PRESCRIPTION DRUG INSURANCE AND ITS EFFECT ON UTILIZATION AND
HEALTH OF THE ELDERLY

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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, elderly (65 years of age or above) people in the United States spent $120.6 billion on prescription drugs or an annual out-of-pocket expenditure of $1,113 per person, which is approximately 5% of the average income of an elderly person (KFF, 2005). These figures become more worrying when one considers that a substantial portion of the elderly lack insurance coverage for prescription drugs. For example in 2002, only 55% of the elderly had uninterrupted prescription drug coverage (KFF, 2005). Advocates for the elderly worry that the combination of rising costs of drugs, limited incomes, and limited insurance coverage creates circumstances for many elderly to go without essential medication, which may have adverse health outcomes. Indeed, studies have indicated that the elderly often skip doses, and that some do not fill prescriptions due to cost (Steinman, Sands & Covinsky, 2001; Kitchman, et al. 2002; Saver, Doescher & Jackson, 2004).

Until recently, Medicare did not cover outpatient prescription drugs. Elderly people had to pay out-of-pocket or obtain coverage from other sources such as Public (Medicaid, Veterans Affair and State Pharmaceutical Assistance Programs), employer-sponsored retiree benefits, Medicare Advantage plans (HMO), and privately purchased Medigap policies. 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 patient's expenditures for prescription drugs (CCH, 2003).

While political objectives were an important part of the explanation of the timing and design of the MMA, creation of the MMA was also motivated by a desire to improve the health of the elderly by lowering the cost of prescription drugs, which in turn would stimulate their use and improve health. Although plausible, there is relatively little evidence to support the

presumed causal relationships underlying the MMA. Few studies have examined the effect of prescription drug coverage on prescription drug use among the elderly and even fewer have examined its effect on health. This study examines the relationship between prescription drug coverage, prescription drug utilization, hospitalization, and the health of the elderly population. Analyses are based on a nationally representative sample from the Medicare Current Beneficiary Survey (MCBS) from the Centers for Medicaid and Medicare Services (CMS) 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. The goal of the study was to obtain estimates of the effect of prescription drug coverage on prescription drug utilization and health that can plausibly be given a causal interpretation.

Conceptual Framework--Demand for Prescription Drug Coverage

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. Therefore, people will be willing to pay to reduce the financial risk associated with illness by buying insurance. The willingness to buy insurance increases with financial risk, which is a function of both the probability of illness and the size of the expected loss associated with illness. Willingness to pay also depends on the degree of risk aversion, as some people's dislike for risk is stronger than others (Cutler & Zeckhauser, 2000).

This model of the demand for insurance is consistent with recent trends in prescription drug use. Technological advances in both pharmaceutical and medical treatments have increased the importance of prescription drugs for maintaining good health, particularly for the elderly. Costs of prescription drugs have also increased significantly over time. Thus there is

considerable uncertainty about the financial risk of illness as it relates to prescription drugs and this uncertainty has increased over time. As a result, the demand for prescription drug coverage among the elderly has been growing in recent years (see Figure 1). The greater desire for prescription drug coverage among the elderly led, in part, to the MMA.

This model of insurance also has important implications for empirical analyses of the effect of prescription drug coverage. It suggests that those with insurance will differ from those without insurance. Those with insurance are likely to be at greater risk illness (need of prescription drugs) and/or be more risk averse. This may be exacerbated by imperfect risk adjustment. So prescription drug use would likely differ between those with and without insurance even if there was no insurance. Most empirical studies have not adequately accounted for this selection effect (Davis, Poisal, Chulis, Zarabozo, & Cooper, 1999; Lillard, Rogowski, & Kington, 1999; Blustein, 2000; Adams, Soumerai, & Ross- Degnan, 2001). Thus, it is unclear how to interpret estimates of the effect of prescription drug coverage reported in earlier studies, as they might be seriously biased estimates of the causal effect of prescription drug coverage on prescription drug utilization and health.

A second principle of the simple insurance model is that insurance-induced utilization of prescription drugs could have relatively few health benefits. Most elderly people use prescription drugs, even if they do not have insurance. So the increased use of prescription drugs associated with insurance, what we will refer to as marginal use, may have fewer health benefits than average use of prescription drugs. Moreover, lower prices are likely to result in some over-utilization—for which the marginal costs are greater than the marginal benefits (Zweifel & Manning, 2000).

The argument in support of the MMA is that providing prescription drug insurance would make prescription drugs more affordable, thereby increasing their use. In turn, this increased use would lead to better health. While the first part is likely true, the magnitude of the response to insurance remains uncertain, as previous studies have not adequately addressed the selection issue and, therefore, have not credibly identified the causal effect of prescription drug coverage on utilization. More importantly, there is little evidence as to the effect of prescription drug coverage on health. So even if utilization of prescription drugs increases with insurance coverage, it is unknown whether such an increase would significantly improve health in a general population.

Prior Literature

Our review of the literature is limited to studies of elderly populations that have been controlled in some way for confounding factors. We begin with studies that use cross-sectional data. Typically, these studies report that insurance coverage, or more generous insurance coverage, results in relatively large increases in utilization of prescription drugs (DHHS, 2000). Stuart and Zacker (1999) reported 15.5% lower annual prescription use for dual eligible Medicare enrollees living in states that imposed Medicaid co-payments compared to those living in states with no co-payments. Blustein (2000) found that drug coverage was associated with a 40% increase in antihypertensive drug purchases by hypertensive patients. Federman, Adams, Ross-Degnan, Soumerai & Ayanian (2001) reported 84% lower odds of HMG-CoA reductase inhibitors (statins) use among elderly with high cholesterol without drug coverage as compared to those with employer-sponsored coverage. Lillard et al. (1999) found that insurance coverage significantly increased the probability of any drug use by 12.2% for those with private insurance.

Several studies have used quasi-experimental research designs. The typical approach is to compare use of prescription drugs pre and post a change in prescription drug coverage or policy (e.g., an increase in co-payment, limit on number of prescriptions). For example, Soumerai et al., (1991) analyzed the impact of a three prescriptions per month limit in the New Hampshire Medicaid program on prescription drug use and hospitalization rates. New Jersey was used as a comparison state. Their analysis was limited to non-institutionalized, white, dual-eligible people who had an average of three prescriptions per month at baseline, including use of at least one prescription drug for a chronic condition. Their results indicated a 35% decline in drug use after the cap was imposed and no significant changes in hospitalization rates.

Johnson et al. (1997) and Chandra et al. (2007) examined the effect of increased prescription drug cost sharing in Medicare managed care plans. Johnson et al. (1997) reported that a 2$ (66%) increase in co-payment resulted in a significant decrease in prescription use of approximately 8% and that it had no effect on hospitalization rates. Chandra et al. (2007) calculated a price elasticity of demand of between -0.46 and -0.2 for Medicare PPOs and -1.4 for Medicare HMO. These elasticities imply reductions in prescriptions filled from the pre-policy mean of 2 to 6% in the PPO and 14.2% in the HMO. In addition, although they found a significant increase in hospitalization rates in the HMO plan (which had increases in co-payments for both prescription and office visits), there was no effect in the PPO plan (which only had an increase in prescription co-payments).

Gawrisankaran and Town (2004) examined the effect of Medicare Managed Care Organization (MCO) penetration with and without prescription drug coverage on elderly mortality using payments to MCO's as instruments. Their preferred (instrumental variables) estimates indicated that a 10-percentage point increase in non-drug MCO penetration increased

mortality by 2.8%. Yang, Gilleskie and Norton (2004) analyzed the effect of supplemental insurance, with and without prescription drug coverage, on prescription drug expenditure, hospital services, and health using MCBS data. They used a dynamic panel model that modeled health as a function of current and lagged utilization. Their results indicated drug coverage increased drug expenditure by 20-35% over a 5-year period and decreased mortality slightly.

The results from these studies consistently show that prescription drug coverage, and the lower cost sharing associated with it, increased utilization of prescription drugs by elderly patients. However, there is a wide range of estimates, which likely reflects the different populations examined. In addition, the observational studies lacked a credible strategy to address selection (Stuart & Zacker, 1999; Lillard et al. 1999; Blustein, 2000; Federman et al. 2001). The quasi experimental studies, while better on this point, have either focused on low-income (Medicaid) population (Soumeari et al. 1991) or on a specific managed care population (Johnson et al. 1997; Gawrisankaran & Town, 2004; Chandra et al. 2007). 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 people, that pay special attention to issues of selection, and which include prescription utilization and health as outcomes.

Empirical Strategy

The fundamental identification problem in estimating the effect of prescription drug coverage on utilization and health is that the same person is never simultaneously observed with and without prescription drug coverage. It is unlikely that the self-selection into coverage is

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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 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) then we can identify the causal effect of prescription drug coverage. The time aspect of this approach, however, introduces the possibility that unmeasured temporal influences (e.g., health status) might change, and bias the estimates of the causal effect of prescription drug coverage.

There are two conditions that determine the efficacy of the fixed-effect analysis. First, there should be sufficient variation in prescription drug coverage within individuals over time. Stuart et al. (2001) reported that 10.6% of non-institutionalized elderly who did not have coverage in 1995 found coverage in 1996, while 7.4% of those who had coverage in 1995 lost it in 1996. Our analysis indicated that, on average, 14% of the sample either gained or lost coverage each year (see Table 2). So there is evidence of significant within-person variation in prescription drug insurance. The second condition is that movement into or out of prescription drug insurance should be random, conditional on controlling for measured characteristics and unmeasured person-specific fixed-effects. To assess the plausibility of this assumption, we conducted a variety of analyses. All of these analyses provided evidence consistent with the assumption underlying the fixed-effect approach. The most compelling of these is a comparison of changes over time in prescription drug use and health status between those who would eventually obtain insurance ("treatment group") and those who either always had insurance or never had insurance ("comparison group"). The fixed-effect approach assumes that, changes in prescription drug use and health over time would be the same for the "treatment" and

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"comparison" groups conditional on covariates. We present the details of this analysis later, but note here that there was no evidence, that trends in prescription drug use or health differed between the "treatment" and "comparison" groups. Similar results were reported by Briesacher et al. (2005) who examined medical care spending before and after gaining prescription insurance coverage of Medicare beneficiaries. While we cannot definitively test the assumption of the fixed effects approach, we believe the evidence supports the plausibility of this approach.

The fixed-effects approach is implemented using the following regression model:

$$Y_{ist} = \alpha_i + \gamma_s + \delta_t + \beta\, PC_{ist} + X_{ist}\Gamma + e_{ist}$$
$$i = 1,...,N \quad \text{(persons)}$$
$$s = 1,...,51 \quad \text{(states)} \tag{1}$$
$$t = 1992,...2000 \quad \text{(years)}$$

where the dependent variable (Y), prescription drug use for example, of a person (*i*) in state (*s*) and at time (*t*) is a linear function of person-specific fixed-effects (α_i), state (γ), and year (δ) effects. State and year dummy variables control for unobserved state or time invariant factors that might be related to utilization. These could include differences in prescribing patterns across geography or technological advances in medicine over time. The vector X represents time varying individual characteristics that might 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) for binary dependent variables and Poisson regression for discrete outcomes. We recognize that OLS might not be the most efficient estimator for binary dependent variables, but in the fixed-effect context, common methods used in these circumstances (e.g. Logistic regression) have limitations that

make OLS preferred. For example, the fixed-effect 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-effect context (Cameron & Trivedi, 1998; Allison & Waterman, 2000).[2] In both cases (OLS and Poisson), standard errors need to be constructed to account for likely biases.[3] 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

The primary data source used in the analyses is the Medicare Current Beneficiary Survey (MCBS)—Cost and Use file from CMS. 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. When the survey started in 1991, there was no limit on duration of follow-up. In 1994, it was decided that a panel will retire after 4 years. So for some individuals there are more than 4 years of data. In addition, approximately 6,000 new people are added to the survey each year to account for non-response and death, to maintain a target sample size of 12,000 individuals. Each respondent is interviewed three times per year over a 4-year period. However, the bulk of the information is recorded on an annual basis. The response rate for the first round is 83% and for the 12th round is approximately 70% (ResDAC, 2003).

The first round of interviews starts in the fall of a given year. In the first round, information regarding health and prescription 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, prescription vials, and any related paperwork to document their prescription use. In the following rounds, information is obtained on prescriptions purchased, charges incurred, and sources of payment for the prescriptions obtained since the previous interview. Respondents are also asked about utilization of other medical services since last interviewed. Aggregated information on the 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 were used. The sample was restricted to non-institutionalized elderly without end-stage renal disease. Individuals with partial year information were removed from the analysis.[4] We also excluded individuals from four US territories and the Commonwealth of Puerto Rico. Finally, states with fewer than 100 observations were removed from the analysis due to estimation concerns with small cell size. The final sample size was 73,490 person-years observation representing an average of 8,166 people per year and a total of 29,120 unique individuals. Of these 29,120 people, 17% had only 1 year of data[5], 20% had 2 years of data available data, 51% 3 years, 9% 4 years, and 4% had 5 years of data.

MCBS respondents report multiple sources of prescription drug coverage and some have coverage for only a few months in the year. Multiple coverage was due to elderly switching from one source of coverage to another or having more than one source of coverage at the same time. To account for this, insurance coverage was calculated for each month. Individual who reported multiple coverage in a month were assigned to the more generous source in the following hierarchical order: public, employer-sponsored, HMO, Medigap, and no drug coverage.[6] A similar hierarchy was used by Laschober et al. (2002). 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 months with coverage (all sources combined).[7]

Several measures of utilization were constructed from self-reported data. Any prescription use was a dichotomous variable equal to 1 if any prescription was reported and 0 otherwise. However, 86% of Medicare beneficiaries use at least one prescription drug in a year (Davis, et al., 1999). As a result, measuring use in this way is limited. Therefore, utilization is also measured using the reported annual number of prescriptions used.

We also examined the effect of prescription drug coverage on hospitalizations. Assuming a beneficial effect of prescription insurance coverage on health, one would expect lower hospitalizations rate for covered individuals, compared to those without prescription coverage. Here prescription coverage would act as a substitute for hospitalization, which is desirable from both consumer and provider perspectives because prescription drugs are less invasive, have fewer complications and have lower cost.

We used a variety of measures of health. A dichotomous variable representing poor health was constructed in which poor health was coded if self-reported health was fair or poor, and good health represent if self–reported health was excellent, very good or good.

A detailed measure of health that is more directly related to prescription use might be more appropriate. Several studies have indicated that prescription drugs improve functional disability. Antiarthritic drugs have been shown to improve gait and walking ability (Hamilton et al., 2001; Genovese et al., 2005; Canete et al., 2006). Similarly, studies have indicated that antidiabetic treatment is associated with improved health status and quality of life (Reza, Taylor, Towse, Ward & Hendra, 2002; Bech, Moses & Gomis, 2003). Prescription drugs used for

mental, cardiovascular and respiratory disorders have also been shown to improve quality of life (Croog et al., 1986; Testa, Anderson, Nackley & Hollenberg, 1993; Israel, Cohn, Dube & Drazen, 1996; Feldman et al., 2003; Hjalmarson et al., 2000; Roman et al., 2005) . Given this evidence, we used activities of daily living (ADL) and instrumental activities of daily living (IADL) as measures of health. These measures have been used extensively in prior studies of elderly health (Blustein, 2000; Federman et al., 2001).

Activities of daily living include eating, dressing, bathing, walking, transferring into and out of a chair, and using the toilet. Instrumental activities of daily living include making meals, using the phone, going shopping, managing money, and doing light or heavy housework. The minimum and maximum scores that an elderly person can have on the ADL and IADL are 0 and 6. Finally, a composite measure of functional disability was constructed that sums ADL and IADL. The composite score values would; therefore range from 0 to12. Furthermore, as prescription drugs can impact some measures of functional disability more than others, the effect of prescription drug coverage on each item of the 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, Richardson, Pietroban, Silva & Turner, 2006).

The analysis controls for age, sex, race, education, urban residence, income, marital status, and smoking status. All analyses include state and year fixed effects.

Results

Descriptive Analysis

The average characteristics of the entire sample and by drug coverage category are presented in Table 1, which reports weighted estimates.[8] The average age of the sample was 75 years; 58% were women and 11% were non-white. Almost every respondent was married at least once in their life and 29% had at least some college education. Average annual income was $25,546 (2000 dollars).

It was evident that there was significant use of prescription drugs by this population. Almost every individual in the sample reported having at least one prescription use. The average number of annual prescriptions was approximately 20. This figure included refills and represented approximately 6 prescriptions per person among those with at least one prescription. Sixty-two percent of the sample had prescription drug coverage with the majority of the coverage provided by employers. In terms of health, 22% of the elderly respondents reported poor or fair health.

Table 1 also shows descriptive information by prescription drug insurance coverage. Elderly people with low incomes and who were living in rural areas were significantly less likely to have any prescription drug coverage. Notably, the demographic and socio-economic differences between those with and without coverage, while often statistically significant were not very large. There was, however, significant heterogeneity among those who had coverage— individuals covered by public programs were quite different than individuals covered by other programs. People with public insurance coverage were similar to those without insurance in terms of demographic and socio-economic characteristics. Therefore, when individuals with different categories of drug coverage were combined, the socio-economic differences between those with and without drug coverage were smaller.

Is there a relationship between prescription drug coverage, and prescription drug use and health evident in Table 1? In the case of use of prescription drugs, those with insurance have greater use and there is a gradient in terms of use according to the generosity of insurance. Those with public insurance, who pay nothing out-of-pocket, have the greatest use and those with Medigap, which is least generous, have the least use. Part of the greater use of prescription drugs may be due to differences in health. Those with public insurance coverage were least healthy. Generally, elderly without insurance coverage reported worse health than individuals with employer, HMO or Medigap insurance coverage. Those in public programs had significantly worse health compared to all others, even those without drug coverage.

Figure 1 shows trends in drug coverage from 1992 to 2000. In 1992, 52% of the elderly reported no prescription drug insurance coverage. This dropped to 31% in 2000. Coverage from public programs remained more or less stable. The gain in coverage came mostly from employer sponsored and HMO coverage.[9]

Figure 2, shows number of prescriptions per person. Elderly in public coverage had the highest prescription drug utilization. The graph also indicates that utilization increased over time. The average number of prescriptions increased by 47% for public programs, 59% for employer-sponsored, 42% in HMO plans, and, 46% with Medigap coverage. For those without any drug, coverage the number of prescriptions increased by 50%.

Was the increase in drug coverage and prescription use associated with improved health? There does not seem to be any trend toward better health, except for those in public programs. There was a slight improvement in functional disability (ADL plus IADL) for elderly in public coverage (Figure 3). For the other groups, it remained stable. The proportion of elderly with poor health also remained stable (Figure 4).

One issue critical to our research design was whether there was sufficient within-person variation in prescription drug coverage. Table 2 shows this variation between year t and year t+1. A series of 2-year constant sample panels were created for 92-93, 93-94, 95-96, 97-98, 98-99, and 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 1 year of data were not included in this table. In each panel there were approximately 5,000 individuals. The data in Table 2 are consistent with the trend shown in Figure 1 and indicate that individuals gained coverage over the years. On average, 14% of the sample changed coverage in each year. The majority of gain was through employer-sponsored coverage, but an equal number of individuals lost employer sponsored coverage. The most stable coverage was public. Overall, the data in Table 2 suggest that there was sufficient variation in prescription drug coverage to implement the fixed-effect approach.

Regression Analysis

Tables 3 to 5 display estimates of the effects of prescription drug coverage on use of prescriptions drugs and hospitalizations. Column 2 presents the estimates of the effect of prescription drug coverage from models that do not include person-specific fixed-effects or controls for individual health. In column 3, estimates are from a model that includes measures of health, as determined by an indicator of poor health and the number of chronic diseases. Including measures of health is intended to control for unmeasured time-varying determinants of prescription drug coverage that are not accounted for by fixed-effects and that might confound estimates. However, we recognize that this approach could be problematic because health could

be affected by drug coverage. Finally, results from the fixed-effect models are presented in columns 4 and 5, corresponding to models in columns 2 and 3.

Estimates of the effect of prescription drug insurance coverage on any drug use are displayed in Table 3 and show that drug coverage had a positive effect on any drug use. Elderly people with public coverage were 8.7 percentage points more likely to have at least one prescription than those with no coverage. Those with employer-sponsored and HMO coverage had a 4.5 percentage point greater probability of having a prescription filled than those without insurance. Finally, for those with Medigap, the probability of at least one prescription was 1.9 percentage points greater than those with no coverage. Adding health indicators to the model (column 3) had little effect on estimates for HMO and Medigap coverage, but significantly reduced estimates of public and employer coverage. This finding suggests that cross-sectional estimates are likely to be biased.

Columns 4 and 5 present the fixed-effects estimates. Coefficients on the drug coverage variables decreased significantly relative to estimates in columns 1 and 2. Estimates in column 4 are small (close to zero) and are no longer statistically significant. Further, we did not see any difference in coefficients between column 4 and 5, when measures of health were added to the fixed-effect models. This suggests that much of the selection into insurance status is accounted for by including controls for person-specific fixed-effects and lends support to the credibility of our fixed-effects results.

Table 4 displays estimates of the effect of drug coverage on annual number of prescriptions. Estimates in column 2 indicate that public coverage increased prescription drugs use by 46.7%, employer-sponsored coverage increased it by 19.7%, HMO coverage by 14.7% and Medigap increased utilization by 17% relative to the uninsured. Adding measures of health

(column 3) had little effect on estimates, except for public coverage. In general, the results indicated 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 revealed a different story. Here, at best, prescription drug coverage has only a moderate effect on utilization. Public coverage increased annual number of prescriptions by 13.7%. Having employer sponsored or HMO coverage increased the annual number of prescriptions by 6%. Medigap coverage had no significant impact on prescription use. Adding measures of health had no effect on fixed-effect estimates bolstering the plausibility for our research approach.

Table 5 presents estimates of the effect of drug coverage on hospitalization. Estimates in column 2 indicate that elderly with public insurance coverage are 6.3 percentage points more likely to have a hospitalization than those without insurance. This is a large effect and, as we will see, primarily a selection effect. Those with Medigap and employer-sponsored insurance also have higher rates of hospitalization than the uninsured, but for these people the coefficients are small—1 to 1.4 percentage points. Adding health status to the model (column 3) reduced the effect of public insurance coverage on hospitalization significantly, and fixed-effect estimates indicated that prescription drug coverage had no statistically significant effect on hospitalization. Most fixed-effect estimates are small relative to the mean; public insurance coverage is associated with the largest effect, 2.3 percentage point, which is approximately 9% of the mean of the uninsured. Overall, estimates in Table 5 suggest that prescription drugs and hospitalization, if related, are complementary treatments.

The next set of tables (Tables 6-8), display estimates of the effect of drug coverage on health, as measured by: poor health status, functional disability (ADL plus IADL), individual measures of ADL and IADL. Table 6 shows the effect of prescription drug insurance coverage

on probability of being in poor health. Estimates from models without person specific fixed-effect suggest that public prescription drug coverage was associated with a higher probability of poor health and that HMO coverage was associated with a lower probability of being in poor health. Adding the number of chronic conditions reduced the magnitude of the estimate for public coverage. Controlling for person-specific fixed-effects, however, reduced these estimates greatly and they were no longer statistically significant. Notably, adding the number of chronic conditions to the fixed-effect model had no effect on the estimates of drug coverage. There is little evidence that prescription drug coverage is related to self-reported poor health.

Tables 7 and 8 present estimates of the effect of drug coverage on functional disability (ADL plus IADL score in Table 7) and individual IADL and ADL items (Table 8). Here, we just discuss the fixed-effect estimates and only fixed-effect estimates are reported in Table 8. Estimates in Tables 7 and 8 provide little evidence that prescription drug coverage is associated with an improvement in ADL or IADL conditions except for those in the HMO group. Prescription drug coverage through a Medicare HMO is associated with approximately 8% fewer functional disabilities. The average score (ADL plus IADL) for uninsured people was 1.53; therefore, drug coverage through a Medicare HMO would be expected to decrease it by 0.13. A similar positive, yet small, impact of HMO coverage was observed for individual ADL and IADL items (Table 8). Those with HMO coverage experienced reduced disability in bathing, dressing, getting out of chair, and heavy housework. Estimates remain similar when we added measures of health to the model (results not shown).

Low Education Group Analysis (Results not Presented)

It is of interest to investigate whether prescription drug coverage 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. Prescription drug coverage might be more beneficial to them compared to other groups who can still purchase prescription drugs in the absence of insurance. For example, 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 low-income population with poor health status (Brook, Lynch, & Riley, 1983). Hence, the effect of prescription drug coverage was assessed for a sample of elderly with no high school education—the group most likely to be in poor health and with limited incomes. In general, the results for this group (not shown) were similar to the analysis using the entire sample. Drug coverage had a positive impact on utilization, and controlling for person-specific fixed-effects reduced the magnitudes of the estimates but they remain statistically significant. Estimates for the low-educated sample suggested a slightly larger effect for public coverage and smaller effect for employer-sponsored coverage. For example, results from fixed-effect analyses indicated that public coverage among the low-educated was associated with 15% increase in annual number of prescriptions; compared with 13.7% for the entire sample. There was no significant impact of drug coverage on health for this sample.

Specification Tests for Fixed-Effect Analysis

The fixed-effect analysis assumes that, in the absence of any change in prescription drug coverage, changes in prescription drug use and health would be the same for those who switch coverage as those who do not switch coverage. To assess the validity of this assumption, we examined the trend in prescription drug use pre- and post-switching insurance status for people

who gain coverage (True Switchers), people who never have coverage (Nevers), and people who always have coverage (Always). For those who did not switch insurance (Always and Nevers), we randomly assign them a (pseudo) switch year. Figure 5 displays these trends. 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 annual number of prescriptions filled. One year prior to switch (-2 to -1), prescription drug use was rising in a similar way for all groups. In the year of the switch (-1 to 0), prescription drug use increased more rapidly for switchers than non-switchers. In the year subsequent to switching (0-1), the trend in prescription drug use is again about the same for switchers and non-switchers. This pattern supports the fixed-effect approach because it shows that in the absence of a change in insurance status, trends in prescription drug use are the same for those who switch and do not switch insurance status. We show a similar figure (Figure 6) for the number of chronic conditions. In this case, there is some evidence that the trend in chronic conditions differs slightly for those who gain insurance after the switch. In the year of the switch, the number of chronic conditions increased more for those who switched than for those who did not switch.

To further assess whether the fixed-effect approach is valid, we estimated models identical to those in Tables 3 through 8, using all observations for non-switchers and only observations on switchers in years prior to switching. We randomly assign those who were true switchers a pseudo-switch year—a year in which they supposedly gained prescription drug coverage. If switchers and non-switchers have similar trends in outcomes, we would expect the coefficient on this pseudo insurance coverage variable to be zero, which is exactly what was found for all outcomes (prescription drug use, hospitalization, poor health, and number of

chronic conditions). In summary, a variety of specification tests provide strong evidence that the fixed-effect design is valid and that estimates could plausibly be interpreted as causal.

Given that statistical analyses indicated that changes in prescription drug insurance coverage appeared to be exogenous (random), conditional on measured covariates and controls for time-invariant person-specific effects, a natural question to ask is why? What are the exogenous factors that caused people to switch insurance coverage? There are a few possible explanations. One factor is the expansion of Medicaid eligibility thresholds (Bruen et al., 1999, 2003; Stone and Yacker, 2002; Schneider et al., 1999). There was also a significant expansion of Pharmaceutical Assistance Programs (PAP) across states. In 1992, only 19 states had some form of PAP program by 2000 almost all states had included some form of drug coverage to their low income elderly who did not qualify for Medicaid. These changes might account for switches into public coverage observed in Table 2.

Expansion of Medicare managed care might account for some of the changes in coverage. Between 1996 and 1999, enrollment in Medicare risk plan (e.g., HMO) increased by 5.1 percentage points (Laschober, et al., 2002). However, the 1997 Balanced Budget Act decreased payments to MCOs and, as a result, many MCOs either terminated or reduced the benefits provided (Pizer and Frakt, 2002; Booske et al. 2002). Those disenrolled and living in areas of low managed care penetration were more likely to enroll in Medigap plans (Laschober et al. 1999; Booske et al. 2002).

For those who gained employer coverage, data from the MCBS indicated that some did so through their spouses or by starting employment. Many picked up drug coverage subsequent to retirement. A Kaiser/Hewitt 2002 Retiree Health Survey reported that 16% of the employers in the survey provided options for stand-alone drug plans or discount cards (KFF, 2002). Hence,

some employees could be expected to pick-up prescription drug benefits at a later time. Results

from the same survey indicated that many employers had increased drug co-payments, which

could results in employee's withdrawing from those plans. Overall, there appeared to be

plausible explanations for the statistical finding that switches in prescription drug coverage

appear to be exogenous, conditional on measured covariates and controls for time-invariant

person-specific effects.

Conclusions

January 1, 2006 was a historical day for the elderly in the United States. For the first

time, a drug benefit became part of the Medicare program. The program is estimated to have a

net cost of $593 billion over a 10-year period (CBO, 2005). However, 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. However, the magnitude of the effect of drug coverage on utilization was smaller than

that found in most previous studies. Public insurance coverage increased prescription drug

utilization by 14%, and employer-sponsored and Medicare HMO coverage increased utilization

by 6%. These estimates were statistically significant. Medigap prescription drug coverage did not

have any significant effect on prescription drug use. These results are consistent with the

generosity of these different insurance plans. Medicaid is the most generous and Medigap the least generous.

Did the greater use of prescription drugs associated with insurance improved health and lower rates of hospitalization? Generally, we found the answer to this question to be "no." We did not find consistent evidence that prescription drugs are a substitute for hospitalization. Nor did we find much evidence that prescription drug coverage improved health and functional disability. The lone exception was prescription drug coverage obtained through a Medicare HMO. In this case, prescription drug coverage was associated with improved functional disability. Similar results were obtained for a sample of low-educated people.

Perhaps it is to be expected that prescription drug insurance would have few health benefits given that prescription drug coverage had relatively small effects on prescription drug use. Alternatively, absence of effect could be due to inappropriate pharmacotherapy either because of excess unnecessary utilization that could even be harmful or non-adherence to therapy on the part of consumers (Budnitz et al., 2006; Zhan et al. 2001; Lazarou, Pomeranz & Corey, 1998). We also acknowledge the limitations of our data in estimating the effect of drug coverage on health. Perhaps, more appropriate measures of health would be intermediate and disease specific health outcomes such as reduction in HbA_{1c} for diabetic patients or blood pressure for hypertensive patients.

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-payments 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. For example, a 6% increase, which is what we

found for employer-sponsored insurance would result in an increase of 6 to 9 million prescriptions annually, provided all uninsured avail of the new benefit.

The analysis also has implications for medication therapy management programs (MTMP) introduced as a part of MMA (CCH, 2003). It is believed that efficacy of prescription drugs depends on proper prescribing and compliance to medication. Under MMA, the providers of drug coverage are required to establish an MTMP for seriously ill beneficiaries. The basic premise is to improve therapeutic outcomes and reduce adverse event by monitoring medication use, coordinating therapy, and providing education and training on drug use. Indeed, prior research supports that intervention by health care providers improves clinical, economic and humanistic outcomes (Buntig & Cranor 2006). Our finding of no effect of drug coverage on health suggests simply providing drug coverage might not be sufficient to improve health and that other interventions such as MTMP might be necessary.

Endnotes

[1] We also experimented with 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.

[2] The negative binomial model is not a true fixed effect model. It does not fully eliminate the influence of unmeasured personal characteristics (Allison & Waterman, 2000).

[3] 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 from the Poisson regression by the square root of the ratio of Pearson chi-square goodness of fit statistics to its degrees of freedom.

[4] 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).

[5] These people will drop out of fixed effects analyses. However, dropping them from all analyses does not alter the results.

[6] In defining drug coverage from public sources, if the individual reports coverage from either Medicaid or any other public source besides Medicare, it was assumed that the supplemental coverage provides drug coverage. This was done because specific drug coverage was not asked when persons reported Medicaid coverage. The vast majority of those on Medicaid have drug coverage (DHHS 2000).

[7] 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 had no coverage for the other seven months this person was assigned to "no drug coverage" category. All analyses were done with this alternative set of variables and results were virtually the same as those presented in the text.

[8] The standard errors, presented were calculated using the balanced repeated replication 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. The mean statistics produced with unweighted and weighted sample were similar.

[9] In the period from 1999-2000 a slight drop in employer sponsored coverage can be observed, which is consistent with reports in prior studies (William Mercer Inc. 2001; Stuart, Singhal et al. 2003). However, a more recent study by Kaiser Family Foundation (2005) reported only 18% uninsured in 2002. Hence, it appears that the overall trend in drug coverage continued to increase even after year 2000.

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Figure 1. Trend in Prescription Drug Coverage (weighted)

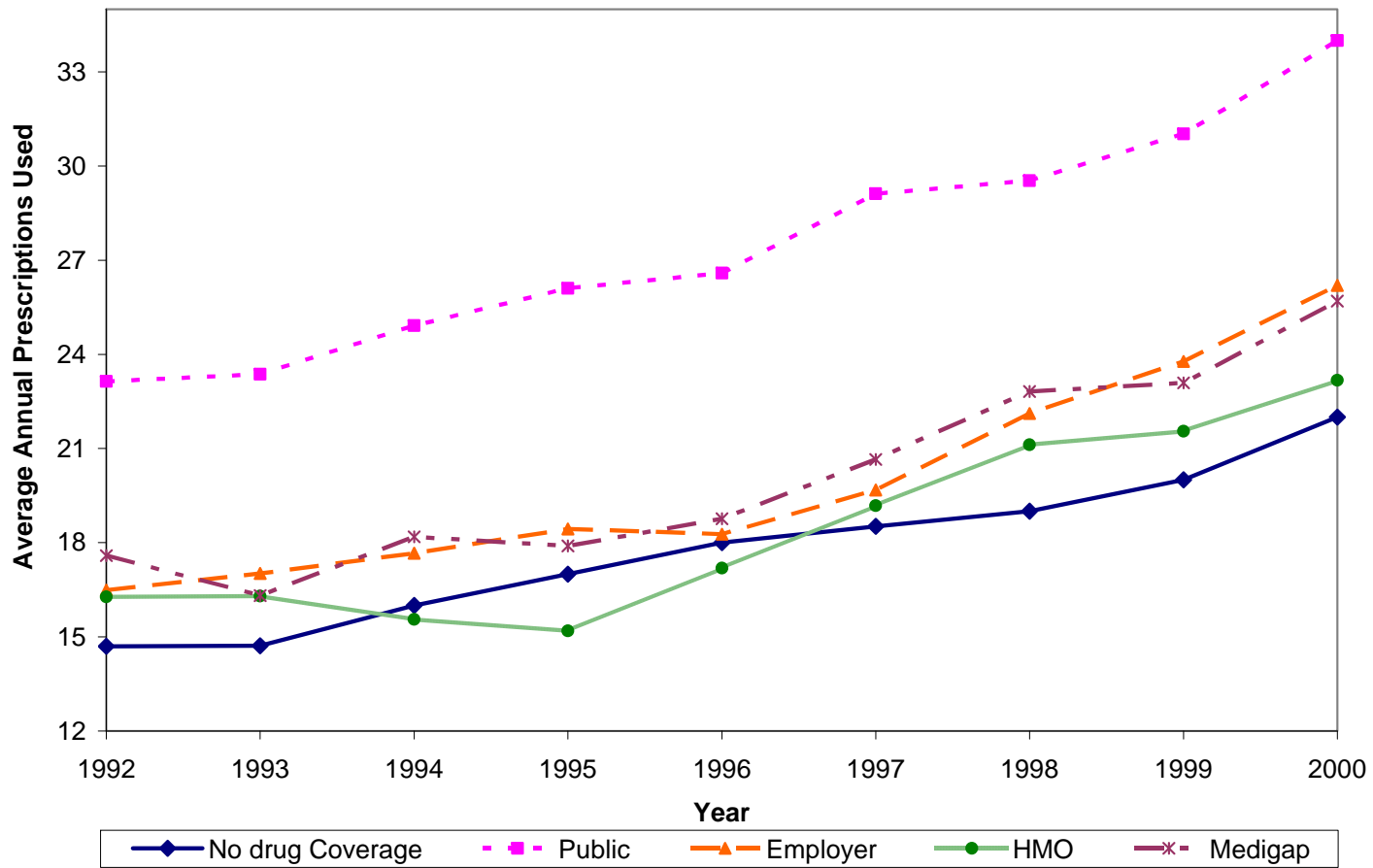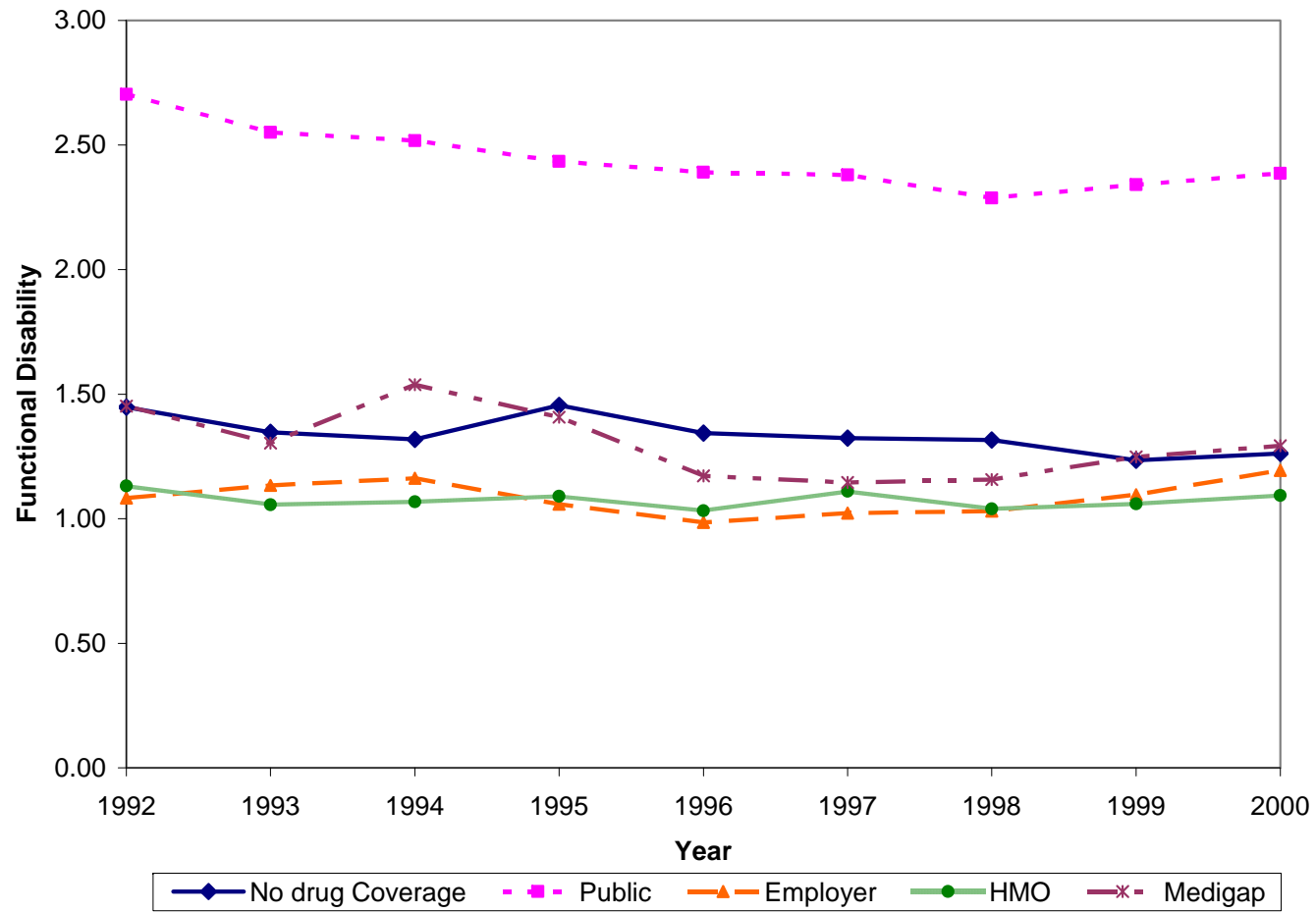Figure 2. Trend in Average Annual Number of Prescriptions (weighted)

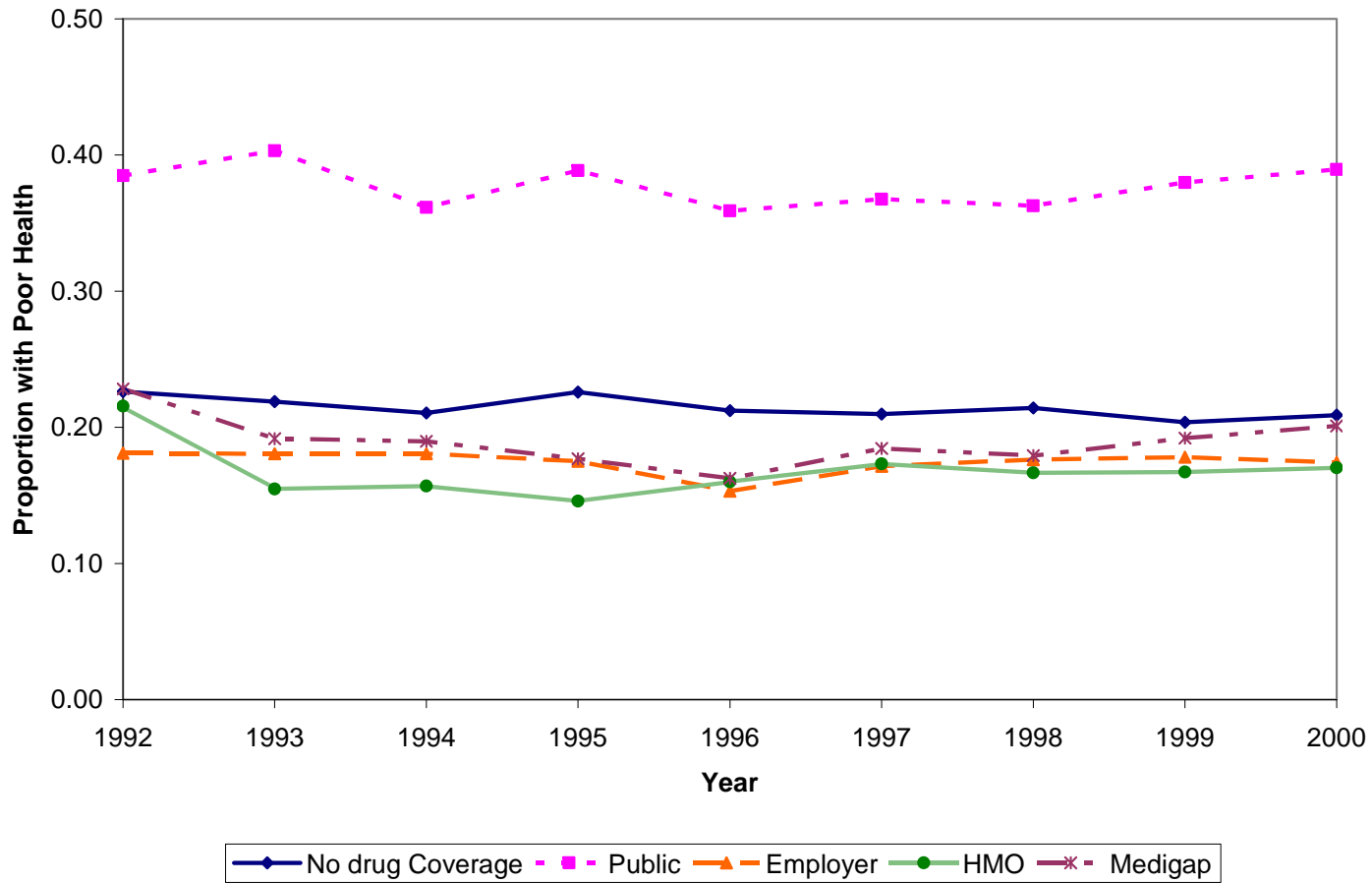Figure 3. Trend in Functional Disability (weighted)
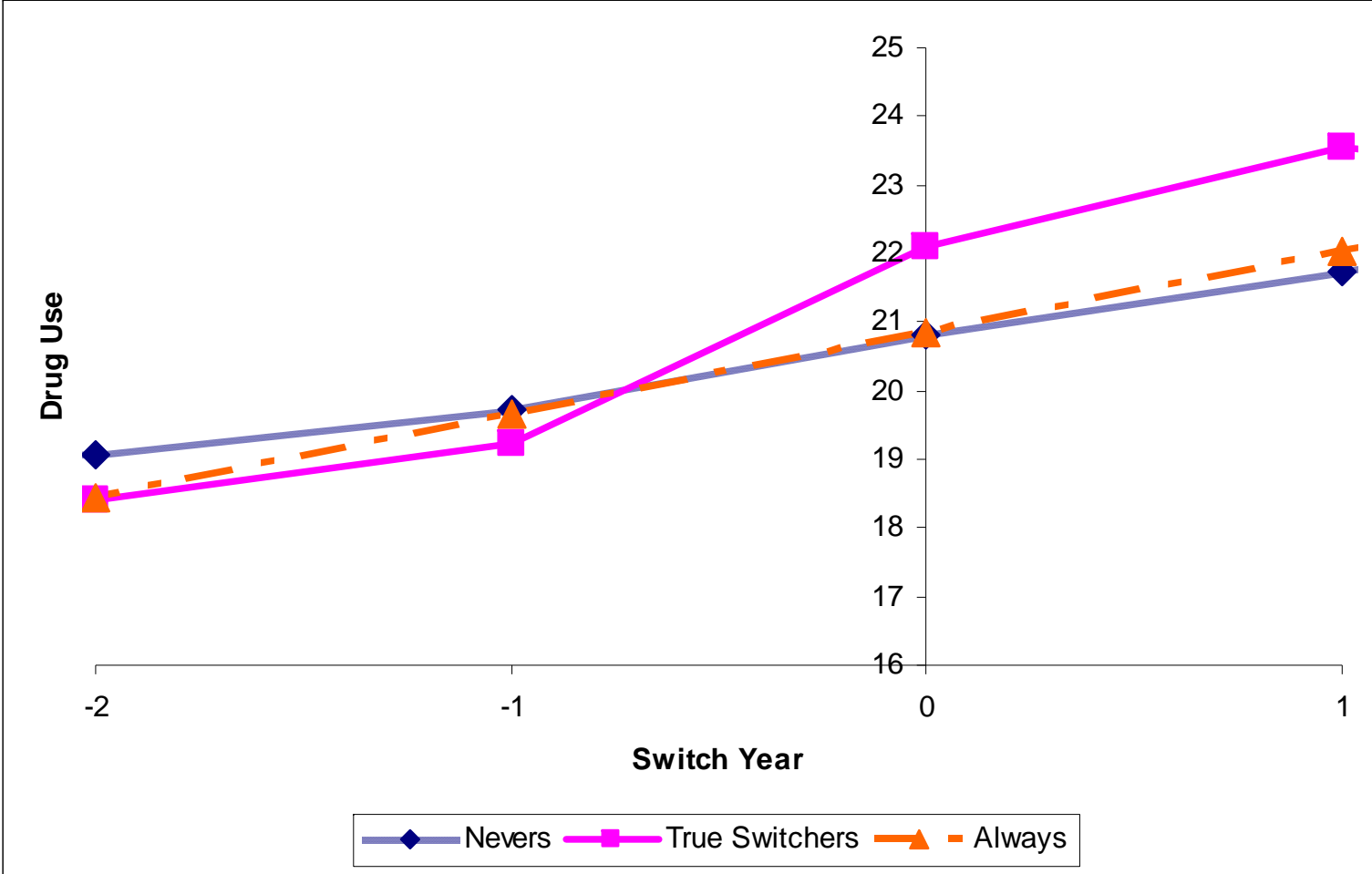
Figure 4. Trend in Health Status (weighted)

Figure 5. Trend in Prescription Drug Use Before and After Drug Coverage Switch, for Switchers and Non-Switchers
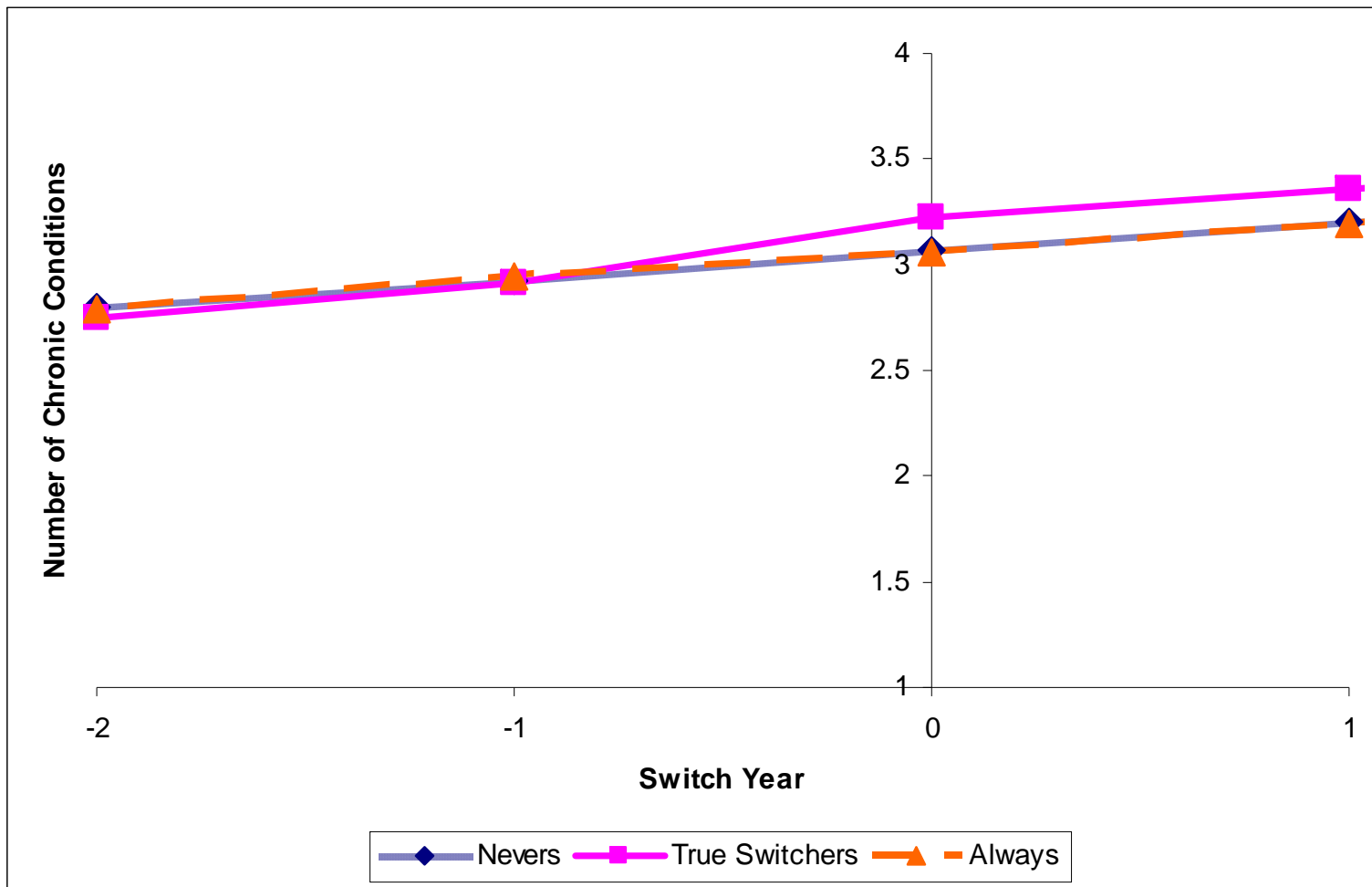
Figure 6. Trend in Number of Chronic Conditions Before and After Drug Coverage Switch, for Switchers and Non-Switchers

Table 1. Average Sample Characteristics, Weighted

Individual characteristics	Variable description	Entire sample	No drug coverage	Any drug coverage	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)	White[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 (proportion)	Married[b]	0.56	0.56	0.56	0.31	0.67	0.57	0.55
	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 (proportion)	No high school[a][b]	0.37	0.40	0.36	0.65	0.25	0.31	0.28
	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 (proportion)	Never smoked[b]	0.40	0.40	0.40	0.44	0.38	0.35	0.44
	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
Prescription drug utilization	Any prescription[a][b]	0.89	0.86	0.91	0.92	0.90	0.90	0.88
	# of prescriptions[b]	20	17.45	21.83	27.68	20.27	19.41	20.24
Hospitalization	Hospitalization[a][b]	0.17	0.17	0.18	0.23	0.17	0.15	0.17
Health status	Poor health[b]	0.22	0.22	0.22	0.38	0.17	0.17	0.19
	Functional disability[b]	1.39	1.35	1.41	2.43	1.08	1.05	1.28
Observations		73,490	27,690 (38%)	45,800 (62%)	11,650 (16%)	21,353 (29%)	6,985 (10%)	5,812 (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 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 weights

Table 2. Average Change in Prescription Drug Insurance Coverage Between Time (t) and 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. Estimates of the Effect of Prescription Drug Insurance Coverage on Any Prescription Drug Use

Type of Prescription Drug Insurance	(2) OLS	(3) OLS with measures of health	(4) OLS fixed-effect	(5) OLS fixed-effect with measures of health
Proportion of months public	0.087	0.050	0.019	0.017
	[0.005]**	[0.005]**	[0.011]	[0.011]
Proportion of months employer-sponsored	0.044	0.029	0.010	0.008
	[0.004]**	[0.004]**	[0.007]	[0.007]
Proportion of months HMO	0.045	0.042	0.008	0.007
	[0.006]**	[0.006]**	[0.010]	[0.010]
Proportion of months Medigap	0.019	0.014	0.002	0.003
	[0.007]**	[0.006]*	[0.008]	[0.008]
Mean of dependent variable for uninsured	0.863	0.863	0.863	0.863
Observations	72970	72619	72970	72619

Notes:
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.
Column 3 and 6 includes indicator for general health status and number of chronic conditions categories (1-2, 3-4, 5 or more)
Robust standard errors in brackets
* significant at p < 0.05; ** significant at p< 0.01%

Table 4. Estimates of the Effect of Prescription Drug Insurance Coverage on Annual Number of Prescriptions

Type of Prescription Drug Insurance	(2) Poisson	(3) Poisson with measures of health	(4) Poisson fixed-effect	(5) Poisson fixed-effect with measures of health
Proportion of months public	0.467 [0.018]**	0.293 [0.015]**	0.137 [0.018]**	0.129 [0.018]**
Proportion of months employer-sponsored	0.197 [0.015]**	0.143 [0.013]**	0.060 [0.013]**	0.060 [0.013]**
Proportion of months HMO	0.147 [0.022]**	0.153 [0.019]**	0.059 [0.017]**	0.059 [0.017]**
Proportion of months Medigap	0.170 [0.023]**	0.144 [0.020]**	0.007 [0.013]	0.011 [0.014]
Mean of dependent variable for uninsured	17.90	17.86	18.72	18.67
Observations	72970	72619	63520	63174

Notes:
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.
Column 3 and 6 includes indicator for general health status and number of chronic conditions categories (1-2, 3-4, 5 or more)
Robust standard errors in brackets
* significant at p < 0.05; ** significant at p< 0.01%

Table 5. Estimates of the Effect of Prescription Drug Insurance Coverage on Hospitalizations

Type of Prescription Drug Insurance	(2) OLS	(3) OLS with measures of health	(4) OLS fixed-effect	(6) OLS fixed-effect with measures of health
Proportion of months public	0.063	0.029	0.023	0.019
	[0.006]**	[0.006]**	[0.018]	[0.018]
Proportion of months employer-sponsored	0.010	0.002	0.015	0.014
	[0.004]*	[0.004]	[0.010]	[0.010]
Proportion of months HMO	-0.005	-0.002	0.006	0.007
	[0.006]	[0.006]	[0.013]	[0.013]
Proportion of months Medigap	0.014	0.010	0.015	0.017
	[0.007]*	[0.006]	[0.012]	[0.012]
Mean of dependent variable for uninsured	0.17	0.17	0.17	0.17
Observations	72970	72619	72970	72619

Notes:
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.
Column 3 and 6 includes indicator for general health status and number of chronic conditions categories (1-2, 3-4, 5 or more)
Robust standard errors in brackets
* significant at $p < 0.05$; ** significant at $p < 0.01\%$

Table 6. Estimates of the Effect of Prescription Drug Insurance Coverage on Self-reported Poor Health

Type of Prescription Drug Insurance	(2) OLS	(3) OLS with measures of health	(4) OLS fixed-effect	(5) OLS fixed-effect with measures of health
Proportion of months public	0.114	0.072	0.030	0.025
	[0.007]**	[0.007]**	[0.017]	[0.017]
Proportion of months employer-sponsored	0.006	-0.008	-0.000	-0.002
	[0.005]	[0.005]	[0.009]	[0.009]
Proportion of months HMO	-0.018	-0.018	-0.007	-0.007
	[0.007]*	[0.007]**	[0.011]	[0.011]
Proportion of months Medigap	0.007	0.001	0.002	0.001
	[0.008]	[0.008]	[0.010]	[0.010]
Mean of dependent variable for uninsured	0.23	0.23	0.23	0.23
Observations	72836	72619	72836	72619

Notes:

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.

Column 3 and 6 includes indicator for number of chronic conditions categories (1-2, 3-4, 5 or more)

Robust standard errors in brackets

* significant at $p < 0.05$; ** significant at $p < 0.01\%$

Table 7. Estimates of the Effect of Prescription Drug Insurance on Functional Disability (ADL plus IADL Score)

Type of Prescription Drug Insurance	(2) Poisson	(3) Poisson with measures of health	(4) Poisson fixed-effect	(5) Poisson fixed-effect with measures of health
Proportion of months public	0.450	0.220	0.025	-0.008
	[0.024]**	[0.021]**	[0.034]	[0.034]
Proportion of months employer-sponsored	0.011	-0.028	0.021	0.019
	[0.024]	[0.021]	[0.029]	[0.029]
Proportion of months HMO	-0.131	-0.102	-0.082	-0.084
	[0.037]**	[0.033]**	[0.040]*	[0.040]*
Proportion of months Medigap	0.040	0.034	-0.017	-0.016
	[0.036]	[0.032]	[0.032]	[0.032]
Mean of dependent variable for uninsured	1.53	1.53	1.53	1.53
Observations	73353	73009	40075	39824

Notes:

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.

Column 3 and 6 includes indicator for general health status and number of chronic conditions categories (1-2, 3-4, 5 or more)

Robust standard errors in brackets

* significant at $p < 0.05$; ** significant at $p < 0.01\%$

Table 8. Estimates of the Effect of Prescription Drug Insurance Coverage on Individual Items of Functional Disability

	ADL							IADL						
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Type of Prescription Drug Insurance	Walking	Bathing	Dressing	Eating	Using chair	Toilet	ADL	Heavy housework	Light housework	Making meals	Shopping	Using phone	Paying bills	IADL
Proportion of months public	0.011 [0.016]	0.005 [0.013]	0.015 [0.011]	0.017 [0.009]*	0.006 [0.014]	0.028 [0.010]**	0.081 [0.045]	-0.001 [0.017]	0.016 [0.013]	0.024 [0.012]*	0.012 [0.014]	0.012 [0.011]	0.024 [0.012]*	0.087 [0.048]
Proportion of months employer-sponsored	0.010 [0.008]	-0.001 [0.006]	0.003 [0.005]	0.001 [0.004]	-0.010 [0.007]	0.002 [0.005]	0.006 [0.022]	0.018 [0.009]	0.003 [0.007]	0.000 [0.006]	0.010 [0.007]	0.006 [0.006]	-0.005 [0.005]	0.033 [0.025]
Proportion of months HMO	-0.000 [0.011]	-0.019 [0.007]*	-0.018 [0.007]**	0.003 [0.004]	-0.022 [0.009]*	-0.008 [0.006]	-0.062 [0.027]*	-0.029 [0.013]*	-0.002 [0.009]	-0.004 [0.007]	-0.006 [0.009]	-0.004 [0.008]	-0.013 [0.007]	-0.058 [0.030]
Proportion of months Medigap	0.004 [0.010]	-0.000 [0.008]	0.005 [0.006]	-0.001 [0.004]	-0.012 [0.008]	0.006 [0.005]	0.002 [0.025]	-0.010 [0.011]	0.002 [0.008]	-0.006 [0.007]	0.002 [0.008]	0.003 [0.007]	0.001 [0.007]	-0.010 [0.029]
Mean of dependent variables for uninsured	0.25	0.12	0.07	0.03	0.13	0.06	0.66	0.33	0.12	0.10	0.16	0.08	0.08	0.86
Observations	72,953	72,951	72,957	72,956	72,956	72,950	72,939	72,938	72,949	72,950	72,954	72,954	72,945	72,911

Notes:
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.
Column 3 and 6 includes indicator for general health status and number of chronic conditions categories (1-2, 3-4, 5 or more)
Robust standard errors in brackets
significant at $p < 0.05$; ** significant at $p < 0.01\%$