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ABSTRACT

The Medicare Modernization Act was recently established, to provide limited drug coverage to the elderly. However, there is limited evidence on how drug coverage might affect health. The goal of this paper is to obtain "causal effects" of prescription drug coverage on drug use, use of other medical services and health of the elderly. We use fixed-effects analysis to control for unmeasured person-specific effects that may confound the relationships of interest. Results show prescription drug coverage, particularly public coverage, significantly increased the utilization of prescription drugs, but had no discernable effect on hospital admissions or health.

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In 2005, the elderly in the United States spent $120.6 billion on prescription drugs with an annual out-of-pocket expenditure of $1,113 per person (KFF, 2005). This figure raises concern because the average annual income of the elderly is only $21,388 (EBRI, 2006), which means the elderly spent approximately five percent of their income on prescription drugs. The numbers become more worrying when one considers that only fifty five percent had prescription drug coverage for the full year in 2002 (KFF, 2005). The combination of rising costs of drugs and limited incomes creates circumstances for many elderly to go without essential medication, which may have adverse health outcomes. Indeed, several studies have indicated that the elderly often skip doses and some do not fill prescriptions due to cost (Kitchman, et al., 2002, Saver, et al., 2004, Steinman, et al., 2001). Steinman et al., (2001) found that eight percent of the elderly who use prescription drugs report self-restriction of medication. A survey of seniors in eight states found that among those without drug coverage, sixty-one percent of diabetes patients and fifty-eight percent of heart disease patients either skipped medicine or failed to fill prescriptions due to cost (Kitchman, et al., 2002).

Until recently, Medicare did not cover outpatient prescription drugs. Elderly persons had to pay out-of-pocket or obtain coverage from other sources such as Medicaid, other public programs (e.g., Veterans Affair and state pharmaceutical assistance programs), employer-sponsored retiree benefits, Medicare + Advantage plans (MA), and privately purchased Medigap policies. Many simply went without coverage. In 2003, the Medicare Prescription Drug, Improvement, and Modernization Drug Act (MMA) established a drug benefit for the Medicare population. The program, which started in January 2006, provides prescription drug coverage through private firms with varying levels of cost sharing based on a person's expenditures on prescription drugs (CCH, 2003).

The primary goal of the MMA was to increase access to prescription drugs and as a result improve elderly health. However, there is limited evidence to support this presumed causal relationship. Relatively few studies have examined the effect of drug coverage on prescription drug use among the elderly and even fewer have examined the effect of drug coverage on health (Adams, et al., 2001a). This study attempts to fill this gap by examining the relationship between prescription drug insurance, prescription drug utilization, and the health of the elderly population.

Analyses are based on the Medicare Current Beneficiary data (MCBS) from the Centers for Medicaid and Medicare Services for years 1992-2000. The study paid particular attention to the non-random nature of prescription drug coverage and the selection bias caused by it. Specifically, the study uses individual level fixed effect analysis. The fixed effects procedure uses within person variation in prescription drug coverage, which under certain conditions may be exogenous, to obtain the effect of insurance coverage on utilization and health. The goal of the study was to obtain estimates of the effect of prescription drug insurance on prescription drug utilization and health that can plausibly be given a “causal” interpretation.

Conceptual Framework--Demand for Prescription Drug Insurance

Economic theory assumes that people are risk averse—they prefer a certain outcome to an uncertain one even if the actuarial value of both is the same (Cutler and Zeckhauser, 2000). Therefore, people will be willing to pay to reduce risk and insurance is the mechanism that reduces risk by pooling (sharing) risk among many individuals. The willingness to pay to reduce risk increases with the risk, which is a function of both the probability of illness and the expected loss associated with that illness. Willingness to pay also depends on the level of risk aversion, as some peoples' dislike for risk is stronger than others.

This simple model of insurance has important implications for empirical analyses. While almost all elderly persons use prescription drugs, there is significant variation in the quantity used and expenditures for prescription drugs. Technological advances in both pharmaceutical and medical treatments have increased the importance of prescription drugs. Costs of drugs have also increased significantly over time. Therefore there is considerable uncertainty about the financial risk of illness as it relates to prescription drugs. Consequently, individuals with higher risk (i.e. those in need of drug coverage) will be more likely to have drug coverage. So even in the absence of insurance, those who are likely to have insurance may use more prescription drugs and be in worse health than those who are unlikely to have insurance.

Most empirical studies have not fully accounted for this selection effect (Adams, et al., 2001b, Blustein, 2000, Davis, et al., 1999, Lillard, et al., 1999). Thus, it is unclear whether previous analyses that find a relationship between prescription drug insurance and utilization have uncovered a causal effect. The observed relationship may simply be due to selection bias. This non-random sorting of persons into insurance coverage may be exacerbated by adverse selection in the insurance market. Persons with larger expenditures—those with poor health—would be more likely to have coverage since it is impossible to perfectly risk adjust—charge each person the actuarially fair price for insurance. Thus, sick persons pay too little and are subsidized by healthy persons who pay too much. This may cause healthy persons to drop coverage leaving an even sicker and more expensive population with insurance.

A second insight of the simple insurance model is that insurance-induced utilization may have relatively few health benefits. Insurance lowers the price of prescription drugs and encourages greater utilization. Indeed, the lower price is likely to result in over-utilization—for which the marginal cost is greater than the marginal benefits (Zweifel and Manning, 2000). Such low-value usage could even harm health because of adverse drug events associated with prescribing (Bates, et al., 1997, Johnson and Bootman, 1995, Lazarou, et al., 1998).

In sum, the MMA was implemented under the premise that prescription drug coverage would increase use of prescription drugs and improve health. While the first part of that statement is likely true, the magnitude of the response to insurance remains uncertain, and more importantly, there is little evidence as to the effect of such coverage on health. Previous studies have not fully addressed the selection issue and therefore have not credibly identified the effect of prescription drug coverage on utilization, and there has been virtually no study of the relationship between prescription drug insurance and health.

Prior Literature

Most of the literature on the effects of prescription drug insurance involves observational studies and few studies have specifically studied the elderly. Estimates from these studies vary considerably. Stuart and Zacker (1999) reported 15.5% lower drug use for Medicaid enrollees living in states that imposed co-pays compared to those who lived in states with no co-pays. Using RAND elderly health supplement to the 1990 Panel Study of Income Dynamics, Lillard et al. (1999) found that insurance coverage significantly increased the probability of drug use among those who use prescription drugs. Blustein (2000) found that the drug coverage increased the likelihood of any antihypertensive drug purchased by 40 percent among hypertensive elderly persons controlling for socioeconomic characteristics, health status, chronic conditions related to hypertension, physician visits, and annual out-of-pocket expenditure (OR=1.4, p=0.002). Federman et al. (2001) reported 84 percent lower odds in use of statins (OR=0.16, 95% CI, 0.05-

0.49) after controlling for socio-demographic factors among elderly with high cholesterol without any drug coverage as compared to those with employer-sponsored coverage.

In sum, the majority of studies in this area have indicated that prescription drug insurance increased drug utilization. However, the cross-sectional data used, and the absence of a convincing research design to address selection, leaves unanswered the question of the causal effect of insurance coverage on drug utilization.

One study that examined a more representative elderly population was Johnson et al. (1997) who studied the effect of increased prescription drug cost sharing on medical care utilization and expenditures in a single large HMO. The HMO provided prescription drug coverage for elderly in Medicare Plus and those enrolled in Social HMO National Demonstration Project. The results indicated that prescription use, in one of the analysis period, decreased by five percent where as the group with no changes in benefit decreased by only one percent. In other analysis periods although the drug use increased, the increase was much smaller compared to the group with no benefit changes. Furthermore, increased co-payment did not translate into higher total medical care expenses or utilization of other medical care services (e.g., outpatient visits, hospitalization and emergency room visits).

There have been several quasi-experimental studies that have examined the effect of prescription drug insurance on utilization. Most of these studies have been limited to the Medicaid population and thus include non-elderly (Nelson, et al., 1984, Reeder and Nelson, 1985, Soumerai, et al., 1987, Soumerai, et al., 1994, Soumerai, et al., 1991). The typical approach is to compare use of prescription drugs pre and post a change in prescription drug insurance (e.g., an increase in co-payment) or policy (e.g., limit on number of prescriptions). Sometimes a comparison group of elderly in another state are used. The results from these studies all indicate that an increase in cost sharing and limits on use reduce use of prescription drugs. However, like the cross-sectional studies, there is a range of estimates, which likely reflects the different populations examined. For example, Soumerai et al., (1987; 1991; 1994) analyzed a three prescriptions per month limit in New Hampshire Medicaid program on drug use and health service utilization. New Jersey was used as a comparison state in some of the analyses. Their analyses indicated that the number of prescriptions dispensed dropped by 30 percent after imposing the cap. The drop was even higher (46 percent) for a cohort of multiple users of drugs (Soumerai et al., 1987). For non-institutionalized, white dual eligible persons that had an average of three prescriptions per month at the baseline there was a 35 percent decline in drug use after the cap was imposed, higher risk (1.8 times) of admission to a nursing home and no significant changes in hospitalization. For the sicker patients the increased risk of admission to nursing home and hospitalization were larger and significant (Soumerai et al., 1991). In a more recent study Briesacher et al. (2005) did not find any evidence of a change in inpatient and physician spending after elderly gained drug coverage.

Only one study that we are aware of examined the effect of prescription drug coverage on health of the elderly population. Gawrisankaran and Town (2004) examined the effect of Medicare Managed Care Organization (MCO) penetration with and without prescription drug coverage on elderly mortality. The authors used payments to MCO as an instrument to account for selection into plans with drug coverage. County fixed effects, year fixed effect, socio-economic status of the county, unemployment rate among others were used as sets of covariates. Their IV estimates indicated that a 10-percentage point increase in non-drug MCO penetration increased mortality by 0.15 percentage point or 2.8 percent (average elderly mortality was 5.08) (Gowrisankaran and Town, 2004).

In summary, the results from previous studies consistently show that prescription drug insurance and the lower cost sharing associated with it increases utilization of prescription drugs in elderly and non-elderly population. However, there is a wide range of estimates and few studies that have examined a broad cross-section of the elderly population. Most studies have focused on low-income (Medicaid) and chronically ill persons. In addition, the research design used in the majority of studies lacks a credible strategy to address selection (Johnson et al.1997; Lillard et al., 1999; Blustein 2000; Federman et al. 2001). Therefore, there is little in these studies that can be used to draw inferences for a broader population of elderly. With respect to health, there is almost no evidence of the effect of prescription drug coverage. It is clear that additional studies are warranted. Specifically, studies that examine a representative sample of elderly persons, that pay special attention to issues of selection, and which include utilization as well as health as an outcome.

Research Design and Methods

The fundamental identification problem in estimating the impact of drug coverage on utilization and health is that the same person is never simultaneously observed with and without prescription drug coverage. And it is unlikely that the self selection into coverage is random. To address this issue, we use a multivariate regression model with controls for person-specific, fixed-effects.[1] Longitudinal data provides a potential solution to the selection problem because over time some people move into and out of prescription drug coverage. Thus, we can observe the same person with and without coverage, although at two different points in time. If this movement is random (conditional on measured covariates) and not affected by health status or

[1] We also tried an instrumental variables approach. However, the instruments (Medicaid eligibility thresholds, managed care payment rates, employer characteristics) while statistically significant in first stage, were weak and second stage estimates were too imprecise to be informative.

other confounding influences, then one can identify the causal effect of drug coverage. The time aspect of this approach, however, introduces the possibility that unmeasured temporal influences may have changed, and it is possible that these temporal changes could bias estimates of the causal effect of prescription drug coverage.

Hence, there are two assumptions of the fixed effect analysis. First, there should be sufficient variation in drug coverage within individuals across time, and second, the variation should not be affected by unmeasured health status or other unmeasured factors that determine the outcomes of interest. Stuart et al. (2001) indicated that 10.6 percent of non-institutionalized elderly who did not have coverage in 1995 found coverage in 1996, while 7.4 percent of those who had coverage in 1995 lost it in 1996. Our analysis also indicated that on average 12 percent of the sample either gained or lost coverage each year (the results presented in later section). So there is evidence of significant within-person variation in drug coverage.

The second assumption implies that movement into or out-of drug coverage should not be affected by unmeasured factors that determine the outcomes of interest. This may be true, for instance, if aspects of health that makes an elderly person seek drug coverage are long-term and not determined within a calendar year. A specification check would be to measure a person's drug use before they gain coverage. If use suddenly rises just before gaining coverage then the fixed effect assumption may not be appropriate as the gain may be a function of adverse health shock. This is tested empirically and the results are presented in later section. In brief, there was no evidence that those obtaining prescription drug coverage did so in response to a significant change in health. There was no significant pre-coverage change in prescription drug use. Similar results were reported by Briesacher et al. (2005) who examined the quarterly medical care spending before and after gaining coverage for the Medicare beneficiaries using MCBS and the Medicare claims data.

The specification of the regression model is as follows:

$$
\begin{aligned}
&Y_{ist} = \alpha_i + \gamma_s + \delta_t + \beta\, PC_{ist} + X_{ist}\Gamma + e_{ist} \\
&i = 1,\ldots, N \ \text{(persons)} \\
&s = 1,\ldots,51 \ \text{(states)} \\
&t = 1992,\ldots 2000 \ \text{(years)}
\end{aligned}
\qquad (1)
$$

where the dependent variable (Y), for example prescription drug use, of a person (*i*) in state (*s*) and at time (*t*) is a linear function of person-specific effects (α_i), state (γ) and year (δ) effects. State and year dummy variables control for unobserved state or time invariant factors that may be related to utilization. These may include differences in prescribing patterns across geography or technological advances in medicine over time. X represents a vector of time invariant individual characteristics that may affect drug use such as demographic and socioeconomic factors. PC represents prescription drug coverage of person (*i)* in state (*s)* and at time (*t)*. Γ and β are the parameter estimates for individual level variable and prescription drug coverage, respectively, and *e* is the error term and represents unmeasured aspect of utilization.

Estimates of equation (1) are obtained using Ordinary Least Squares (OLS) and Poisson regression models. Models for binary dependent variables are estimated by OLS and for discrete outcomes, we use Poisson. We recognize that OLS may not be the most efficient estimator for binary dependent variables, but in the fixed-effects context, common methods used in these circumstances (e.g. Logistic regression) have limitations that make OLS preferred. For example, the fixed-effects Logistic model assumes that the person-specific fixed effect has an infinite distribution and as a result drops observations for which the dependent variable does not change over time even though there may be significant variation in the right hand side variables. The

Poisson model also has an advantage over other methods (e.g., Negative Binomial) in the fixed effects context (Allison and Waterman, 2000, Cameron and Trivedi, 1998).[2] In both cases (OLS and Poisson), standard errors need to be constructed to account for likely biases. Therefore, we construct what are commonly referred to as robust standard errors (Wooldridge, 2002). Despite the preference for OLS and Poisson, use of Logistic and Negative Binomial regression yielded qualitatively similar results to those reported.

Data Sources

The primary data source used in the analyses is the Medicare Current Beneficiary Survey- Cost and Use file from Center for Medicare and Medicaid Services (CMS). The Medicare Current Beneficiary Survey (MCBS) is a national representative, continuous, survey of aged, disabled and institutionalized Medicare beneficiaries (CMS, 2000). The MCBS sample is drawn from the Medicare enrollment file. Initially, when the survey started in 1991 there was no limit on duration of follow up. In 1994 it was decided that a panel will be retired after respondents have been interviewed for four consecutive years. So for some individuals there is more than four years of data. In addition, each year in the fall the sample is replenished to account for non-response and death to maintain a target sample size of 12,000 individuals. In this way, 6,000 new persons are added to the survey every year. The subject is interviewed 12 times in a four-year period. However, the bulk of the information is recorded on an annual basis. The response rate for the first round is around 83 percent and for the 12th round is approximately 70 percent (ResDAC, 2003).

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[2] The negative binomial model is not a true fixed effect model. It does not fully eliminate the influence of unmeasured personal characteristics (Allison and Waterman 2000). To adjust Poisson standard errors, Allison and Waterman (2000) and Wooldridge (2002) suggest adjusting standard errors using deviance statistics. Specifically, the method multiplies the standard error by the square root of the ratio of Pearson chi-square goodness of fit statistics to its degree of freedom.

As for the structure of the interview, the first round of interviews starts in the fall of a given year. In the first round, information regarding health and prescription drug insurance, insurance premiums, demographics, health status and information on access to care is collected. After the first round, subjects are advised to retain receipts, bills, drug vials and any related paperwork to document the drug use. In the following rounds, information is obtained on drugs purchased, charges incurred and sources of payment for the drugs since last interviewed. Respondents are also asked about utilization of other medical services since last interviewed. Aggregated information on use of medical services from Medicare claims files is also included in the data.

For the purpose of this analysis, data from 1992 to 2000 was used. The sample was restricted to non-institutionalized elderly--those 65 years and above without end stage renal disease. The sample size was 84,951 person-year observations. In addition, persons with part year information were removed from the analysis. [3] We also excluded individuals from four US territories (American Samoa, Guam, Northern Marine Islands, and US Virgin Island), and Commonwealth of Puerto Rico. Finally, states with less than 100 observations such as Delaware, Hawaii , Montana, Nebraska , North Carolina , New Hampshire, Oregon, Rhode Island, South Dakota, Utah, Vermont and Wyoming were removed from the analysis due to estimation concerns with small cell size. During data cleaning another nine observations were deleted. The final sample size was 73,490 person-year observations representing an average of 8,166 persons per year with a total of 29,120 unique individuals. Of these 21,120 persons, 17 percent had only

[3] These are 5,250 individuals whom MCBS label as “ghosts”. Ghosts are individuals who enter the survey in the fall; these individuals are reassigned identification numbers next year. However as these ghosts identification numbers were reused in the initials years of surveys, it becomes difficult to follow these individuals. Moreover, as ghosts enter the survey in the fall they only have part year information available, therefore it was decided to remove this part year information from the analysis. In addition, elderly who died during the interview year, their information was not used for that year (4,842 observations).

one year of data, 20 percent had two years of data available data, 51 percent three years, 9 percent four years and 4 percent had five years of data.

Variable Definitions

Prescription Drug Coverage

Elderly report multiple sources of prescription drug coverage, but may have coverage for only few months in the year. However, the proportion with multiple sources of coverage is only 20 percent. Multiple coverage's is due to the fact that elderly are switching from one source of coverage to another, or they have more than one source of coverage at the same time. To account for this, coverage was calculated for each month in the year. If an individual reported multiple coverage in a month they were assigned to the more generous source in the following hierarchical order; public (Medicaid, pharmaceutical assistance programs, and VA), employer-sponsored, Medicare HMO, Medigap and no drug coverage. A similar hierarchy was used by Laschober et al. (2002).[4] Finally, the proportion of months in each category was calculated. These categories were then used as independent variable in the regression analysis. In addition, any drug coverage was also defined as the proportion of month with coverage (all sources combined).[5]

[4] In defining drug coverage from public sources, if the individual reports coverage from either Medicaid or any other public source besides fee for service Medicare, it was assumed that the supplemental coverage also provides drug coverage. This was done because specific drug coverage question for early years are not available. However, as the vast majority of those on Medicaid have drug coverage the difference is not substantial (DHHS 2000).

[5] We also constructed alternative measures of drug coverage using five mutually exclusive categories that were created based on the proportion of coverage in a year. For instance, if the person reported Medicaid coverage for five months but has no coverage for the other seven months in a year, this person was assigned to "no drug coverage" category for that year. All analyses were done with this alternative set of variables and results were virtually the same as those presented below.

Drug use

Several measures of utilization were constructed from self-reported data. Any prescription use is a dichotomous variable equal to one if any prescription was dispensed and zero otherwise. This measure has been used extensively in prior studies (Adams, et al., 2001b, Lillard, et al., 1999, Stuart and Coulson, 1993). Eighty six percent of Medicare beneficiary use at least one prescription drug in a year (Davis, et al., 1999). As a result, measuring use by any prescription dispensed is relatively limited. To address this issue, we also measured utilization using the reported number of prescriptions dispensed. Again, it is one of the most commonly used measures in evaluating drug utilization (Lingle, et al., 1987, Stuart and Coulson, 1993).

Use of other medical care services

The study examines the effect of drug coverage on annual number of hospital admissions. The rationale behind using this is that if drug coverage is health improving, then there should be lower hospital admissions for this group of individuals as compared to those without any drug coverage (Lingle, et al., 1987, Soumerai, et al., 1994, Soumerai, et al., 1991).

Measures of Health

We use self-perceived general health status to measure health. Specifically, the respondents were asked whether “in general, compared to other people your age, would you say that your health is excellent/very good/good/fair/poor”. A dichotomous variable representing poor health was constructed based on the five-category response. General health status was coded as one if self-reported health was fair or poor and zero otherwise.

A detailed measure of health that is more directly related to drug use may be more appropriate. We use activities of daily living (ADL) and instrumental activities of daily living

(IADL) to measure health of the elderly. These measures have been used extensively in prior studies (Blustein, 2000; Federman et al., 2001). Activities of daily living include eating, dressing, bathing, walking, transferring in and out of chair, and using the toilet. IADL includes making meals, using the phone, going shopping, managing money, and doing light and heavy housework. The minimum and maximum score that an elderly can have on the ADL and IADL is zero and six. Finally, a composite measure of functional disability was constructed from the activity of daily living and instrumental activities of daily living. The composite score values would range from 0-12. In addition, as ADL is a more severe level of functional disability compared to IADL; scores on items of ADL and IADL were also used as separate measures (Kassner and Jackson, 1998). Furthermore, as drugs may impact some measures of functional disability more than others, effect of drug coverage on each individual item of ADL and IADL was also assessed. Prior studies have used each item separately and have shown that each individual item is a sensitive measure of functional disability (Cook, et al., 2006, Doody, et al., 2004).

The use of above health measures is appropriate if prescription drug use has an impact on these aspects of health. Several studies have indicated that prescription drugs improve functional disability. Arthritic drugs have been shown to improve gait and walking ability (Canete, et al., 2006, Genovese, et al., 2005, Hamilton, et al., 2001). Similarly, studies have indicated that diabetic treatment is associated with improved health status and quality of life (Bech, et al., 2003, Reza, et al., 2002). Prescription drugs used for mental disorder, cardiovascular and respiratory disorder have also been known to improve functional disability and quality of life (Croog, et al., 1986, Feldman, et al., 2003, Hjalmarson, et al., 2000, Israel, et al., 1996, Roman, et al., 2005, Testa, et al., 1993). Hence, there is significant evidence that drug use effects functional disability and health status.

Other variables

The analysis controls for age, sex, race, education, urban residence, income, marital status and smoking status. All analyses include state and year fixed effects. In some analyses of utilization, we include general health status to control for selection into drug coverage.

Results

Descriptive Analysis

The average characteristics of the entire sample and by drug coverage category are presented in table 1. The table reports weighted estimates.[6] Results show that 58% of sample was female and 11% non-Caucasian. Average age was 75 years with an annual real income of $25,546. Three-fourth of the sample resides in a Metropolitan Statistical Area (urban area). Almost every one was married at least once in their life and only 29% had college or higher degrees. It was evident that there is significant use of prescription drugs for this population. Almost every person dispensed at least one prescription in the last year. The average number of prescriptions dispensed was fairly high around 20. This includes refills and represents approximately six prescriptions per capita among those with at least one prescription dispensed.

[6] The standard errors, presented were calculated using the balanced repeated replication (brr) weights provided with the data. Replicated weights are sampling weights produced by creating several small samples. MCBS contains 100 replication weights. Estimates were calculated using both the full sample weight and each of the replicate weights and then the difference in the estimate was used to calculate the standard error. STATA svr command was used to calculate parameter estimates and the reported standard errors. The mean statistics produced with unweighted and weighted sample were similar. Standard error increased after adjusting for complex sampling design; however, the increase was relatively minor.

In terms of health and medical care use, twenty-two percent of elderly reported poor or fair health. Sixty-two percent of the sample had prescription drug coverage with the majority of the coverage provided by employers. These average characteristics are similar to the characteristics of elderly in U.S. (Census, 2000).

Table 1 also shows descriptive information by drug coverage. Older elderly persons with low income, living in a rural area were less likely to have any prescription drug coverage. Surprisingly, on average the demographic and socio-economic differences between those with and without coverage are not that large. There was, however, significant heterogeneity among those who had coverage—individuals covered by public programs are different than individuals covered by other programs. More importantly, the people with a public program are similar to those without insurance in terms of demographic and socio-economic characteristics, and because of this when individuals with different categories of drug coverage were pooled together; the socio-economic differences between drug coverage and no drug coverage became smaller.

Is there a relationship between drug insurance and health? Generally, elderly without coverage had worse health and lower drug utilization as compared to individuals with employer, Medicare HMO or Medigap coverage. There is, however, some evidence of selection in the public programs. Elderly in public programs had worse health compared to elderly without drug coverage.

Figure 1 shows trends in drug coverage from 1992 to 2000. Drug coverage was increasing during this period. In 1992, 52% of the elderly did not report any drug coverage. This dropped down to 31% in 2000, indicating a 21 percentage point gain. Coverage from public programs remained more or less stable. The gains are mainly coming from employer sponsored, HMO coverage, and some from Medigap coverage. In the period from 1999-2000 a slight drop in employer sponsored coverage was seen, this is consistent with prior studies (William Mercer Inc. 2001; Stuart, Singhal et al. 2003). However, a study by Kaiser Family Foundation (2005) reported only 18% uninsured in 2002. Hence, it appears that the overall trend in drug coverage continues to increase even after year 2000.

Figures 2 to 5 show trends in drug utilization and health for the sample. Figure 2, shows number of prescriptions dispensed per capita over time. Elderly in public coverage have highest utilization. The graph also indicates that utilization has increased over time. The average number of prescription dispensed increased by 42 percent in HMO plans (or MA plans), 47 percent for public programs, 46 percent with Medigap coverage and 59 percent for employer-sponsored. For those without any drug coverage the number of prescriptions dispensed increased by 50 percent.

Was the increase in drug coverage and prescription use associated with improved health? On an average there does not seem to be any trend towards better health, except for those in public programs. Average hospitalization remained stable (figure 3). There was a slight improvement in functional disability of elderly in public coverage (figure 4). For the other groups, it remained stable. Proportion of elderly with poor health across the year also remaind stable (figure 5).

One issue critical to our research design is whether there was sufficient within person variation in drug coverage. Table 2 shows this variation between year t and year t+1. The table was constructed as follows. A series of two-year constant sample panels were created for 92-93, 93-94, 95-96, 97-98, 98-99, 99-00. The first year of each panel was denoted by year t and the second year by year t+1 and then the panels were aggregated. Individuals with only one year of data were not included in this table. In each panel there were approximately 5,000 individuals.

The numbers in the table are consistent with the trend shown in figures 1 and indicate that individuals gained coverage over the years. On an average 14% of the sample changed coverage in each year; of these 6.25% gained coverage and 6.26 % lost coverage. The majority of gain was through coverage from employer-sponsored, but an equal number of individuals lost employer sponsored coverage. The most stable coverage was public. Overall, figures in table 2 suggest there was significant variation in prescription drug coverage.

Regression Analysis

Tables 3 to 5 display estimates of the effects of drug coverage on use of prescriptions drugs and medical services. The presentation of tables is as follows. Column 2 presents the estimates of the effect of drug coverage from models that do not include person fixed effects or controls for individual health. In column 3, estimates are from a model that includes health status. Introducing, health status as a covariate is intended to control for unmeasured determinants of drug coverage, but including it may be problematic since it may be affected by drug coverage. The variable is coded as one if the individual reports fair or poor health, and is zero if the individual reports good, very good or excellent health. Finally, results from the fixed effect models are presented in columns 4 and 5, corresponding to models in columns 2 and 3. The fixed effects analysis controls for all time-invariant characteristics of the individual that may be correlated with drug coverage and outcome of interest.

Effect of Drug Coverage on Drug Use

Estimates of effect of drug coverage on any drug use are displayed in table 3. Estimates show that drug coverage has a positive effect on any drug use. Elderly persons with public coverage are 8.7 percentage points more likely to have at least one prescription dispensed, holding everything else constant, compared to those with no coverage. Those with employer-sponsored and HMO coverage have a four and a half percentage point higher probability of having a prescription filled than those without insurance. Finally, for those in Medigap, insurance increased probability of at least one drug dispensed by only 1.9 percentage points. Adding health status (column 3) has little effect on estimates. However, once person-specific fixed effects are added, coefficients on the drug coverage variables decrease significantly, are small (close to zero) and are no longer statistically significant.

Tables 4, displays estimates of the effect of drug coverage on annual number of prescriptions dispensed. Estimates in column 2 indicate that pubic coverage increased drug use by 46.7%. Those with employer sponsored coverage had 19.7% higher utilization compared to those without any drug coverage, and HMO coverage was associated with 14.7% higher utilization. Medigap increased utilization by 17%. Adding health status (column 3) had little effect on estimates. In general, the results indicate very high utilization among those insured and are similar to previous cross-sectional findings (Bluestein, 2000; Federman et al., 2001). Controlling for individual fixed effects reveals a different story. Here, at best, prescription drug coverage has only a moderate effect on utilization. Public coverage, which includes Medicaid and pharmaceutical assistance programs, increased annual number of prescription dispensed by 13.6 percent. Having an employer sponsored or HMO coverage increased the annual number of prescriptions dispensed by six percent. Medigap coverage had no significant impact on drug use.

Model Specification Test for Fixed Effect Analysis

The fixed effects analysis assumes that in the absence of any change in prescription drug coverage, changes in prescription drug use would be the same for those who switch coverage as those who do not switch coverage. To assess the validity of this assumption, Figure 6 displays average drug use before and after switching coverage for people who gain coverage (True Switcher), people who never have coverage (Nevers), and people who always have coverage (Always). The X-axis indexes time prior to and after the switch of insurance; zero represents the switch year and years pre- and post-switch are labeled accordingly. The Y-axis is the average deviation from the mean of dependent variable (annual number of prescription filled). One year prior to switch (-2 to -1), there was no significant increase in prescription drug use among switchers, although drug use was rising for all groups. In the year of the switch, prescription drug use increases more rapidly for switchers than non-switchers. In the year subsequent to switching (0-1), the trend in prescription drug use is about the same for switchers and non-switchers. Two years (1-2) after the switch, prescription drug use is relatively constant among switchers and continues to rise among non-switchers, but there are relatively few observations in the switching group that may account for this data point.

The fact that switchers did not appear to experience a significant increase in prescription drug use prior to switching is confirmed by more formal tests. Specifically, we tested whether year dummy variables had different effects between switchers and non-switchers in years prior to switching. Interactions between an indicator of being a switcher and year dummy variables were not statistically significant from zero individually, or jointly.

To further investigate whether there was any difference in the time path of prescription drug use between switchers and non-switchers prior to switching, we drop observations on switchers in years after they switch. Thus the sample includes all non-switchers and switchers in the years prior to switching. We then randomly assign a pseudo switch year to those who would eventually switch and estimate the same model as in Table 4 for annual number of prescriptions dispensed. We used a dichotomous measure of prescription drug coverage. The coefficient of this “pseudo” drug coverage variable should be zero if there was no relationship between drug use and coverage controlling for covariates and individual level fixed effects. Indeed this was the case; the coefficient on the pseudo drug coverage was 0.009 (0.9 percent) and not significantly different from zero. In sum, these specification tests provide strong evidence that the fixed effects design is valid and that estimates may plausibly be interpreted as causal.

Effect of Drug Coverage on Hospital Admissions

Estimates of effect of drug coverage on hospital admission are presented in table 5. Estimates in column 2 indicate that elderly with public coverage have 39.6 percent more hospitalization as compared to those without any drug coverage. Adding health status to this model reduces the effect on hospitalization to 28.2 percent. After controlling for time invariant individual characteristics, public coverage was only associated with 9.6 percent more admissions as compared to those without drug coverage, and was not significantly different from zero. Other categories of prescription drug coverage have no statistically significant effects on hospitalizations. While estimates in column 2 indicate that those with HMO coverage have 10.4% fewer hospitalization as compared to those without drug coverage, controlling for individual fixed effects, reduces this estimate to close to zero. Most other estimates are also small, except for those associated with Medigap. In this case, prescription drug coverage is associated with a 13.3 percent increase in hospital admissions. Overall, estimates in Table 5 suggest that prescription drugs and hospitalizations are complementary treatments.

Effect of Drug Coverage on Health

The next set of tables (tables 6-7), displays the effect of drug coverage on health, as measured by: a) poor health status, b) functional disability (score on daily activity of limitation scale and instrumental activity of daily limitation scale), and c) individual measures of activity of daily living and instrumental activity of daily living.

Table 6 shows the effect of drug coverage on being in poor health and on functional disability (ADL plus IADL score). For each outcome, a model with and without person-specific fixed effects is estimated. Estimates from models without person fixed effects suggest that public prescription drug coverage is associated with a higher probability of poor health and HMO coverage is associated with a lower probability of being in poor health. Controlling for person fixed effects, however, reduces these estimates greatly and they are no longer statistically significant. In sum, there is little evidence that prescription drug coverage is related to these measures of health.

Table 7 displays fixed effects estimates of the effect of drug coverage on individual IADL and ADL items. Estimates in Table 7 provide little evidence that prescription drug coverage is associated with an improvement in ADL or IADL conditions. The only group which appears to be doing somewhat better is the HMO group, but even here estimates are quite small in magnitude.

Low Education Group Analysis (Results not Presented)

It may be of interest to see if drug insurance has a different effect for economically disadvantaged individuals. Economically disadvantaged individuals are more likely to be in poor health and in greatest need of medical care. Drug insurance may be more beneficial to them compared to other groups who can still purchase the medical care. For instance, the RAND Health Insurance Experiment did not find any effect of health insurance on the health of the general population but the study indicated reduction in blood pressure for the low income population with poor health status (Brook, et al., 1983). Hence, the effect of drug coverage was also assessed in elderly with no high school education- the group most likely to be in poor health.

In general the results for this group (not shown) were similar to the analysis using the entire sample. Drug coverage has a positive impact on utilization and controlling for person-specific fixed effects reduces the magnitudes of the estimates, but they remain statistically significant. Estimates for the low-educated sample suggest a slightly bigger impact for public coverage and lower impact for employer-sponsored coverage. For instance, results from fixed effect analysis indicate that public coverage among the low-educated is associated with 15 percent more annual number of prescriptions; the similar estimate for the entire sample was 13.6 percent. There was no significant impact of drug coverage on health.

Discussion and Conclusions

January 1st 2006 was a historical day for the elderly in the United States. For the first time in the history of Medicare, a drug benefit became part of the program. The program is estimated to have a net cost of $593 billion over a ten year period (CBO, 2005). However, at this time very little is known as to what can be expected from this expansion, as there is little research examining the effects of prescription drug coverage on prescription drug use, medical care use, and health of the elderly that can be considered “causal”. In this study, we have tried to address this shortfall.

Several studies have indicated that the elderly skip doses or do not fill prescriptions due to cost (Steinman et al., 2001; Kitchman et al., 2002; Saver et al., 2004). For these elderly, insurance can help because it decreases the price of the drugs making them accessible. The results of this study indicated that drug coverage increased drug use and thereby improved access. This was evident in models that do and do not control for time-invariant personal characteristics. However, the magnitude of the effect of drug coverage on utilization differed significantly across the two methods. In models without individual fixed effect, public coverage increased average annual number of prescriptions dispensed by 47%; employer sponsored coverage was associated with 20% higher utilization; HMO coverage increased utilization by 15%; and Medigap increased utilization by 17%. All the associations were statistically significant. Controlling for person-specific fixed effects, however, reduced the magnitudes of the estimates substantially; public coverage increased utilization by 14%, and employer-sponsored and HMO coverage increased utilization by six percent. These estimates were statistically significant. Medigap coverage did not have any significant impact on drug use.

The ultimate reason for providing a drug benefit through Medicare part D was to influence health positively. If drugs are beneficial this should eventually lead to improved health. This improved health may also translate into lower hospitalization. A study by Lichtenberg (2001) argues for the beneficial effect of newer and more costly drugs in reducing use of other medical services. In the year 2005, of the total $325 billion spent on Medicare 37% was due to hospitalization. So if drug coverage substitutes for hospitalizations then it justifies the $593 billion that will be spent in the next 10 years with Medicare part D.

We did not find any evidence of a beneficial effect of prescription drug coverage on hospital admission and measures of health such as self-reported health, and functional disability (IADL, ADL). This was true for subgroup analysis of low-educated persons. Perhaps this is to be expected given that prescription drug coverage had relatively small effects on prescription drug use. It is unlikely that the increase in prescription drugs associated with insurance would have large health effects. Elderly people appear to obtain the necessary drugs with or without insurance.

There are several reasons why an effect on health may not have been observed. Increase utilization does not always help and in fact some of the additional care may be harmful to the patients. Drug utilization is generally associated with side effects of varying severity and can lead to serious adverse events. Medication-related problems have been rated as the fifth most costly disease with a spending of $84.6 billion (Alliance for Aging, 1998). Increased use of combinations of drugs can also be associated with detrimental drug-drug interactions. Every year billions are spent in treating drug-related mishaps (Bates, et al., 1997, Johnson and Bootman, 1995, Lazarou, et al., 1998). A recent study found that patients discontinued use of antipsychotic drugs because of adverse events (Schneider, et al., 2006). There has been a trend towards use of newer drugs, which may not have been tested for long-term health effects. A study by Duggan (2003) did not find any positive effect of switching to newer and more costly drugs in the Medicaid schizophrenic patients. Vioxx®, one of the most commonly used drugs for arthritis was withdrawn from the market when it was found to be linked to increased risk of cardiovascular events (Kolata, 2004).

Another possible explanation is inappropriate pharmacotherapy. The rate of inappropriate prescribing is approximately 20% in elderly (Beers, 1997, Zhan, et al., 2001). Some of the prescribed drugs are contraindicated and can cause severe side effects. A recent study reported that every year approximately 700,000 individuals are treated in emergency departments because of adverse events of which 16.7 percent are hospitalized. The study found higher risk in elderly with elderly twice as more likely to have emergency department visits because of adverse events and seven times more likely to be hospitalized (Budnitz, et al., 2006). Many a time's inappropriate prescribing is due to defragmentation of the system and failure to monitor drug use. Non compliance because of inadequate understanding of the therapy can also lead to poor health outcomes.

So what do these results imply about the benefits of Medicare Part D? It is difficult to estimate the actual impact of Medicare part D from this study because the program has co-pays and an expenditure range during which coverage is not provided. Based on the results of fixed effect analysis, one would expect to observe a relatively small increase in utilization, particularly because Part D is not very generous. A coverage which is as generous as Medicaid may increase utilization by 13.6% or as high as 15% in the low income subsidized group. This would increase the total number of prescriptions dispensed in the country by 16-20 million in a given year. However, the structure of the coverage is not generous as Medicaid, except for low income elderly, and therefore, the actual drug use may increase by only 6% or 6-9 million prescriptions annually, provided all uninsured avail themselves of the new benefit.

If the impact of drug coverage on health was not observed because of inappropriate therapy then there may be areas for improvements, especially for some segment of the population. Perhaps, one of the most important aspects of the MMA act is the introduction of medication therapy management programs (MTMP) (CCH, 2003). This requires the providers of drugs coverage to establish an MTMP for certain beneficiaries that have multiple chronic diseases or receive multiple drugs or have a specified expenditure. The idea is to improve therapeutic outcomes and reduce adverse event by monitoring medication use, coordinating therapy, assessing response to medication, and providing education and training on drug use. A recent longitudinal study indicated that education and long term medication therapy management by certified educators and pharmacists significantly improved clinical, economic and humanistic outcomes in asthma patients. The number of patients with emergency visits decreased from 9.9% to 1.3% whereas hospitalization decreased from 4% to 1.9% (Bunting and Cranor, 2006).

We acknowledge the limitation of our data in estimating the impact of drug coverage on health. Perhaps, more appropriate measures of health would be intermediate and disease specific health outcome such as reduction in $Hb1A_c$ for diabetic patients or blood pressure for hypertensive patients. Future analyses that study the long term effect of drug coverage and measures more sensitive to drug use is an important area of research. Furthermore, the analysis does not distinguish between drug insurance and the heterogeneity in the benefit that comes with insurance. To overcome this individual were classified into different insurance groups. Nevertheless, within groups heterogeneity may exist especially in HMO and employer sponsored plans. For instance, benefit may differ across the MA plans or across employers. This would be more of an issue in the cross-sectional model rather than fixed effect models that use longitudinal information on a person. The analysis included state fixed effects or state dummies that would account for some of the differences in plans that is due to geographic area.

The primary objective of this study was to provide estimates of effect of drug coverage on drug utilization and other health. Drug use was found to be significantly greater among individuals with drug coverage. Based on the results of fixed effect analysis, one would expect to observe an increase in utilization depending on the generosity of the coverage of the prescription drug plan (PDP) and MA plans. The study did not find a significant effect of drug coverage on health outcomes, which indicates simply providing drug coverage, may not be sufficient. Other interventions such as improving prescribing and adherence to medication therapy through the greater involvement of clinicians especially pharmacists is warranted. This research study indicated significant selection bias and cautions against using results from available literature that have not accounted for unobserved differences between individuals. Finally, the fixed effect method used in this study offered a valuable approach in controlling for selection bias.

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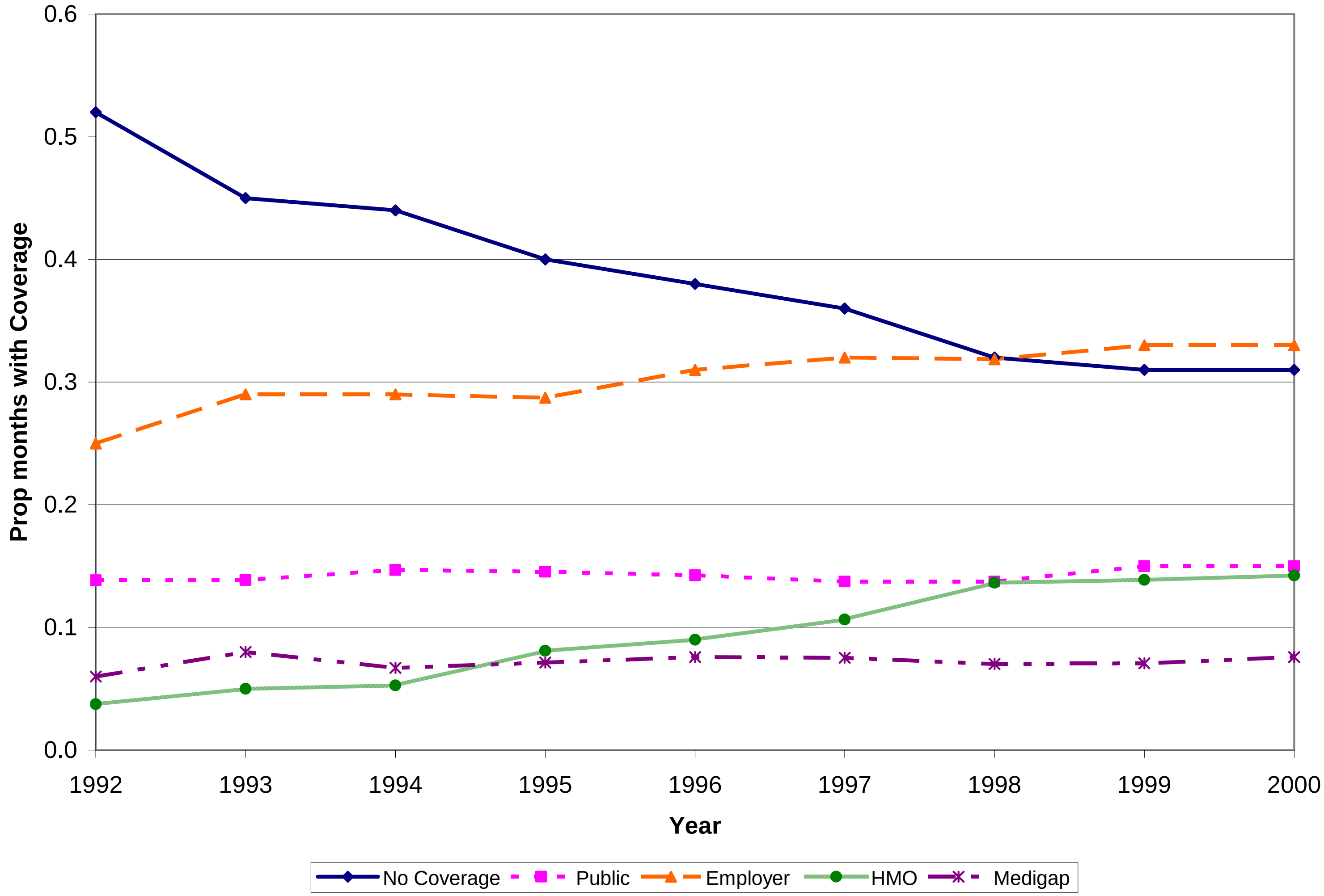

Figure 1 Trend in Drug Coverage (proportion of months with coverage, weighted)

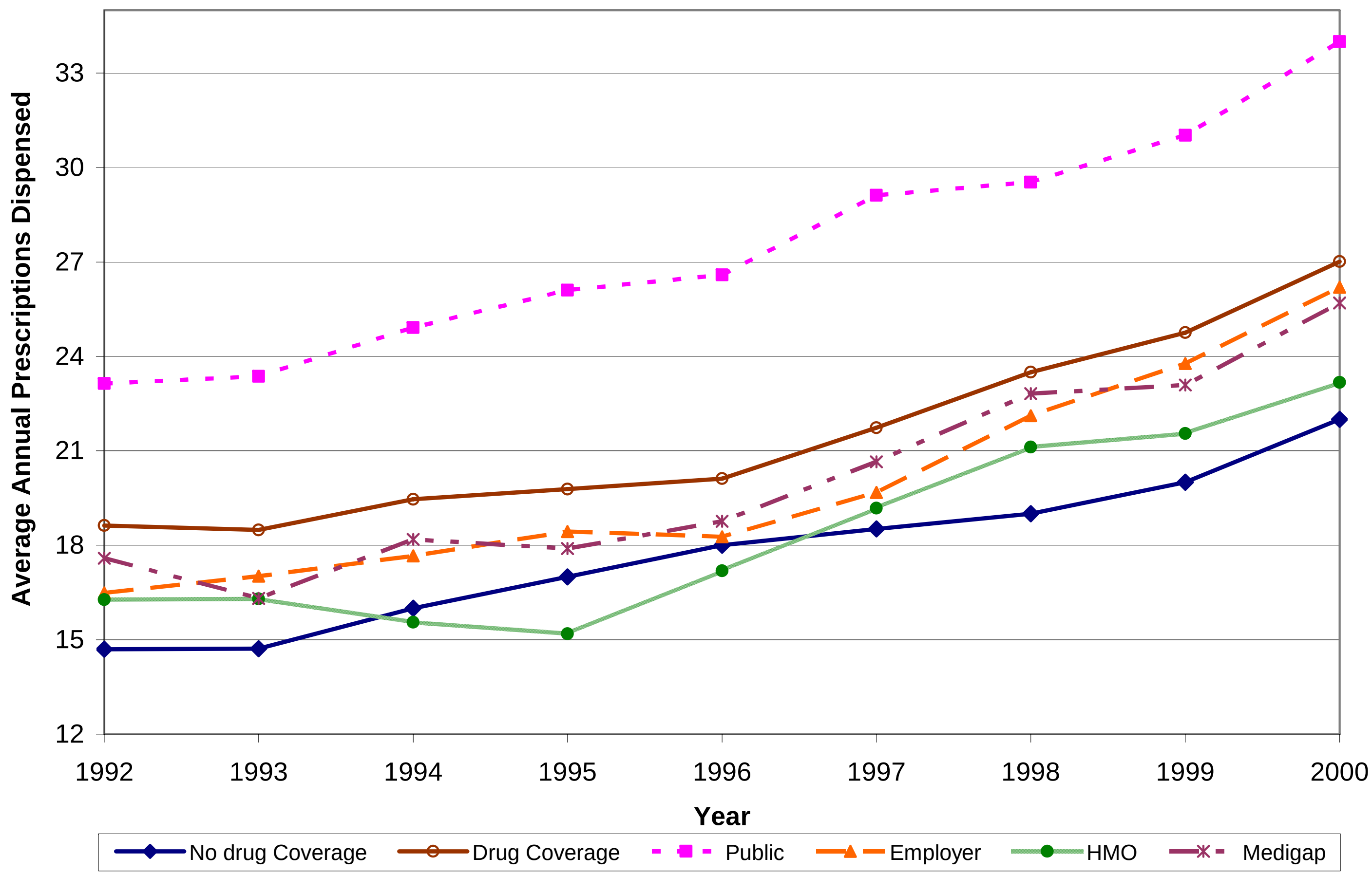

Figure 2 Trend in Average Number of Prescriptions Dispensed (weighted)

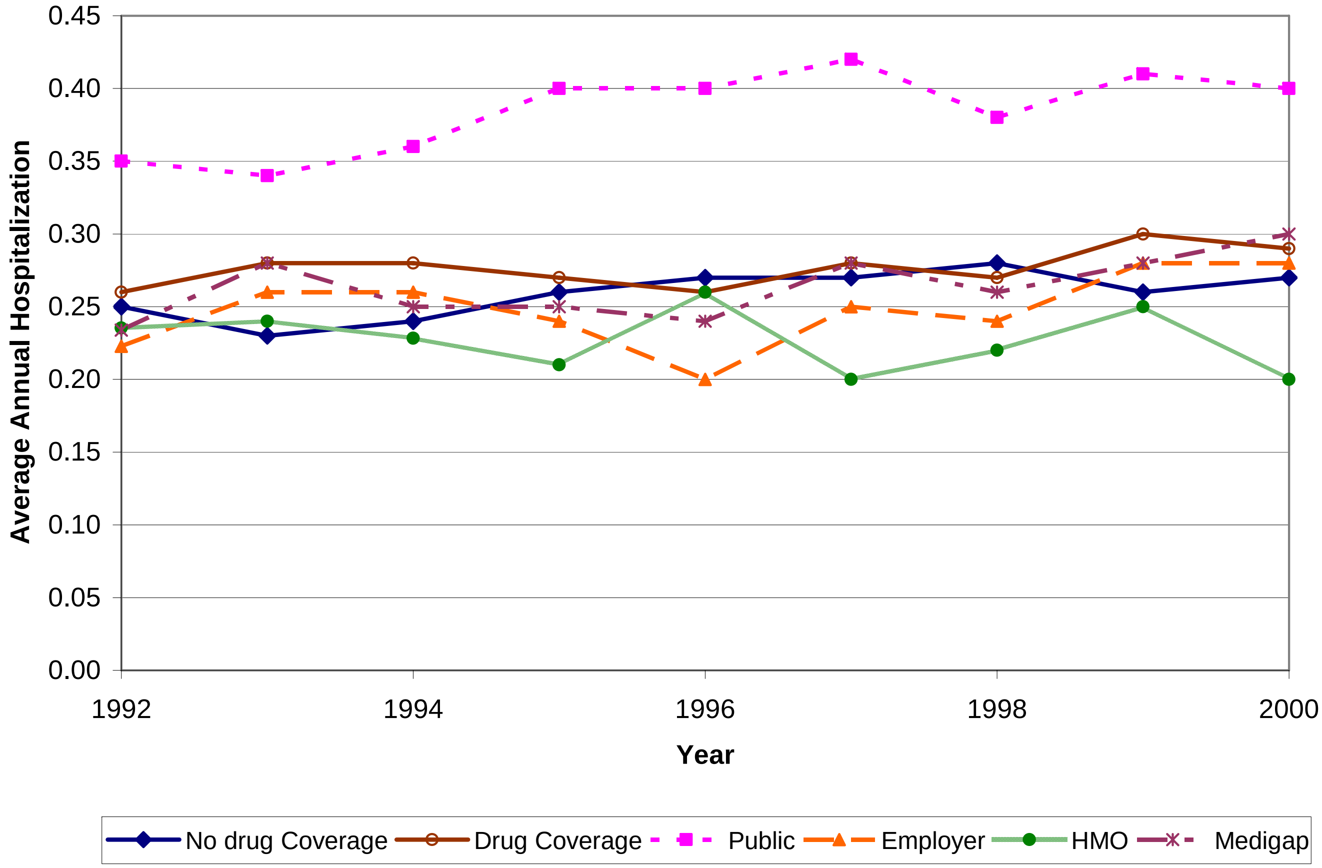

Figure 3 Trend in Hospital Admissions (weighted)

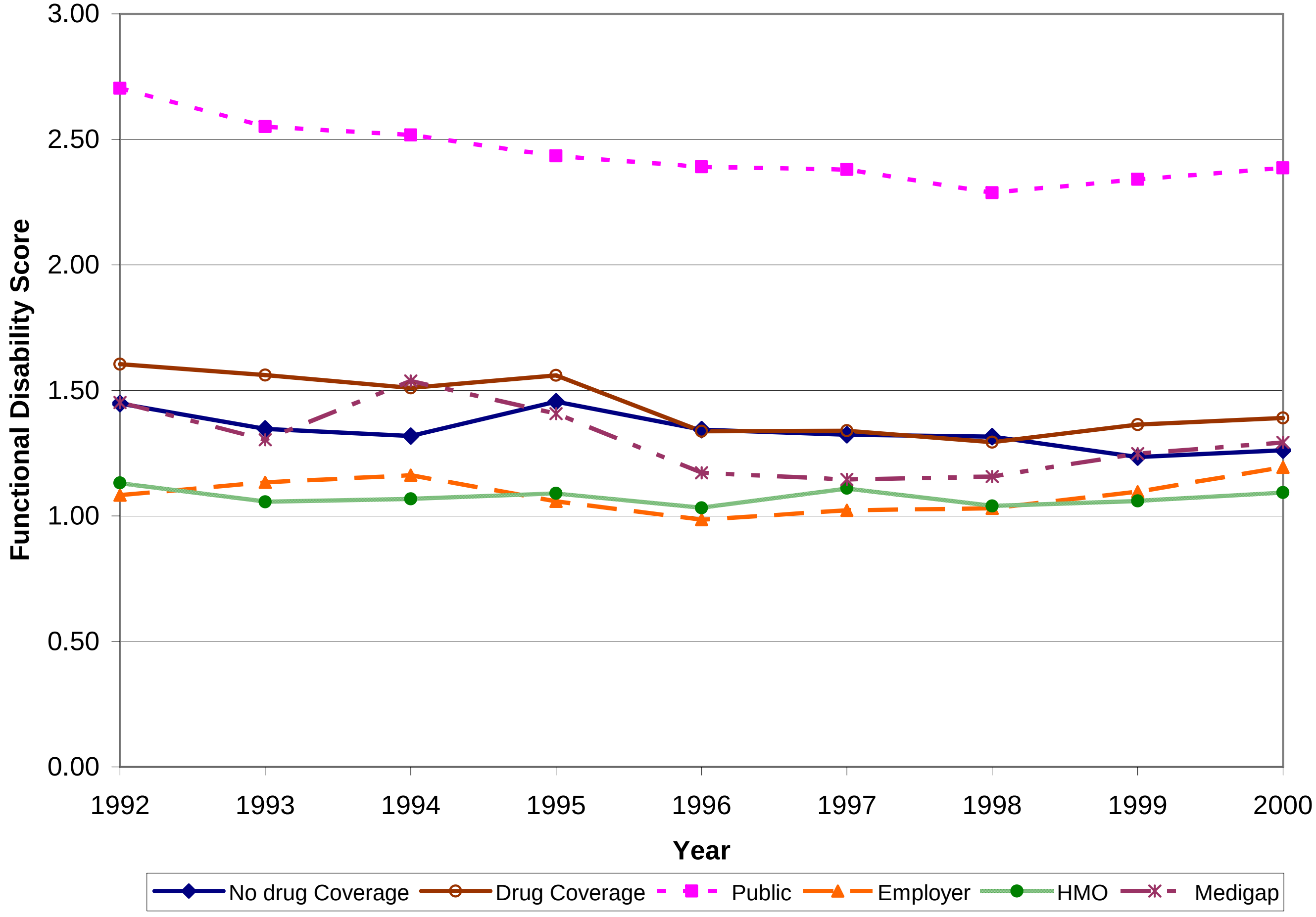

Figure 4 Trend in Functional Disability

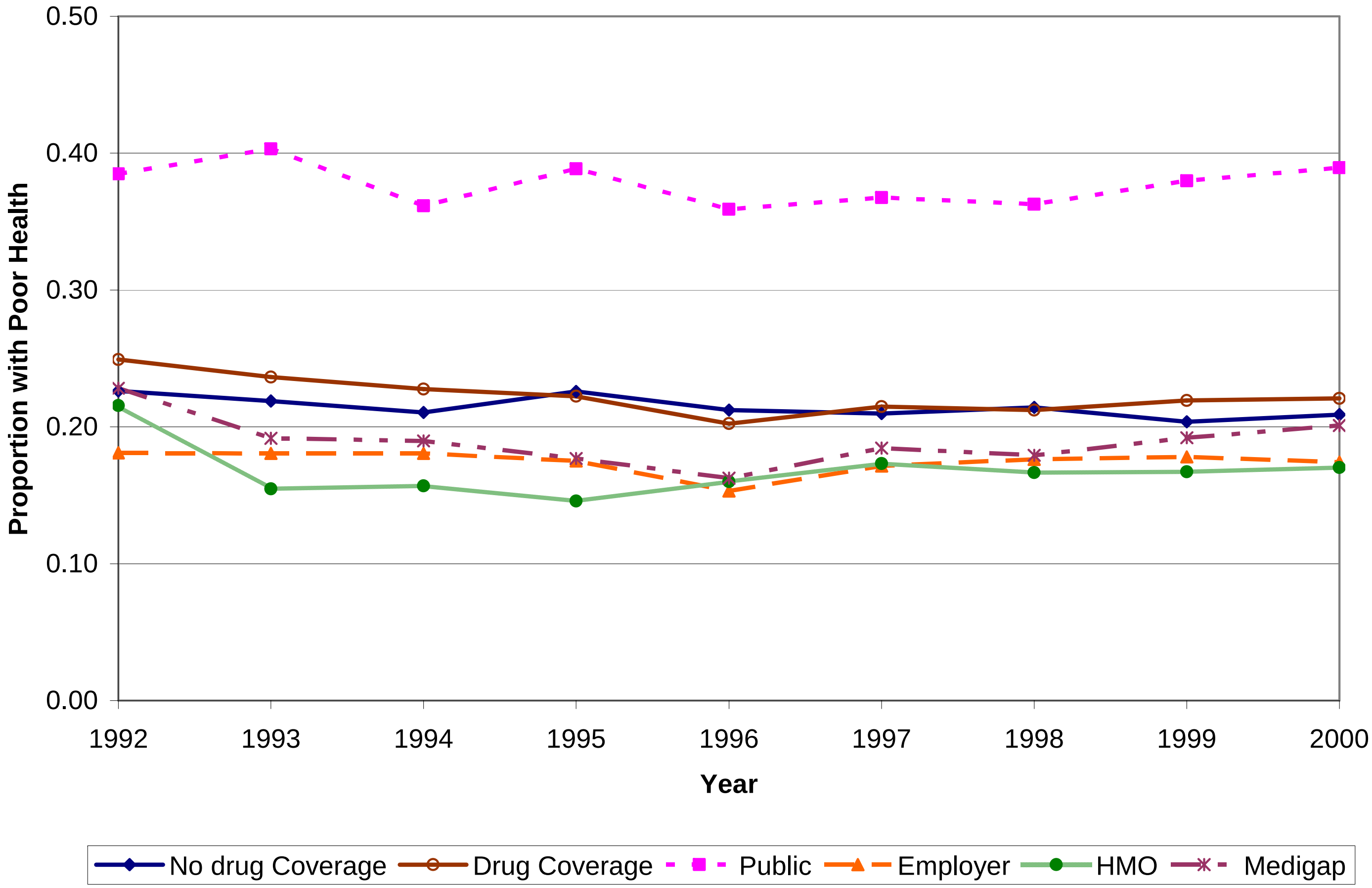

Figure 5 Trend in Health Status (proportion with poor health)

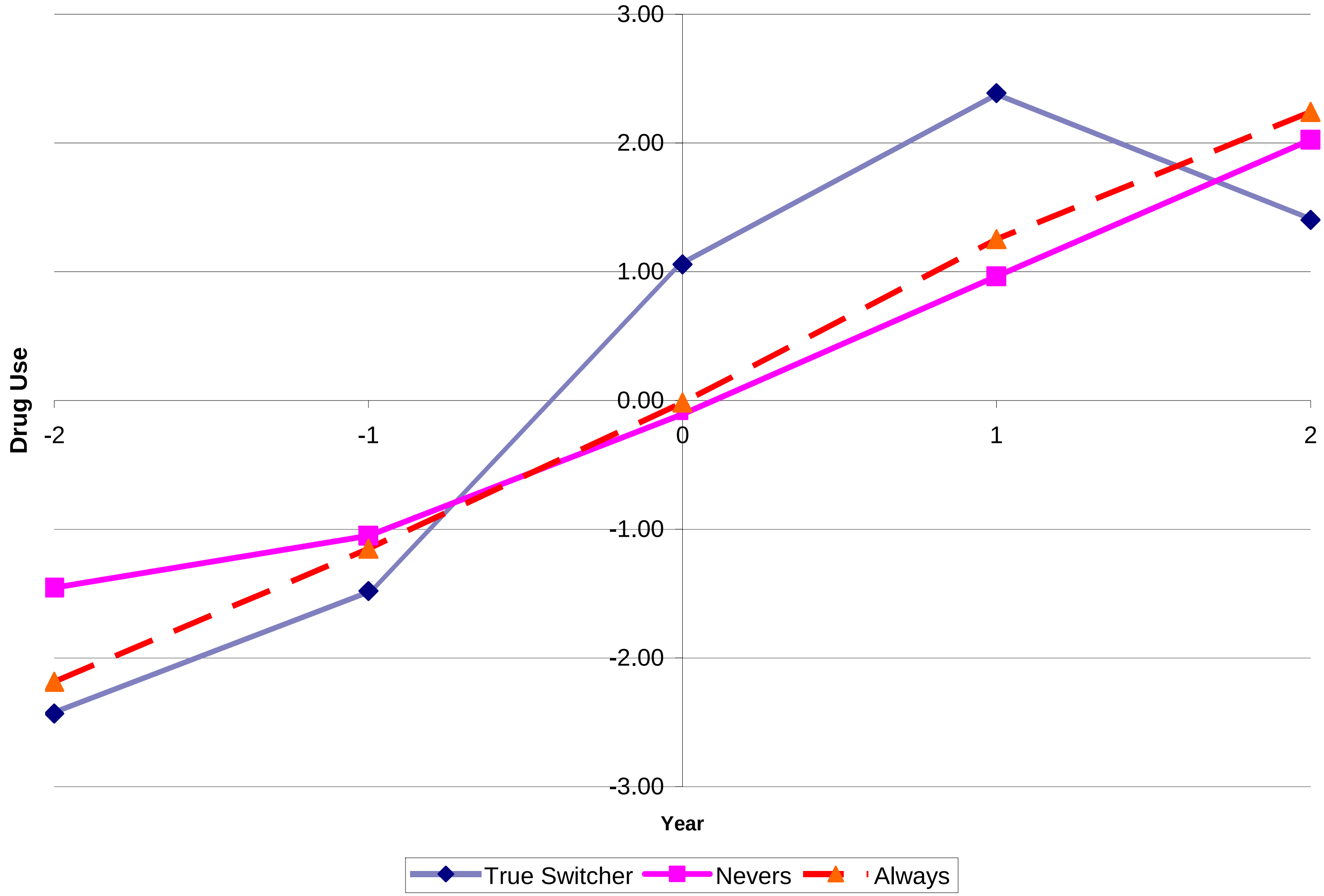

Figure 6 Trend in Drug Use Before and After Drug Coverage Switch, for Switchers and Non-Switchers

TABLE 1
AVERAGE SAMPLE CHARACTERISTICS, WEIGHTED

Individual Characteristics	**Variable Description**	**Entire Sample**	**No Drug Coverage**	**Drug Coverage Combined**	Public	Employer	HMO	Medigap
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sex (proportion)	Female[a,b]	0.58	0.57	0.59	0.70	0.54	0.57	0.63
Race (proportion)	Caucasian[a,b]	0.88	0.90	0.87	0.69	0.93	0.88	0.96
	African-American[b]	0.08	0.07	0.08	0.19	0.05	0.07	0.03
	Other[a,b]	0.03	0.02	0.04	0.12	0.01	0.05	0.01
Age (years)	Age[a,b]	75	76	75	76	74	75	76
Income ($)	Income[a,b]	25,546	22,908	27,084	12,699	33,543	25,593	29,951
Urban(proportion)	Urban[a,b]	0.74	0.67	0.79	0.73	0.80	0.95	0.67
Marital Status	Married[b]	0.56	0.56	0.56	0.31	0.67	0.57	0.55
(proportion)	Widowed[a,b]	0.33	0.34	0.33	0.50	0.25	0.31	0.36
	Divorced[b]	0.06	0.06	0.06	0.10	0.04	0.08	0.05
	Separated[a,b]	0.01	0.01	0.01	0.03	0.01	0.01	0.00
	Not married[b]	0.04	0.03	0.04	0.06	0.03	0.03	0.04
Education	No high school[a,b]	0.37	0.40	0.36	0.65	0.25	0.31	0.28
(proportion)	High school[b]	0.33	0.34	0.33	0.21	0.37	0.36	0.36
	Some college[a,b]	0.15	0.14	0.15	0.08	0.17	0.19	0.18
	College Plus[a,b]	0.14	0.12	0.16	0.06	0.21	0.14	0.18
Smoking Status	Never Smoked[b]	0.40	0.40	0.40	0.44	0.38	0.35	0.44
(proportion)	Former Smoker[a,b]	0.48	0.47	0.49	0.43	0.52	0.53	0.46
	Current Smoker[a,b]	0.12	0.13	0.11	0.14	0.10	0.12	0.11
Utilization	At least one prescription[a,b]	0.89	0.86	0.91	0.92	0.90	0.90	0.88
	Number of prescription[a,b]	20	17.45	21.83	27.68	20.27	19.41	20.24
	Hospitalization[a,b]	0.27	0.26	0.28	0.39	0.25	0.23	0.26
Health Status	Poor Health[b]	0.22	0.22	0.22	0.38	0.17	0.17	0.19
	ADL + IADL score[b]	1.39	1.35	1.41	2.43	1.08	1.05	1.28
N		73,490	27,690	45,800	11,650	21,353	6,985	5,812
			(38%)	(62%)	(16%)	(29%)	(10%)	(8%)

Notes:
Source: MCBS Survey Cost and Use File, 1992-2000
[a] The difference was found to be statistically significant between no drug coverage and drug coverage group using t-test or chi-square test at $p < 0.05$. The standard errors are adjusted for complex survey design using replication brr weights
[b] The difference was found to be statistically significant between different sources of drug coverage using chi-square or one-way ANOVA at $p < 0.05$. The standard errors are adjusted for complex survey design using replication brr weights

TABLE 2
AVERAGE CHANGE IN DRUG COVERAGE BETWEEN TIME (t) & TIME (t+1)

	Public (t+1) # (%)	Employer (t+1) # (%)	HMO (t+1) # (%)	Medigap (t+1) # (%)	No Coverage (t+1) # (%)	**Total # (%)**	**% Change**
Public (t)	6482 (14.63)	53 (0.12)	54 (0.12)	14 (0.03)	168 (0.38)	6771 (15.28)	
Employer (t)	119 (0.27)	11526 (26.01)	267 (0.60)	322 (0.73)	719 (1.62)	13748 (29.23)	
HMO (t)	61 (0.14)	181 (0.41)	3338 (7.53)	19 (0.04)	286 (0.65)	3885 (8.77)	
Medigap (t)	54 (0.12)	267 (0.62)	60 (0.14)	2331 (5.26)	724 (1.63)	3445 (7.77)	
No Coverage (t)	475 (1.07)	848 (1.91)	599 (1.35)	853 (1.92)	14487 (32.69)	17262 (38.95)	
Total (%)	7191 (16.23)	12884 (29.07)	4318 (9.74)	3539 (7.99)	16384 (36.97)	44316 (100%)	**14**

TABLE 3
OLS ESTIMATES OF THE EFFECT OF DRUG COVERAGE ON ANY DRUG USE

Any Drug Use	**(2)**	**(3)**	**(4)**	**(5)**
	OLS model	Adding Health Status (HS)	Fixed Effect	Fixed Effect with HS
Proportion of months public	0.087	0.076	0.019	0.019
	[0.005]**	[0.005]**	[0.014]	[0.014]
Proportion of months employer	0.044	0.044	0.010	0.010
	[0.004]**	[0.004]**	[0.009]	[0.009]
Proportion of months HMO	0.045	0.046	0.008	0.008
	[0.006]**	[0.006]**	[0.013]	[0.013]
Proportion of months Medigap	0.019	0.018	0.003	0.002
	[0.007]**	[0.007]**	[0.011]	[0.011]
Mean of dependent variable for uninsured	0.863			

Source: MCBS Survey Cost and Use File, 1992-2000
Reference category is months with no drug coverage
Covariates included in model are female, age categories (age70-74, age75-79, age 80 or more), race categories (African-American, other race), marital status (widowed, divorced, separated, not married), income categories (income $10,000-$15,000 income, income $15,000-$20,000, income $20,000-$30,000, income $30,000-$40,000, income $40,000-$50,000, income $50,000 or more), education categories (no completed high school, high school completed, some college), rural, smoking status (current smoker, former smoker), year fixed effect, state fixed effect.
Robust standard errors in brackets
* significant at $p < 0.05$; ** significant at $p < 0.01$%

TABLE 4
POISSON ESTIMATES OF THE EFFECT OF DRUG COVERAGE ON ANNUAL NUMBER OF PRESCRIPTIONS DISPENSED

Annual prescriptions dispensed	**(2)**	**(3)**	**(4)**	**(5)**
	Poisson model	Adding Health Status (HS)	Fixed Effect	Fixed Effect with HS
Proportion of months public	0.467	0.395	0.136	0.133
	[0.018]**	[0.017]**	[0.024]**	[0.025]**
Proportion of months employer	0.197	0.192	0.060	0.060
	[0.015]**	[0.014]**	[0.017]**	[0.018]**
Proportion of months HMO	0.147	0.159	0.059	0.059
	[0.022]**	[0.020]**	[0.023]*	[0.024]*
Proportion of months Medigap	0.170	0.165	0.007	0.009
	[0.023]**	[0.022]**	[0.020]	[0.021]
Mean of dependent variable for uninsured	18.7			

Source: MCBS Survey Cost and Use File, 1992-2000
Reference category is months with no drug coverage
Covariates included in model are female, age categories (age70-74, age75-79, age 80 or more), race categories (African-American, other race), marital status (widowed, divorced, separated, not married), income categories (income \$10,000-\$15,000 income, income \$15,000-\$20,000, income \$20,000-\$30,000, income \$30,000-\$40,000, income \$40,000-\$50,000, income \$50,000 or more), education categories (no completed high school, high school completed, some college), rural, smoking status (current smoker, former smoker), year fixed effect, state fixed effect.
Robust standard errors in brackets
* significant at $p < 0.05$; ** significant at $p < 0.01$%

TABLE 5
POISSON ESTIMATES OF THE EFFECT OF DRUG COVERAGE ON ANNUAL NUMBER OF HOSPITALIZATIONS

Annual hospital admissions	**(2)**	**(3)**	**(4)**	**(5)**
	Poisson model	Adding Health Status	Fixed Effect	Fixed Effect with HS
Proportion of months public	0.396 [0.035]**	0.282 [0.034]**	0.096 [1.414]	0.109 [2.145]
Proportion of months employer	0.062 [0.031]*	0.054 [0.030]	0.032 [1.074]	0.038 [1.629]
Proportion of months HMO	-0.104 [0.049]*	-0.080 [0.048]	-0.019 [1.475]	-0.028 [2.239]
Proportion of months Medigap	0.082 [0.048]	0.078 [0.046]	0.133 [1.278]	0.133 [1.935]
Mean of dependent variable for uninsured	0.267			

Source: MCBS Survey Cost and Use File, 1992-2000
Reference category is months with no drug coverage
Covariates included in model are female, age categories (age70-74, age75-79, age 80 or more), race categories (African-American, other race), marital status (widowed, divorced, separated, not married), income categories (income \$10,000-\$15,000 income, income \$15,000-\$20,000, income \$20,000-\$30,000, income \$30,000-\$40,000, income \$40,000-\$50,000, income \$50,000 or more), education categories (no completed high school, high school completed, some college), rural, smoking status (current smoker, former smoker), year fixed effect, state fixed effect.
Robust standard errors in brackets
* significant at $p < 0.05$; ** significant at $p < 0.01\%$

TABLE 6
ESTIMATES OF THE EFFECT OF DRUG COVERAGE ON
PERCEIVED HEALTH STATUS AND FUNCTIONAL DISABILITY

	Perceived health status		Functional disability (ADL and IADL score)	
(1)	**(2)** OLS	**(3)** Fixed effect	**(4)** Poisson model	**(5)** Fixed Effect
Proportion of months public	0.114 [0.007]**	0.030 [0.021]	0.428 [0.024]**	0.027 [0.043]
Proportion of months employer	0.006 [0.005]	-0.000 [0.011]	0.029 [0.024]	0.022 [0.036]
Proportion of months HMO	-0.018 [0.007]*	-0.007 [0.014]	-0.121 [0.037]**	-0.083 [0.050]
Proportion of months Medigap	0.007 [0.008]	0.002 [0.012]	0.055 [0.037]	-0.015 [0.040]
Mean of dependent variable for uninsured	0.25		1.74	

Source: MCBS Survey Cost and Use File, 1992-2000
Reference category is months with no drug coverage
Covariates included in model are female, age categories (age70-74, age75-79, age 80 or more), race categories (African-American, other race), marital status (widowed, divorced, separated, not married), income categories (income \$10,000-\$15,000 income, income \$15,000-\$20,000, income \$20,000-\$30,000, income \$30,000-\$40,000, income \$40,000-\$50,000, income \$50,000 or more), education categories (no completed high school, high school completed, some college), rural, smoking status (current smoker, former smoker), year fixed effect, state fixed effect.
Robust standard errors in brackets
* significant at $p < 0.05$; ** significant at $p < 0.01\%$

TABLE 7
OLS FIXED EFFECT ESTIMATES OF THE EFFECT OF DRUG COVERAGE ON FUNCTIONAL DISABILITY

	ADL						IADL					
	Walking	Bathing	Dressing	Eating	Using chair	Toilet	Heavy House work	Light House Work	Making Meals	Shopping	Using Phone	Paying Bills
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Proportion of months public	0.011 [0.021]	0.004 [0.017]	0.016 [0.014]	0.017 [0.011]	0.006 [0.018]	0.028 [0.013]*	-0.001 [0.021]	0.016 [0.017]	0.024 [0.016]	0.012 [0.018]	0.012 [0.014]	0.024 [0.015]
Proportion of months employer	0.010 [0.011]	-0.000 [0.008]	0.003 [0.007]	0.001 [0.005]	-0.010 [0.009]	0.002 [0.006]	0.018 [0.012]	0.003 [0.009]	0.000 [0.008]	0.010 [0.009]	0.006 [0.007]	-0.005 [0.007]
Proportion of months HMO	-0.000 [0.015]	-0.018 [0.009]	-0.018 [0.009]*	0.003 [0.005]	-0.022 [0.012]	-0.008 [0.008]	-0.029 [0.016]	-0.002 [0.011]	-0.004 [0.010]	-0.006 [0.011]	-0.004 [0.010]	-0.013 [0.009]
Proportion of months Medigap	0.004 [0.012]	0.000 [0.010]	0.005 [0.007]	-0.001 [0.006]	-0.012 [0.011]	0.006 [0.007]	-0.010 [0.014]	0.002 [0.010]	-0.006 [0.008]	0.002 [0.010]	0.003 [0.009]	0.001 [0.009]
Mean of dependent variables for uninsured	0.27	0.14	0.09	0.04	0.15	0.07	0.35	0.14	0.12	0.18	0.09	0.10

Source: MCBS Survey Cost and Use File, 1992-2000
Reference category is months with no drug coverage
Covariates included in model are female, age categories (age70-74, age75-79, age 80 or more), race categories (African-American, other race), marital status (widowed, divorced, separated, not married), income categories (income \$10,000-\$15,000 income, income \$15,000-\$20,000, income \$20,000-\$30,000, income \$30,000-\$40,000, income \$40,000-\$50,000, income \$50,000 or more), education categories (no completed high school, high school completed, some college), rural, smoking status (current smoker, former smoker), year fixed effect, state fixed effect.
Robust standard errors in brackets, * significant at $p < 0.05$; ** significant at $p< 0.01$%