92	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

SC refers to supplemental coverage, DC to drug coverage. In subsamples of propensity-matched pairs defined by drug coverage or employer-provided drug coverage, the N for the miner-plus group represents the number of unduplicated observations. However, mean expenditures and percentiles are weighted according to the number of times the miner-plus observation matches to an observation with drug coverage or employer-provided drug coverage.

Sources: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare, dwelling in the community, and in fee-for-service Medicare for the full year. See text for additional detail.

Exhibit 2.A.6

Expenditures for Miner-plus and Exact Match Comparison Groups: Additional Detail

Male, All Pairs

Obs		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	310	309	310	309	310	309	310	309	310	309	310	309
2	Mean	1141.2	970.51	3030.9	2542.36	2640.8	2220.35	5588.74	4433.13	2781.28	2250.98	1664.37	1323.16
3	STD	1256.66	1335.2	10027.97	11050.74	9819.83	10713.18	13819.4	13013.87	3986.69	3021.42	2469.89	2048.43
4	p_99	6685.49	5521.66	36352.15	42599.27	33705.75	41047.27	68957.57	59865.66	16410.15	13704.76	11661.63	10622.73
5	p_95	3611.69	3183.54	19995.76	12082.22	17544.29	10670.87	31924.48	19062.49	11003.89	8287.6	7086.07	4848.4
6	p_90	2845.12	2468.23	9445.15	7140	7331.56	5289.58	13447.31	11365.67	7581.09	6660.36	4605.43	3516.03
7	P_75	1612.47	1303.72	0	0	0	0	3171.11	3024.84	3368.63	2872.1	1908.52	1672.13
8	Median	735.09	546.85	0	0	0	0	997.72	877.42	1321.23	1247.47	696.19	575.59
9	p_25	267.3	114.38	0	0	0	0	235.21	152.95	462.31	380.09	205.7	120.55
10	p_10	53.83	0	0	0	0	0	34.29	0	180.87	120.27	20.05	0
11	p_5	0	0	0	0	0	0	0	0	85	45.1	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

Male, Pairs in Which Match Member has SC & DC

Obs		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	217	217	217	217	217	217	217	217	217	217	217	217
2	Mean	1138.2	1190.99	3366.2	3127.82	3017.62	2909.4	6101.29	5462.73	2751.99	2563.42	1697.92	1529.55
3	STD	1304.36	1471.64	10926.85	12952.17	10599.71	12655.18	14908.02	15242.36	3662.63	3362.62	2662.36	2347.71
4	p_99	6698.28	5969.51	36352.15	43436.25	33705.75	42688.25	68957.57	71241.29	16256.63	16598.77	11673.81	11956.51
5	p_95	3511.69	3699.01	21698.67	15234.99	20928.67	12914.99	37335.24	26839.67	12158.99	9166.38	7207.36	5233.17
6	p_90	2940.99	2864.22	9671.9	8380.36	8054.4	6988.33	15517.37	13922.33	8129.22	6540.81	5612.81	4029.19
7	P_75	1682.23	1688.28	0	0	0	0	3220.88	3893.37	3388.63	3023.68	1902.11	1808.39
8	Median	729.33	739.65	0	0	0	0	1084.25	1017.46	1318.31	1454.95	703	698.44
9	p_25	267.3	298.36	0	0	0	0	343.06	285.02	546.4	467.69	219.7	152.95
10	p_10	54	20.98	0	0	0	0	33.54	0	175.25	125.6	20	0
11	p_5	0	0	0	0	0	0	0	0	65	60	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

Male, Pairs in Which Match Member has Employer-provided SC & DC

Obs		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	120	120	120	120	120	120	120	120	120	120	120	120
2	Mean	1081.99	1073.31	3073.41	3629.76	2758.47	2478.43	5070.25	4844.4	2659.48	2700.98	1623.15	1586.07
3	STD	1173.49	1166.56	8266.98	8931.59	7805.93	8210.16	11476.87	10787.88	3710.49	3759.41	2644.33	2619.76
4	p_99	6008.62	5531.98	36352.15	43436.25	33705.75	42688.25	51689.07	50865.88	17921.79	20136.41	13932.62	15097.53
5	p_95	3914.61	3966.21	25006.69	14284.45	24310.69	12736.45	36426.24	20303.44	11712.9	9000.02	7205.56	5202.04
6	p_90	2932.27	2534.19	9528.32	8717.71	7559.5	7975.71	13299.83	13469.72	7091.06	7095.6	4414.38	3958.72
7	P_75	1396.92	1663.6	0	0	0	0	2916.37	2766.64	3056.96	3051.26	1716.61	1903.85
8	Median	717.8	710.29	0	0	0	0	978.66	990.1	1342.49	1452.93	696.84	659.28
9	p_25	276.79	192.79	0	0	0	0	206.37	251.65	420.41	512.79	140.53	176.98
10	p_10	35.07	14.58	0	0	0	0	28.81	19.36	157.28	223.03	3.89	3.79
11	p_5	0	0	0	0	0	0	0	0	67.5	88.3	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

SC refers to supplemental coverage, DC to drug coverage.

Sources: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare, dwelling in the community, and in fee-for-service Medicare for the full year. See text for additional detail.

Female, All Pairs

Obs		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	342	341	342	341	342	341	342	341	342	341	342	341
2	Mean	1630.36	1126.43	1986.96	1869.46	1782.73	1747.06	4151.02	3894.88	2386.45	2011.06	1463.13	1193.43
3	STD	1694.03	1331.96	6020.11	6947.76	5746.25	6586.14	8439.42	11643.51	3242.65	2616.65	2179.37	1934.56
4	p_99	7374.21	6689.52	32727.79	27136.84	31112.44	25723.72	49271.07	42586.57	17448.66	16472.66	11324.02	11879.46
5	p_95	4472.4	3546.49	12009.13	8889.31	9784.71	7510.56	20072.18	16273.5	8158.09	7261.04	5090.74	4680.87
6	p_90	3605.58	2483.3	5576	4742.89	4571.71	3866.84	9894.54	8988.6	6072.93	5040.37	3663.75	3214.73
7	P_75	2156.73	1546.73	0	0	0	0	3708.36	3046.27	2983.59	2387.36	1794.92	1339.38
8	Median	1040.08	763.04	0	0	0	0	964.79	812.38	1268.26	1037.98	688.51	554.59
9	p_25	389.46	284.92	0	0	0	0	272.9	239.62	471.3	447.12	225.3	169.35
10	p_10	98.12	38.76	0	0	0	0	83.88	8.59	198.1	121.76	40.51	0
11	p_5	4.96	0	0	0	0	0	7.88	0	114.45	46.93	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

Female, Pairs in Which Match Member has SC & DC

Obs		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	226	226	226	226	226	226	226	226	226	226	226	226
2	Mean	1644.62	1303.39	2088.39	1568.19	1866.68	1328.9	4276.74	3490.24	2496.09	2153.07	1626.82	1239.1
3	STD	1607.91	1484.84	6454.81	4506.48	6176.19	4236.31	9762.09	7024.09	3019.54	2738.11	2117.25	1782.53
4	p_99	7374.21	6262.42	35714.01	27071.84	34976.01	25227.59	52768.66	32238.12	13814.62	15426.52	10374.88	7922.63
5	p_95	4746.21	3886.24	12009.13	8469.94	9784.71	7420.78	18009.75	16273.5	8684.36	7274.33	5090.74	4680.87
6	p_90	3605.58	3038.1	5894.24	5048.56	5118.24	4089.5	10508.04	9416.34	6488.37	6585.38	3739.05	3325.01
7	P_75	2187.13	1749.52	0	0	0	0	3957.67	3093.26	3203.36	2546.76	1993.66	1442.96
8	Median	980.2	911.78	0	0	0	0	1093.72	1085.42	1376.61	1263.16	765.51	670.26
9	p_25	391.56	369.29	0	0	0	0	270.37	264.4	520.08	502.67	234.64	238.01
10	p_10	56.12	80	0	0	0	0	82.9	20	188.6	141.62	37.99	1.9
11	p_5	10.9	0	0	0	0	0	0	0	96.21	73.46	0	0
12	p_1	0	0	0	0	0	0	0	0	0	0	0	0

Female, Pairs in Which Match Member has Employer-provided SC & DC

Obs		total drug exp		total inpt exp		tot covered inpt exp		total covered exp		total phys exp		total covered phys exp	
		Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P	Match	M-P
1	n	108	108	108	108	108	108	108	108	108	108	108	108
2	Mean	1660.07	1683.1	2216.73	1809.16	2033.1	1628.73	4978.84	2902.2	2704.59	1900.8	1694.11	1034.98
3	STD	1675.74	1636.14	6257.84	6864.7	5959.56	4761.91	11213.24	7149.09	3365.71	2104.94	2416.17	1263.11
4	p_99	6516.7	9067.02	35714.01	27071.84	34976.01	25227.59	52768.66	31543.76	17448.66	6530.61	13662	5904.57
5	p_95	6042.03	4802.54	16667.42	9055.34	15407.82	6545.95	18754.73	9275.68	8663.7	7181.86	5090.74	4107.79
6	p_90	3605.58	3746.54	6426.35	5622.04	5647.79	4332.56	14433.73	5285.46	6778.74	6585.38	4181.83	2280.06
7	P_75	2266.18	1909.05	0	0	0	0	4196.72	2379.34	3416.22	2389.68	2268.07	1280.88
8	Median	974.7	998.05	0	0	0	0	1342.8	810.66	1620.79	1177.82	979.96	582.32
9	p_25	434.52	503.9	0	0	0	0	267.42	267.27	503.96	508.08	239.97	252.84
10	p_10	74.96	80	0	0	0	0	99.68	79.1	230.58	161	70.88	26.89
11	p_5	27	0	0	0	0	0	26.51	1.8	140.12	93.19	15.25	0
12	p_1	0	0	0	0	0	0	0	0	25	0	0	0

SC refers to supplemental coverage, DC to drug coverage.

Sources: 1995-2000 MCBS. Unduplicated observations. Entitled to Parts A & B of Medicare, dwelling in the community, and in fee-for-service Medicare for

Appendix 3.A: Aim 3: Sensitivity of Results to Exclusion Criteria

By necessity, our sample excluded individuals who died or entered a long-term care facility during the course of the year, because of the potential for incomplete data on these individuals' drug utilization even before the transition[40]. It is possible to get a sense of the likely bias introduced by this exclusion by comparing how individuals who had complete data in 1999 but who died or entered a nursing home in 2000 (especially early in 2000) differed in 1999 from those who did not make these transitions. If there were significant differences, then that suggests that individuals' drug expenditures tended to change in the months preceding a transition and that the exclusion criteria potentially impacted results.

Specifically, we created indicator variables to identify individuals who died, entered long term care facilities, or joined Medicare HMOs in 2000 and included those indicator variables in the estimation of models of drug expenditures in 1999. We found that, controlling for health status via the HCC categories, individuals who died within the first six months of 2000 had drug expenditures that were 56 percent higher than the reference group (alive, not in HMOs, and dwelling in the community at the end of 2000). (See Exhibit B1.) This does imply that drug expenditures increased in the months leading up to death and that our estimates of the levels of expenditures may be biased downwards because of this exclusion. We also found that individuals who entered nursing homes in the first six months of 2000 had drug expenditures that were 53 percent lower than the reference group, imposing a bias in the other direction. Ideally, one would also use interaction terms to explore the impact of our sample selection criteria on individual parameter estimates, but this was not possible given the sample sizes involved.

Exhibit 3.A.1

Estimated Effect of Upcoming Transitions on Drug Expenditures
In Concurrent Models of 1999 Drug Expenditures
Model 4A: Base Model, HCC Indicators, and Indicators for Transitions

	N	Regression Coefficient	P Value
Deceased Jan-June 2000	121	.56	.003
Deceased July-Dec 2000	113	.17	.352
Entered facility Jan-June 2000	56	-.53	.049
Entered facility July-Dec 2000	56	-.14	.60
Entered MHMO 2000	47	-.04	.87

Source: 1999 Cross-Sectional File, supplemented with data on transitions in 2000, (excluded individuals who leave the panel between 1999 and 2000), Medicare Current Beneficiary Survey, (N=5425)

While the magnitude of the estimated individual effects was large, the magnitude of the expected bias was still small because the numbers of affected observations were relatively small. Based on these regression results, estimated mean drug expenses in 1999 for the universe of observations with two

[40] Our sample also excluded new entrants because data from the previous year are needed to create the claims-based condition indicators. Unfortunately the structure of our data set did not allow us to explore the impact of this exclusion.

years of data available were $1350. If the sample selection criteria were imposed (i.e. individuals with transitions in 2000 were excluded), the estimate of mean expenses became $1342. This net downward bias of $8 consists of a downward bias of $10 due to the exclusion of individuals who died in 2000 slightly mitigated by an upward bias due to the exclusion of individuals who entered facilities or entered Medicare HMOs but did not die. Bear in mind that the bias in this exhibit has two sources - first differences in the rates of the HCCs among the subpopulations and second differences in mean drug expenditures controlling for the HCCs (the differences captured in the regression coefficients reported above).

Exhibit 3.A.2

Mean Predicted Drug Expenditures 1999

Based on Concurrent Model of 1999 Drug Expenditures
Model 4A: Base Model, HCC Indicators, and Indicators for Transitions

N	N	P>|t| Predicted Mean Drug Expenditures
All observations	5425	$1350
Exclude observations with death, facility, MHMO (N excluded=355)	5070	$1342
Exclude deceased only (N excluded=234)	5191	$1340

Transitions are not mutually exclusive.

Source: 1999 Cross-Sectional File, supplemented with data on transitions in 2000, (excluded individuals who leave the panel between 1999 and 2000), Medicare Current Beneficiary Survey, (N=5425)

Appendix 3.B: Aim 3: Additional Exhibits

Exhibit 3.B.1

1999 Cross-Sectional Sample Characteristics
By Nature of Drug and Supplemental Coverage

Characteristic	Beneficiaries with Any Drug Coverage (N=5,822)	Beneficiaries with No Drug Coverage		
		All (N=2,245)	With Supplemental insurance (N=1,657)	Without Supplemental insurance (N=588)
Gender				
Female	55.3%	56.7%	58.7%	51.0%
Male	44.7	43.3	41.3	49.0
Medicare Entitlement Status				
Disabled	17.3	12.8	6.2	31.5
Aged but previously disabled	6.3	4.8	4.4	6.0
Age, (Years)				
< 65	17.3	12.8	6.2	31.5
65-69	14.5	12.9	12.4	14.5
70-74	22.5	21.7	22.8	18.5
75-79	18.6	18.6	21.4	10.5
80+	27.0	34.1	37.4	24.8
Metropolitan Status				
Rural	30.1	43.9	43.5	45.1
Urban	69.9	56.1	56.6	54.9
Detailed Census Regions				
New England	3.1	2.5	2.8	1.7
Middle Atlantic	17.6	11.3	11.2	11.6
East North Central	17.6	18.6	19.0	17.4
West North Central	5.7	11.5	13.9	4.9
South Atlantic	21.4	23.3	21.0	29.6
East South Central	6.0	8.2	8.2	8.2
West South Central	11.0	11.7	10.6	14.6
Mountain	5.5	5.1	5.1	4.9
Pacific	10.7	6.2	6.5	5.3
Puerto Rico	1.4	1.7	1.7	1.7

Source:1999 Cross-Sectional File, Medicare Current Beneficiary Survey,1999, (N=8067).

Exhibit 3.B.2

Univariate Statistics on Actual Total 1999 Drug Expenditures and Predicted Medicare Expenditure (Ybase*), 1999

	All Beneficiaries (N=8,067)	Beneficiaries with Any Drug Coverage (N=5,822)	Beneficiaries with No Drug Coverage		
			All (N=2,245)	With Supplemental insurance (N=1,657)	Without Supplemental insurance (N=588)
Drug Expenditures					
Mean	$1354	$1566[A]	$804	$867	$624
Std dev	$1726	$1901	$957	$958	$930
Predicted Medicare Expenditures (Ybase*)					
Mean	$6,051	$6,368	$5,229	$5,557	$4,304
Std dev	$5285	$5554	$4409	$4538	$3881
Median	$4,374	$4,635	$3,880	$4,140	$3,204
Minimum	$1,212	$1,212	$1,212	$1,212	$1,212
Maximum	$58,793	$58,793	$40,221	$40,221	$35,300

A Mean expenditures for beneficiaries with Medicaid drug coverage (N=1317) were $1849 while mean expenditures for beneficiaries with drug insurance from another source (N=4505) were $1482.

* Predicted Medicare Part A & B expenditure from DCG-HCC risk adjuster.

Source: 1999 Cross-Sectional File, Medicare Current Beneficiary Survey,1999, (N=8067).

Exhibit 3.B.3

Frequency Distribution of Self-reported Health Conditions* in 1999 Cross-Sectional Sample

Self-reported Conditions	All Beneficiaries (N=8,067)	Beneficiaries with Any Drug Coverage (N=5,822)	Beneficiaries with No Drug Coverage		
			All (N=2,245)	With Supplemental insurance (N=1,657)	Without Supplemental insurance (N=588)
Heart disease	14.7%	16.0%	11.3%	12.3%	8.5%
Cancer	6.9	6.6	7.6	8.9	4.1
Arthritis	15.8	16.5	13.8	15.0	10.5
Lung disease	1.8	2.0	1.4	1.0	2.6
Mental disorders	6.1	7.2	3.1	2.1	6.0
Alzheimer's disease	0.9	0.9	1.0	1.0	0.9
Diabetes	1.8	1.7	2.1	2.3	1.4
Hypertension	42.7	44.5	38.2	40.4	32.0
Osteoporosis	2.8	2.9	2.5	3.1	0.9
Stroke	2.6	2.6	2.7	2.8	2.4
BPH	5.7	5.9	5.0	5.7	2.9
Paralysis	1.6	1.5	1.8	1.4	2.9
Parkinson's disease	0.4	0.4	0.3	0.3	0.2
Hip fracture	0.8	0.7	0.3	0.9	0.7

Source:1999 Cross-Sectional File, Medicare Current Beneficiary Survey,1999, (N=8067).

Exhibit 3.B.4

Frequency Distribution of Medical Conditions in 1999 Cross-Sectional Sample
Medical Conditions Defined According to HCC Model

HCC No.	Hierarchical Conditions Categories	All Beneficiaries (N=8,067)	Beneficiaries with Any Drug Coverage (N=5,822)	Beneficiaries with No Drug Coverage		
				All (N=2,245)	With Supplemental insurance (N=1,657)	Without Supplemental insurance (N=588)
1	HIV/AIDS	0.3%	0.5%	0.0%	0.0%	0.0%
2	Septicemia/Shock	1.2	1.3	0.9	0.8	1.0
3	Central Nervous System Infection	0.4	0.5	0.1	0.1	0.2
4	Tuberculosis	0.2	0.1	0.3	0.3	0.2
5	Opportunistic Infections	0.2	0.2	0.2	0.2	0.2
6	Other Infectious Diseases	16.4	17.1	15.0	16.1	10.5
7	Metastatic Cancer and Acute Leukemia	1.3	1.3	1.2	1.5	0.7
8	Lung, Upper Digestive Tract, and Other Specified	1.2	1.3	1.0	0.9	0.7
9	Lymphatic, Head and Neck, Brain, and Other	1.4	1.3	1.4	1.7	0.9
10	Breast, Prostate, Colorectal and Other Cancer	7.6	7.4	8.2	9.2	5.4
11	Other Respiratory and Heart Neoplasms	0.4	0.5	0.3	0.4	0.2
12	Other Digestive and Urinary Neoplasms	3.5	3.7	3.1	3.5	1.4
13	Other Neoplasms	6.7	6.5	7.1	8.0	4.8
14	Benign Neoplasms of Skin, Breast, Eye	7.5	7.9	6.5	7.2	4.6
15	Diabetes with Renal Manifestation	0.9	1.2	0.4	0.4	0.2
16	Diabetes with Neurologic or Peripheral Complications	2.3	2.7	1.3	1.2	1.5
17	Diabetes with Acute Complications	0.8	0.9	0.5	0.6	0.3
18	Diabetes with Ophthalmologic Manifestations	1.8	1.9	1.4	1.5	1.2
19	Diabetes with No or Unspecified Complications	13.4	14.1	11.5	12.4	9.0
20	Type I Diabetes Mellitus	4.9	5.7	3.0	3.1	2.4

Exhibit 3.B.4

Frequency Distribution of Medical Conditions in 1999 Cross-Sectional Sample
Medical Conditions Defined According to HCC Model

21	Protein-Calorie Malnutrition	0.8	1.0	0.6	0.5	0.3
22	Other Significant Endocrine and Metabolic Disorders	1.9	2.1	1.3	1.4	1.2
23	Disorders of Fluid/Electrolyte/Acid-Base	8.5	9.1	7.1	7.7	4.8
24	Other Endocrine/Metabolic/Nutritional Disorder	39.0	39.9	36.3	40.8	24.2
25	End-Stage Liver Disease	0.2	0.2	0.1	0.2	0.0
26	Cirrhosis of Liver	0.4	0.5	0.1	0.1	0.2
27	Chronic Hepatitis	0.3	0.3	0.1	0.1	0.2
28	Acute Liver Failure/Disease	0.1	0.1	0.1	0.1	0.0
29	Other Hepatitis and Liver Disease	1.9	2.1	1.3	1.2	1.5
30	Gallbladder and Biliary Tract Disorders	1.4	1.6	1.1	1.5	0.3
31	Intestinal Obstruction/Perforation	2.0	2.2	1.5	1.6	1.2
32	Pancreatic Disease	0.8	0.8	0.7	0.7	0.5
33	Inflammatory Bowel Disease	0.6	0.6	0.6	0.7	0.2
34	Peptic Ulcer, Hemorrhage, Other Specified Disorder	6.3	6.9	4.9	5.4	2.9
35	Appendicitis	0.1	0.1	0.0	0.1	0.0
36	Other Gastrointestinal Disorders	23.8	24.8	21.1	24.1	12.8
37	Bone/Joint/Muscle Infections/Necrosis	1.1	1.1	1.1	1.1	0.9
38	Rheumatoid Arthritis and Inflammatory Co	4.9	5.1	4.5	5.0	3.1
39	Disorders of the Vertebrae and Spinal Disease	9.5	9.7	9.3	10.4	5.6
40	Osteoarthritis of Hip or Knee	6.8	6.9	6.6	7.6	3.6
41	Osteoporosis and Other Bone/Cartilage Disorder	10.9	11.2	10.6	12.6	4.3
42	Congenital/Developmental Skeletal and Co	0.1	0.1	0.0	0.1	0.0
43	Other Musculoskeletal and Connective Tissue	26.8	27.8	24.1	25.4	21.1
44	Severe Hematological Disorders	1.1	1.1	1.0	1.0	0.5

Exhibit 3.B.4

Frequency Distribution of Medical Conditions in 1999 Cross-Sectional Sample
Medical Conditions Defined According to HCC Model

45	Disorders of Immunity	0.7	0.7	0.7	0.7	0.7
46	Coagulation Defects and Other Specified	3.8	3.9	3.5	4.2	1.5
47	Iron Deficiency and Other/Unspecified	14.7	15.5	12.8	13.7	10.0
48	Delirium and Encephalopathy	1.4	1.6	0.9	0.8	0.7
49	Dementia	3.9	4.0	3.7	4.2	1.9
50	Senility, Non-psychotic Organic Brain Syndrome	0.6	0.7	0.4	0.5	0.2
51	Drug/Alcohol Psychosis	0.4	0.5	0.2	0.2	0.2
52	Drug/Alcohol Dependence	0.9	1.0	0.7	0.5	1.4
53	Drug/Alcohol Abuse, Without Dependence	2.4	2.5	2.3	2.1	2.6
54	Schizophrenia	1.9	2.4	0.7	0.2	1.9
55	Major Depressive, Bipolar, and Paranoid	3.4	4.0	2.0	1.6	2.9
56	Reactive and Unspecified Psychosis	1.0	1.1	0.6	0.6	0.7
57	Personality Disorders	0.1	0.1	0.0	0.0	0.0
58	Depression	3.9	4.2	3.4	3.9	2.0
59	Anxiety Disorders	0.7	0.8	0.4	0.4	0.2
60	Other Psychiatric Disorders	2.9	3.0	2.8	3.0	1.9
61	Profound Mental Retardation/Developmental	0.0	0.0	0.0	0.0	0.0
62	Severe Mental Retardation/Developmental	0.0	0.0	0.0	0.0	0.2
63	Moderate Mental Retardation/Developmental	0.0	0.0	0.0	0.0	0.0
64	Mild/Unspecified Mental Retardation/Developmental	0.8	0.9	0.5	0.5	0.5
65	Other Developmental Disability	0.1	0.1	0.1	0.1	0.2
66	Attention Deficit Disorder	0.1	0.1	0.0	0.0	0.0
67	Quadriplegia, Other Extensive Paralysis	0.3	0.3	0.0	0.0	0.2
68	Paraplegia	0.2	0.2	0.1	0.1	0.0
69	Spinal Cord Disorders/Injuries	0.8	0.9	0.7	0.8	0.7
70	Muscular Dystrophy	0.1	0.1	0.1	0.0	0.3

Exhibit 3.B.4

Frequency Distribution of Medical Conditions in 1999 Cross-Sectional Sample
Medical Conditions Defined According to HCC Model

71	Polyneuropathy	2.9	3.1	2.5	2.7	2.0
72	Multiple Sclerosis	0.4	0.4	0.3	0.3	0.2
73	Parkinsons and Huntington's Diseases	1.1	1.3	0.7	0.7	0.3
74	Seizure Disorders and Convulsions	2.9	3.1	2.4	2.1	3.1
75	Coma, Brain Compression/Anoxic Damage	0.1	0.2	0.1	0.1	0.0
76	Mononeuropathy, Other Neurological Conditions	5.1	5.3	4.7	5.3	3.1
77	Respirator Dependence/Tracheostomy Status	0.1	0.1	0.1	0.1	0.0
78	Respiratory Arrest	0.2	0.3	0.2	0.1	0.2
79	Cardio-Respiratory Failure and Shock	2.8	3.0	2.3	2.5	1.5
80	Congestive Heart Failure	12.9	14.0	10.2	11.5	5.8
81	Acute Myocardial Infarction	1.3	1.4	1.0	1.2	0.5
82	Unstable Angina and Other Acute Ischemic	3.3	3.6	2.6	3.1	1.2
83	Angina Pectoris/Old Myocardial Infarction	5.7	6.2	4.7	5.1	3.2
84	Coronary Atherosclerosis/Other Chronic Ischemia	13.2	13.8	11.7	13.8	6.0
85	Heart Infection/Inflammation, Except Rheumatism	0.4	0.4	0.3	0.2	0.3
86	Valvular and Rheumatic Heart Disease	9.7	10.3	8.4	9.4	5.4
87	Major Congenital Cardiac/Circulatory Deficiency	0.0	0.1	0.0	0.0	0.0
88	Other Congenital Heart/Circulatory Disease	0.4	0.4	0.3	0.3	0.2
89	Hypertensive Heart and Renal Disease	0.8	1.0	0.4	0.4	0.2
90	Hypertensive Heart Disease	3.4	3.5	2.9	3.3	1.9
91	Hypertension	37.3	37.6	36.5	39.3	29.1
92	Specified Heart Arrhythmias	11.4	12.4	9.0	10.8	3.6
93	Other Heart Rhythm and Conduction Disorder	5.4	5.5	5.1	5.9	3.1
94	Other and Unspecified Heart Disease	1.3	1.3	1.3	1.3	0.9

Exhibit 3.B.4

Frequency Distribution of Medical Conditions in 1999 Cross-Sectional Sample
Medical Conditions Defined According to HCC Model

95	Cerebral Hemorrhage	0.4	0.4	0.3	0.3	0.3
96	Ischemic or Unspecified Stroke	4.2	4.5	3.7	3.7	3.4
97	Precerebral Arterial Occlusion and Trans	4.7	4.5	5.1	6.7	0.7
98	Cerebral Atherosclerosis and Aneurysm	0.6	0.6	0.5	0.6	0.2
99	Cerebrovascular Disease, Unspecified	0.2	0.3	0.2	0.2	0.2
100	Hemiplegia/Hemiparesis	0.9	1.0	0.7	1.0	0.2
101	Diplegia (Upper), Monoplegia, and Other Specified	0.3	0.3	0.3	0.3	0.2
102	Speech, Language, Cognitive, Perceptual	0.6	0.6	0.6	0.6	0.7
103	Cerebrovascular Disease Late Effects, Unspecified	0.7	0.7	0.8	0.8	0.5
104	Vascular Disease with Complications	1.9	2.0	1.7	1.9	0.9
105	Vascular Disease	9.9	10.2	9.3	10.7	4.8
106	Other Circulatory Disease	7.8	8.1	6.8	7.3	5.4
107	Cystic Fibrosis	0.1	0.1	0.0	0.0	0.0
108	Chronic Obstructive Pulmonary Disease	13.7	14.4	12.0	12.9	8.7
109	Fibrosis of Lung and Other Chronic Lung Disorder	1.6	1.7	1.4	1.6	0.9
110	Asthma	2.5	2.8	2.0	1.9	2.0
111	Aspiration and Specified Bacterial Pneumonia	0.7	0.8	0.7	0.7	0.2
112	Pneumococcal Pneumonia, Emphysema, Lung	0.7	0.6	0.7	0.8	0.5
113	Viral and Unspecified Pneumonia, Pleurisy	6.4	6.7	5.5	6.1	3.7
114	Pleural Effusion/Pneumothorax	2.5	2.7	2.0	2.2	1.4
115	Other Lung Disorders	9.2	9.5	8.4	9.1	6.5
116	Legally Blind	0.3	0.3	0.2	0.2	0.2
117	Major Eye Infections/Inflammations	0.3	0.3	0.3	0.3	0.3
118	Retinal Detachment	0.5	0.5	0.6	0.7	0.0
119	Proliferative Diabetic Retinopathy	0.7	0.8	0.6	0.6	0.3

Exhibit 3.B.4

Frequency Distribution of Medical Conditions in 1999 Cross-Sectional Sample
Medical Conditions Defined According to HCC Model

120	Diabetic and Other Vascular Retinopathies	4.3	4.7	3.2	3.6	1.5
121	Retinal Disorders, Except Detachment	7.9	7.6	8.7	10.6	3.4
122	Glaucoma	10.2	10.7	9.1	10.2	5.4
123	Cataract	28.0	28.1	27.7	33.0	12.4
124	Other Eye Disorders	7.6	7.5	7.9	8.5	6.1
125	Significant Ear, Nose, and Throat Disorders	0.8	0.9	0.4	0.5	0.2
126	Hearing Loss	3.5	3.7	3.0	3.4	1.9
127	Other Ear, Nose, Throat, and Mouth Disorders	26.8	27.8	24.1	26.0	18.7
128	Kidney Transplant Status	0.4	0.6	0.1	0.0	0.5
129	End Stage Renal Disease	0.0	0.0	0.0	0.0	0.0
130	Dialysis Status	0.3	0.4	0.0	0.0	0.2
131	Renal Failure	2.3	2.4	2.3	2.4	1.5
132	Nephritis	0.3	0.3	0.3	0.3	0.2
133	Urinary Obstruction and Retention	5.4	5.5	5.1	5.6	3.6
134	Incontinence	3.4	3.6	3.0	3.2	2.2
135	Urinary Tract Infection	14.4	15.1	13.0	13.4	10.7
136	Other Urinary Tract Disorders	7.4	7.7	6.7	7.2	4.8
137	Female Infertility	0.0	0.0	0.0	0.0	0.0
138	Pelvic Inflammatory Disease and Other Specified	2.7	2.9	2.0	2.2	1.2
139	Other Female Genital Disorders	9.6	10.1	8.3	9.3	5.1
140	Male Genital Disorders	14.3	14.8	12.7	14.3	8.5
141	Ectopic Pregnancy	0.0	0.0	0.0	0.0	0.0
142	Miscarriage/Abortion	0.0	0.0	0.0	0.0	0.0
143	Completed Pregnancy With Major Complications	0.0	0.0	0.0	0.0	0.0
144	Completed Pregnancy With Complications	0.0	0.0	0.0	0.0	0.2
145	Completed Pregnancy Without Complication	0.1	0.1	0.0	0.0	0.2

Exhibit 3.B.4

Frequency Distribution of Medical Conditions in 1999 Cross-Sectional Sample
Medical Conditions Defined According to HCC Model

146	Uncompleted Pregnancy With Complications	0.0	0.0	0.0	0.0	0.0
147	Uncompleted Pregnancy With No or Minor Complications	0.0	0.0	0.0	0.0	0.0
148	Decubitus Ulcer of Skin	0.7	0.7	0.6	0.7	0.3
149	Chronic Ulcer of Skin, Except Decubitus	2.0	1.9	2.1	2.2	1.5
150	Extensive Third-Degree Burns	0.0	0.0	0.0	0.0	0.2
151	Other Third-Degree and Extensive Burns	0.0	0.0	0.0	0.0	0.0
152	Cellulitis, Local Skin Infection	7.0	7.3	6.3	6.8	4.4
153	Other Dermatological Disorders	22.6	22.9	21.9	24.8	13.6
154	Severe Head Injury	0.0	0.0	0.0	0.0	0.0
155	Major Head Injury	0.8	0.9	0.6	0.6	0.5
156	Concussion or Unspecified Head Injury	0.7	0.8	0.5	0.6	0.2
157	Vertebral Fractures	0.9	1.0	0.8	0.9	0.2
158	Hip Fracture/Dislocation	1.2	1.0	1.7	2.1	0.5
159	Major Fracture, Except of Skull, Vertebrae	1.2	1.2	1.4	1.3	1.2
160	Internal Injuries	0.2	0.3	0.2	0.2	0.2
161	Traumatic Amputation	0.1	0.2	0.0	0.0	0.0
162	Other Injuries	16.9	17.5	15.4	16.6	12.1
163	Poisonings and Allergic Reactions	5.1	5.6	4.0	4.2	2.9
164	Major Complications of Medical Care	2.9	3.0	2.4	2.7	1.7
165	Other Complications of Medical Care	1.4	1.5	1.0	1.2	0.7
166	Major Symptoms, Abnormalities	41.0	43.1	35.8	39.5	24.7
167	Minor Symptoms, Signs, Findings	23.3	23.2	23.7	24.8	20.2
168	Extremely Low Birthweight Neonates	0.0	0.0	0.0	0.0	0.0
169	Very Low Birthweight Neonates	0.0	0.0	0.0	0.0	0.0
170	Serious Perinatal Problem Affecting Newborn	0.1	0.1	0.1	0.2	0.0
171	Other Perinatal Problems Affecting Newborn	0.1	0.1	0.0	0.0	0.0

Exhibit 3.B.4

Frequency Distribution of Medical Conditions in 1999 Cross-Sectional Sample
Medical Conditions Defined According to HCC Model

172	Normal, Single Birth	0.0	0.0	0.0	0.0	0.0
173	Major Organ Transplant	0.0	0.0	0.0	0.0	0.0
174	Major Organ Transplant Status	0.1	0.1	0.0	0.0	0.0
175	Other Organ Transplant/Replacement	0.2	0.2	0.2	0.2	0.2
176	Artificial Openings for Feeding or Elimination	0.6	0.7	0.5	0.5	0.3
177	Amputation Status, Lower Limb/Amputation	0.2	0.2	0.2	0.2	0.0
178	Amputation Status, Upper Limb	0.0	0.0	0.0	0.1	0.0
179	Post-Surgical States/Aftercare/Elective	26.9	27.5	25.5	29.3	14.3
180	Radiation Therapy	0.5	0.5	0.4	0.4	0.0
181	Chemotherapy	0.8	0.8	0.8	1.0	0.3
182	Rehabilitation	2.8	3.0	2.6	2.7	2.0
183	Screening/Observation/Special Exams	64.1	65.1	61.3	67.8	43.0
184	History of Disease	14.2	14.0	14.9	17.0	8.8
185	Oxygen	0.0	0.0	0.0	0.0	0.0
186	CPAP/IPPB/Nebulizers	0.0	0.0	0.0	0.0	0.0
187	Patient Lifts, Power Operated Vehicles	0.0	0.0	0.0	0.0	0.0
188	Wheelchairs, Commodes	0.0	0.0	0.0	0.0	0.0
189	Walkers	0.0	0.0	0.0	0.0	0.0

Source:1999 Cross-Sectional File, Medicare Current Beneficiary Survey,1999, (N=8067).

Exhibit 3.B.5

R-squares associated with Concurrent Models of 1999 Drug Expenditures Using Different Risk-adjusters By Nature of Drug and Supplemental Coverage

Model		Adjusted R-square (Log Model)				
				Beneficiaries with No Drug Coverage		
		All Beneficiaries (N=8,067)	Beneficiaries with Any Drug Coverage (N=5,822)	All (N=2,245)	With Supplemental insurance (N=1,657)	Without Supplemental insurance (N=588)
Model 1 (1999)	Base Model*	0.015	0.017	0.049	0.082	0.036
Model 2 (1999)	Base model + log (Ybase)**	0.16	0.14	0.20	0.20	0.24
Model 3 (1999)	Base model + self-reports of health conditions in the last one year***	0.15	0.13	0.21	0.21	0.26
Model 4 (1999)	Base model + claims-based indicators for 128 conditions	0.30	0.26	0.39	0.35	0.41

Base model: Y = f (age, currently disabled, previously disabled, gender, metro status, detailed census regions)

Fit is adjusted R Square when model is re-estimated using the population noted.

** Predicted Medicare Part A & B payment from DCG-HCC risk adjuster.

*** Self-reported conditions include heart disease, cancer, arthritis, lung disease, mental illness, Alzheimer's, diabetes, hypertension, osteoporosis, stroke, benign prostatic hypertrophy, paralysis, Parkinson's, hip fracture.

Source: 1999 Cross-Sectional Sample, Medicare Current Beneficiary Survey, 1999 (N=8061)

Exhibit 3.B.6

R-squares Associated with Concurrent Models of 1999 Drug Expenditures Statified by Medicare Entitlement Status

Model		Adjusted R-square (Log Model)	
		Aged Beneficiaries (N=6,772)	Disabled Beneficiaries (N=1,295)
Model 1 (1999)	Base Model*	0.009	0.026
Model 2 (1999)	Base model + log (Ybase)**	0.14	0.21
Model 3 (1999)	Base model + self-reports of health conditions in the last one year***	0.15	0.14
Model 4 (1999)	Base model + claims-based indicators for 128 conditions	0.32	0.25

Base model: Y = f (age, currently disabled, previously disabled, gender, metro status, detailed census regions.

** Predicted Medicare Part A & B payment using HCC-risk adjuster.

*** Self-reported conditions include heart disease, cancer, arthritis, lung disease, mental illness, Alzheimer's, diabetes, hypertension, osteoporosis, stroke, benign prostatic hypertrophy, paralysis, Parkinson's, hip fracture.

Source:1999 Cross-Sectional File, Medicare Current Beneficiary Survey,1999, (N=8067).

Exhibit 3.B.7

R-squares associated with Prospective Models of 2000 Drug Expenditures using Different Risk-adjusters By Nature of Drug and Supplemental Coverage

Model		Adjusted R-square (Log Model)				
				Beneficiaries with No Drug Coverage		
		All Beneficiaries (N=4,978)	Beneficiaries with Any Drug Coverage (N=3,659)	All (N=1,319)	With Supplemental insurance (N=939)	Without Supplemental insurance (N=380)
Model 1P	Base Model*	0.015	0.021	0.064	0.10	0.037
Model 2P	Base model + log (Ybase)**	0.15	0.14	0.19	0.19	0.24
Model 3P	Base model + self-reports of health conditions in the last one year***	0.14	0.12	0.23	0.22	0.28
Model 4P	Base model + claims-based indicators for 128 conditions	0.29	0.25	0.39	0.33	0.43
Model 5P	Base Model + lagged drug expenditures	0.697	0.668	0.71	0.71	0.68
Model 6P	Model 2 + lagged drug expenditures	0.70	0.67	0.71	0.71	0.68
Model 7P	Model 3 + lagged drug expenditures	0.70	0.67	0.71	0.71	0.68
Model 8P	Model 4 + lagged drug expenditures	0.70	0.67	0.71	0.71	0.65

* Base model: Y = f (age, currently disabled, previously disabled, gender, metro status, detailed census regions).

** Predicted Medicare Part A & B payment from DCG-HCC risk adjuster.

*** Self-reported conditions include heart disease, cancer, arthritis, lung disease, mental illness, Alzheimer's, diabetes, hypertension, osteoporosis, stroke, benign prostatic hypertrophy, paralysis, Parkinson's, hip fracture.

Source: 1999/2000 Longitudinal Sample, Medicare Current Beneficiary Survey, (N = 4978)

Exhibit 3.B.8

Estimated Effects on Drug Expenditures (Log Models)

Independent Variable Name	Variable Code	1999 Concurrent Model (Model 4 1999)		2000 Concurrent Model (Model 4 2000)		1999-2000 Prospective Model without Lagged Drug Spending (Model 4P)		1999-2000 Prospective Model with Lagged Drug Spending (Model 8P)	
		Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value
Aged but previously Medicare disabled	disaged	0.35	0.000	0.33	0.000	0.45	0.000	0.09	0.240
Disabled	disabled	0.54	0.000	0.45	0.000	0.54	0.000	0.01	0.834
Age 70-74 years	age74	-0.06	0.409	-0.14	0.063	-0.07	0.441	-0.01	0.798
Age 75-79 years	age79	-0.06	0.459	-0.06	0.463	0.00	0.982	0.10	0.096
Age 80 years or older	age80plus	-0.16	0.030	-0.15	0.039	-0.14	0.118	0.02	0.731
Female	female99	0.09	0.085	0.16	0.002	0.08	0.265	0.00	0.991
Rural	rural99	-0.08	0.096	-0.15	0.001	-0.10	0.119	-0.05	0.255
New England	neweng	-0.21	0.112	-0.30	0.021	-0.28	0.098	-0.07	0.508
Middle Atlantic	midatl	-0.22	0.003	-0.16	0.024	-0.19	0.046	-0.01	0.832
East North Central	encentral	-0.05	0.475	0.06	0.375	-0.01	0.910	-0.01	0.900
West North Central	wncentral	-0.21	0.025	-0.15	0.105	-0.24	0.042	-0.16	0.037
East South Central	escentral	-0.02	0.840	-0.08	0.412	0.08	0.533	0.00	0.967
West South Central	wscentral	0.10	0.185	0.01	0.900	-0.02	0.824	-0.12	0.061
Mountain	mountain	-0.12	0.251	-0.10	0.315	-0.03	0.840	-0.10	0.249
Pacific	pacific	0.05	0.562	-0.18	0.032	-0.13	0.211	-0.10	0.145
Puerto Rico	puertorico	-0.16	0.397	0.01	0.959	0.10	0.680	0.19	0.219
Kidney Transplant Status	hcc128	**1.62**	0.000	**1.53**	0.000	**1.68**	0.000	**0.57**	0.048
Schizophrenia	hcc54	**1.53**	0.000	**1.60**	0.000	**1.37**	0.000	**0.39**	0.005
Hypertensive Heart Disease	hcc90	**1.09**	0.000	**0.95**	0.000	**1.14**	0.000	**0.24**	0.021
Hypertension	hcc91	**1.05**	0.000	**0.99**	0.000	**1.02**	0.000	**0.20**	0.000
Congestive Heart Failure	hcc80	**0.99**	0.000	**0.91**	0.000	**0.99**	0.000	**0.26**	0.000
Inflammatory Bowel Disease	hcc33	**0.72**	0.009	**0.91**	0.000	**0.73**	0.029	0.10	0.654
Major Depressive, Bipolar, and Paranoid Disorder	hcc55	**0.72**	0.000	**0.88**	0.000	**0.81**	0.000	0.17	0.105

Exhibit 3.B.8

Estimated Effects on Drug Expenditures (Log Models)

		1999 Concurrent Model (Model 4 1999)		2000 Concurrent Model (Model 4 2000)		1999-2000 Prospective Model without Lagged Drug Spending (Model 4P)		1999-2000 Prospective Model with Lagged Drug Spending (Model 8P)	
Independent Variable Name	**Variable Code**	**Regression Coefficient**	**p-value**	**Regression Coefficient**	**p-value**	**Regression Coefficient**	**p-value**	**Regression Coefficient**	**p-value**
Parkinson's and Huntington's Diseases	hcc73	**0.65**	0.001	**0.87**	0.000	**0.75**	0.005	0.13	0.457
Diabetes with Ophthalmologic Manifestation	hcc18	**0.62**	0.001	**0.53**	0.005	**0.71**	0.003	0.20	0.192
Seizure Disorders and Convulsions	hcc74	**0.62**	0.000	**0.65**	0.000	**0.75**	0.000	0.16	0.141
Hypertensive Heart and Renal Disease	hcc89	**0.57**	0.018	**0.69**	0.002	0.41	0.193	-0.05	0.819
Glaucoma	hcc122	**0.54**	0.000	**0.43**	0.000	**0.49**	0.000	0.03	0.666
Other Endocrine/Metabolic/Nutritional Disorders	hcc24	**0.49**	0.000	**0.46**	0.000	**0.43**	0.000	**0.08**	0.039
Reactive and Unspecified Psychosis	hcc56	**0.48**	0.036	0.14	0.549	0.47	0.146	-0.09	0.663
Angina Pectoris/Old Myocardial Infarction	hcc83	**0.47**	0.000	**0.35**	0.000	**0.53**	0.000	0.08	0.289
Asthma	hcc110	**0.46**	0.001	**0.47**	0.000	**0.44**	0.011	0.12	0.291
Coronary Atherosclerosis/Other Chronic Ischemia	hcc84	**0.45**	0.000	**0.44**	0.000	**0.38**	0.000	0.01	0.810
Diabetes with No or Unspecified Complications	hcc19	**0.44**	0.000	**0.51**	0.000	**0.53**	0.000	**0.16**	0.004
Screening/Observation/Special Exams	hcc183	**0.43**	0.000	**0.37**	0.000	**0.43**	0.000	0.03	0.425
Osteoporosis and Other Bone/Cartilage Disorder	hcc41	**0.40**	0.000	**0.25**	0.000	**0.40**	0.000	0.10	0.107
Diabetes with Neurologic or Peripheral Complication	hcc16	**0.39**	0.015	**0.42**	0.003	0.33	0.135	-0.04	0.794
Rheumatoid Arthritis and Inflammatory Co	hcc38	**0.38**	0.000	**0.40**	0.000	**0.36**	0.006	0.04	0.621
Chronic Obstructive Pulmonary Disease	hcc108	**0.38**	0.000	**0.33**	0.000	**0.35**	0.000	0.06	0.315
Minor Symptoms, Signs, Findings	hcc167	**0.36**	0.000	**0.44**	0.000	**0.38**	0.000	0.08	0.097
Depression	hcc58	**0.36**	0.001	**0.45**	0.000	**0.39**	0.009	0.03	0.722
Major Symptoms, Abnormalities	hcc166	**0.35**	0.000	**0.39**	0.000	**0.33**	0.000	0.06	0.226
Post-Surgical States/Aftercare/Elective	hcc179	**0.29**	0.000	**0.31**	0.000	**0.33**	0.000	**0.09**	0.034
Peptic Ulcer, Hemorrhage, Other Specified	hcc34	**0.28**	0.003	**0.20**	0.029	0.10	0.406	-0.07	0.379

Exhibit 3.B.8

Estimated Effects on Drug Expenditures (Log Models)

Independent Variable Name	Variable Code	1999 Concurrent Model (Model 4 1999)		2000 Concurrent Model (Model 4 2000)		1999-2000 Prospective Model without Lagged Drug Spending (Model 4P)		1999-2000 Prospective Model with Lagged Drug Spending (Model 8P)	
		Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value
Diabetic and Other Vascular Retinopathies	hcc120	**0.27**	0.022	0.15	0.191	0.21	0.160	-0.01	0.928
Incontinence	hcc134	**0.26**	0.033	**0.22**	0.044	**0.34**	0.029	0.14	0.166
Urinary Obstruction and Retention	hcc133	**0.24**	0.021	0.01	0.890	0.11	0.424	-0.03	0.694
Other Musculoskeletal & Connective Tissue Disorder	hcc43	**0.22**	0.000	**0.31**	0.000	**0.18**	0.008	-0.02	0.679
Osteoarthritis of Hip or Knee	hcc40	**0.21**	0.018	**0.23**	0.005	**0.28**	0.016	0.05	0.521
Specified Heart Arrhythmias	hcc92	**0.21**	0.006	**0.15**	0.035	0.16	0.094	0.01	0.924
Other Gastrointestinal Disorders	hcc36	**0.20**	0.000	**0.25**	0.000	**0.24**	0.001	**0.10**	0.028
Disorders of the Vertebrae and Spinal Disorder	hcc39	**0.20**	0.012	**0.27**	0.000	0.15	0.134	0.02	0.776
Other Injuries	hcc162	**0.19**	0.002	**0.15**	0.011	0.13	0.097	0.02	0.762
Other Ear, Nose, Throat, and Mouth Disorder	hcc127	**0.18**	0.000	**0.13**	0.007	**0.18**	0.005	0.05	0.199
Other Female Genital Disorders	hcc139	**0.16**	0.036	0.09	0.244	**0.24**	0.018	0.10	0.120
Vascular Disease	hcc105	**0.15**	0.046	0.02	0.741	0.13	0.195	0.02	0.788
Other Lung Disorders	hcc115	**0.15**	0.045	**0.19**	0.016	0.05	0.618	-0.12	0.056
Other Dermatological Disorders	hcc153	**0.15**	0.006	**0.18**	0.001	0.12	0.080	0.01	0.746
Gallbladder and Biliary Tract Disorders	hcc30	**-0.37**	0.043	0.01	0.966	-0.22	0.340	0.03	0.837
Diabetes with Renal Manifestation	hcc15	0.45	0.072	**0.57**	0.015	0.55	0.110	0.21	0.354
Cerebral Atherosclerosis and Aneurysm	hcc98	0.45	0.124	0.01	0.959	0.51	0.199	-0.06	0.814
Chemotherapy	hcc181	0.31	0.241	-0.32	0.194	0.25	0.470	0.05	0.819
Other Respiratory and Heart Neoplasms	hcc11	0.26	0.437	0.12	0.744	0.50	0.310	0.48	0.133
Fibrosis of Lung and Other Chronic Lung	hcc109	0.26	0.142	0.01	0.944	0.24	0.281	0.06	0.692
Disorders of Immunity	hcc45	0.23	0.399	0.38	0.086	-0.10	0.789	-0.27	0.253
Pancreatic Disease	hcc32	0.22	0.380	-0.02	0.914	0.25	0.421	0.08	0.706
Unstable Angina and Other Acute Ischemic	hcc82	0.21	0.095	**0.32**	0.007	0.28	0.101	0.08	0.480

Exhibit 3.B.8

Estimated Effects on Drug Expenditures (Log Models)

Independent Variable Name	Variable Code	1999 Concurrent Model (Model 4 1999)		2000 Concurrent Model (Model 4 2000)		1999-2000 Prospective Model without Lagged Drug Spending (Model 4P)		1999-2000 Prospective Model with Lagged Drug Spending (Model 8P)	
		Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value
Lung, Upper Digestive Tract, and Other Specified	hcc8	0.21	0.316	0.16	0.401	0.30	0.279	0.13	0.490
Other Psychiatric Disorders	hcc60	0.20	0.113	0.18	0.153	**0.35**	0.033	0.07	0.519
Acute Myocardial Infarction	hcc81	0.20	0.320	0.06	0.759	0.21	0.443	0.05	0.785
Cerebral Hemorrhage	hcc95	0.20	0.575	-0.38	0.305	**-1.02**	0.026	**-0.70**	0.019
Speech, Language, Cognitive, Perceptual	hcc102	0.18	0.518	0.28	0.254	0.29	0.486	0.10	0.717
Benign Neoplasms of Skin, Breast, Eye	hcc14	0.16	0.061	0.10	0.252	0.23	0.036	0.09	0.183
Vertebral Fractures	hcc157	0.16	0.490	0.26	0.222	0.11	0.740	0.07	0.736
Retinal Detachment	hcc118	0.15	0.610	0.30	0.322	0.13	0.720	0.09	0.697
Rehabilitation	hcc182	0.13	0.316	-0.08	0.529	0.16	0.351	0.10	0.360
Other Neoplasms	hcc13	0.13	0.153	0.07	0.463	0.19	0.098	0.07	0.356
Spinal Cord Disorders/Injuries	hcc69	0.12	0.608	0.37	0.079	0.08	0.800	0.00	0.997
Disorders of Fluid/Electrolyte/Acid-Base	hcc23	0.12	0.177	0.15	0.088	0.17	0.154	0.12	0.122
Metastatic Cancer and Acute Leukemia	hcc7	0.12	0.558	0.38	0.064	-0.13	0.662	-0.20	0.326
Poisonings and Allergic Reactions	hcc163	0.12	0.226	**0.19**	0.040	0.10	0.440	0.02	0.851
Chronic Ulcer of Skin, Except Decubitus	hcc149	0.12	0.456	0.25	0.087	-0.15	0.510	-0.03	0.824
Anxiety Disorders	hcc59	0.11	0.672	0.37	0.152	0.18	0.591	0.19	0.374
Diabetes with Acute Complications	hcc17	0.10	0.683	**0.51**	0.040	0.30	0.353	0.28	0.190
Aspiration and Specified Bacterial Pneumonia	hcc111	0.10	0.693	-0.20	0.450	-0.40	0.276	-0.40	0.097
Artificial Openings for Feeding or Elimination	hcc176	0.10	0.731	-0.04	0.868	0.38	0.300	0.17	0.472
Severe Hematological Disorders	hcc44	0.10	0.654	0.04	0.857	-0.08	0.757	-0.18	0.297
Retinal Disorders, Except Detachment	hcc121	0.09	0.251	0.03	0.739	-0.03	0.767	-0.13	0.052
Coagulation Defects and Other Specified	hcc46	0.09	0.438	-0.04	0.700	0.02	0.878	-0.08	0.426
Other Circulatory Disease	hcc106	0.09	0.277	0.05	0.514	0.10	0.362	0.01	0.925

Exhibit 3.B.8

Estimated Effects on Drug Expenditures (Log Models)

Independent Variable Name	Variable Code	1999 Concurrent Model (Model 4 1999)		2000 Concurrent Model (Model 4 2000)		1999-2000 Prospective Model without Lagged Drug Spending (Model 4P)		1999-2000 Prospective Model with Lagged Drug Spending (Model 8P)	
		Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value
Hearing Loss	hcc126	0.08	0.504	-0.14	0.209	0.16	0.301	0.06	0.550
Other Infectious Diseases	hcc6	0.08	0.217	0.07	0.227	0.04	0.600	-0.02	0.679
Breast, Prostate, Colorectal and Other Cancers	hcc10	0.08	0.378	0.10	0.219	0.14	0.225	0.01	0.872
Intestinal Obstruction/Perforation	hcc31	0.07	0.682	0.05	0.741	0.01	0.979	-0.09	0.527
Type I Diabetes Mellitus	hcc20	0.07	0.577	-0.02	0.839	0.05	0.742	-0.01	0.895
Viral and Unspecified Pneumonia, Pleurisy	hcc113	0.06	0.518	-0.02	0.845	0.01	0.935	-0.02	0.784
Protein-Calorie Malnutrition	hcc21	0.06	0.808	0.12	0.602	0.07	0.846	-0.04	0.866
Cellulitis, Local Skin Infection	hcc152	0.06	0.515	-0.04	0.650	0.11	0.322	0.11	0.135
Other Significant Endocrine and Metabolic Disorder	hcc22	0.04	0.791	0.25	0.095	0.12	0.595	-0.04	0.805
Renal Failure	hcc131	0.04	0.806	0.21	0.130	0.28	0.184	0.19	0.165
Mononeuropathy, Other Neurological Conditions	hcc76	0.04	0.716	-0.07	0.478	0.10	0.425	0.09	0.286
Polyneuropathy	hcc71	0.03	0.794	-0.06	0.647	0.08	0.667	0.03	0.825
Dementia	hcc49	0.03	0.792	0.02	0.879	0.07	0.668	0.06	0.530
Cataract	hcc123	0.03	0.551	**0.12**	0.019	0.09	0.152	0.05	0.288
Precerebral Arterial Occlusion	hcc97	0.03	0.805	0.05	0.617	0.08	0.563	0.06	0.523
History of Disease	hcc184	0.03	0.706	0.05	0.392	-0.01	0.891	-0.03	0.594
Significant Ear, Nose, and Throat Disorder	hcc125	0.02	0.926	0.30	0.173	0.30	0.363	0.14	0.517
Pelvic Inflammatory Disease and Other Specified	hcc138	0.02	0.879	0.22	0.107	0.19	0.273	0.13	0.262
Other Heart Rhythm and Conduction Disorder	hcc93	0.01	0.913	-0.05	0.618	-0.13	0.288	-0.09	0.266
Iron Deficiency and Other/Unspecified	hcc47	0.01	0.886	0.01	0.888	-0.09	0.277	-0.07	0.189
Proliferative Diabetic Retinopathy	hcc119	0.01	0.973	-0.17	0.505	0.04	0.907	0.05	0.831

Exhibit 3.B.8

Estimated Effects on Drug Expenditures (Log Models)

Independent Variable Name	Variable Code	1999 Concurrent Model (Model 4 1999)		2000 Concurrent Model (Model 4 2000)		1999-2000 Prospective Model without Lagged Drug Spending (Model 4P)		1999-2000 Prospective Model with Lagged Drug Spending (Model 8P)	
		Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value
Pneumococcal Pneumonia, Emphysema, Lung	hcc112	0.00	0.988	-0.12	0.656	-0.06	0.880	-0.26	0.291
Valvular and Rheumatic Heart Disease	hcc86	0.00	0.971	-0.11	0.160	0.00	0.967	-0.01	0.903
Other Eye Disorders	hcc124	0.00	0.996	**0.20**	0.013	0.07	0.526	-0.02	0.794
Vascular Disease with Complications	hcc104	-0.01	0.969	-0.07	0.687	-0.08	0.717	-0.04	0.759
Ischemic or Unspecified Stroke	hcc96	-0.01	0.955	0.02	0.874	0.16	0.335	0.11	0.272
Decubitus Ulcer of Skin	hcc148	-0.01	0.962	-0.16	0.465	0.05	0.887	0.00	0.996
Male Genital Disorders	hcc140	-0.02	0.824	0.09	0.194	0.01	0.889	0.00	0.975
Cerebrovascular Disease Late Effects, Unspecified	hcc103	-0.03	0.907	0.22	0.427	-0.06	0.855	-0.05	0.842
Cardio-Respiratory Failure and Shock	hcc79	-0.03	0.817	-0.03	0.815	0.18	0.361	0.13	0.293
Other Urinary Tract Disorders	hcc136	-0.03	0.697	0.06	0.498	0.07	0.568	0.07	0.314
Urinary Tract Infection	hcc135	-0.04	0.591	-0.02	0.733	-0.10	0.260	-0.07	0.239
Mild/Unspecified Mental Retardation	hcc64	-0.05	0.843	-0.06	0.839	0.20	0.508	0.12	0.518
Delirium and Encephalopathy	hcc48	-0.06	0.755	-0.11	0.523	0.15	0.583	0.26	0.136
Senility, Non-psychotic Organic Brain Syndrome	hcc50	-0.08	0.771	0.05	0.873	0.25	0.485	0.31	0.188
Major Fracture, Except of Skull, Vertebrae	hcc159	-0.09	0.666	-0.03	0.876	-0.34	0.191	-0.25	0.135
Major Complications of Medical Care	hcc164	-0.09	0.502	-0.04	0.757	-0.16	0.369	-0.03	0.831
Other Hepatitis and Liver Disease	hcc29	-0.10	0.515	0.09	0.570	0.01	0.949	0.06	0.633
Other and Unspecified Heart Disease	hcc94	-0.13	0.493	0.14	0.453	0.00	0.986	0.11	0.508
Other Complications of Medical Care	hcc165	-0.13	0.479	0.05	0.766	-0.32	0.175	-0.14	0.359
Drug/Alcohol Psychosis	hcc51	-0.14	0.690	-0.40	0.262	0.44	0.425	0.49	0.170
Major Head Injury	hcc155	-0.14	0.556	0.20	0.431	-0.42	0.205	0.03	0.872
Lymphatic, Head and Neck, Brain, Other	hcc9	-0.15	0.409	0.12	0.525	-0.01	0.975	0.21	0.175

Exhibit 3.B.8

Estimated Effects on Drug Expenditures (Log Models)

Independent Variable Name	Variable Code	1999 Concurrent Model (Model 4 1999)		2000 Concurrent Model (Model 4 2000)		1999-2000 Prospective Model without Lagged Drug Spending (Model 4P)		1999-2000 Prospective Model with Lagged Drug Spending (Model 8P)	
		Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value	Regression Coefficient	p-value
Cancer									
Bone/Joint/Muscle Infections/Necrosis	hcc37	-0.17	0.443	0.45	0.053	-0.34	0.262	-0.25	0.209
Drug/Alcohol Dependence	hcc52	-0.17	0.457	0.17	0.551	0.13	0.667	-0.10	0.623
Other Digestive and Urinary Neoplasms	hcc12	-0.17	0.156	0.03	0.784	-0.07	0.639	0.02	0.831
Pleural Effusion/Pneumothorax	hcc114	-0.22	0.150	-0.12	0.450	**-0.44**	0.034	-0.17	0.216
Drug/Alcohol Abuse, Without Dependence	hcc53	-0.22	0.118	-0.19	0.126	-0.24	0.185	-0.01	0.914
Hemiplegia/Hemiparesis	hcc100	-0.22	0.357	-0.09	0.677	-0.19	0.579	-0.22	0.323
Radiation Therapy	hcc180	-0.24	0.445	-0.13	0.650	-0.16	0.720	0.15	0.619
Hip Fracture/Dislocation	hcc158	-0.26	0.203	-0.09	0.621	-0.08	0.766	-0.09	0.599
Traumatic Amputation	hcc161	-0.26	0.660	0.18	0.759	-0.38	0.588	0.05	0.912
Septicemia/Shock	hcc2	-0.29	0.167	-0.07	0.748	-0.52	0.068	-0.21	0.259
Central Nervous System Infection	hcc3	-0.36	0.310	0.11	0.731	-0.34	0.515	-0.15	0.651
Concussion or Unspecified Head Injury	hcc156	-0.41	0.112	-0.07	0.777	-0.60	0.082	-0.28	0.202
Internal Injuries	hcc160	-0.57	0.199	0.50	0.214	-0.33	0.560	0.13	0.722
Lagged Drug Expenditure	logawp99	NA	-	NA	-	NA	-	**0.76**	0.000
Regression Constant	_cons	3.85	0.000	4.06	0.000	4.19	0.000	1.43	0.000

Based on a regression of Ln Drug Expenditures on the variables shown. In concurrent models, all variables are measured in the year specified. In prospective models, dependent variable is measured in 2000 and other variables are measured in 1999.

Omitted categories: Age 65-69 years, Male, Urban, South Atlantic.

Source 1999 Cross-Sectional Sample (N=8067), 2000 Cross-Sectional Sample (N=7,992), 1999/2000 Longitudinal Sample (N=4978), Medicare Current Beneficiary Survey.

Exhibit 3.B.9

Coefficients on Lagged Drug Expenditures in Prospective Models of 2000 Drug Expenditures (Log Models)

Models		Regression Coefficient	P>|t|	[95 Percent Conf. Interval]	
Model 5P	Base Model with lagged drug expenditures*	0.81	0.000	.80	.83
Model 6P	Base model, log (Ybase), and lagged drug expenditures**	0.79	0.000	.78	.81
Model 7P	Base model, self-reports of health conditions in the last one year, and lagged drug expenditures***	.80	0.000	.80	.81
Model 8P	Base model, claim-based indicators for 128 conditions, and lagged drug expenditures	.76	0.000	.74	.78

* Base model: Y = f (age, currently disabled, previously disabled, gender, metro status, detailed census regions) Lagged drug expenditures entered in log form.

** Predicted Medicare Part A & B payment from DCG-HCC risk adjuster.

*** Self-reported conditions include heart disease, cancer, arthritis, lung disease, mental illness, Alzheimer's, diabetes, hypertension, osteoporosis, stroke, benign prostatic hypertrophy, paralysis, Parkinson's, hip fracture.

Source: 1999/2000 Longitudinal Sample, Medicare Current Beneficiary Survey.