Insurance Coverage and Healthcare

Effect of Prescription Drug Coverage on Health of the Elderly

Nasreen Khan, Robert Kaestner, and Swu-Jane Lin

Objective. To estimate the effect of prescription drug insurance on health, as measured by self-reported poor health status, functional disability, and hospitalization among the elderly.

Data. Analyses are based on a nationally representative sample of noninstitutionalized elderly (≥ 65 years of age) from the Medicare Current Beneficiary Survey (MCBS) for years 1992–2000.

Study Design. Estimates are obtained using multivariable regression models that control for observed characteristics and unmeasured person-specific effects (i.e., fixed effects).

Principal Findings. In general, prescription drug insurance was not associated with significant changes in self-reported health, functional disability, and hospitalization. The lone exception was for prescription drug coverage obtained through a Medicare HMO. In this case, prescription drug insurance decreased functional disability slightly. Among those elderly with chronic illness and older (71 years or more) elderly, prescription drug insurance was associated with slightly improved functional disability.

Conclusions. Findings suggest that prescription drug coverage had little effect on health or hospitalization for the general population of elderly, but may have some health benefits for chronically ill or older elderly.

Key Words. Insurance, prescription drugs, health, outcome assessment (health care)

In 2003, the Medicare Prescription Drug, Improvement, and Modernization Act (MMA) established a prescription drug benefit for the Medicare population. The program, which started in January 2006, provides prescription drug insurance through privately sponsored insurance plans with varying levels of cost sharing depending on a person's income and expenditures for prescription drugs (CCH 2003). While political objectives were an important part of the explanation of the passage and design of the MMA, creation of the MMA was also motivated by a desire to improve the health of the elderly.

Technological advances in both pharmaceutical and medical treatments had increased the importance of prescription drugs for maintaining good health, particularly for the elderly. Costs of prescription drugs had also increased significantly over time and studies had indicated that the elderly often skip doses, and that some do not fill prescriptions due to cost (Steinman, Sands, and Covinsky 2001; Kitchman et al. 2002; Saver, Doescher, and Jackson 2004; Soumerai et al. 2006). Thus, by lowering the cost of prescription drugs, the MMA would improve health by stimulating use of prescription drugs.

While plausible, there is relatively little evidence to support the presumed causal relationships underlying the MMA. There have been relatively few studies of the effect of prescription drug insurance on use of prescription drugs by the elderly, and even fewer that examined a nationally representative sample (Goldman, Joyce, and Zheng 2007). Estimates of the effect of insurance coverage on use of prescription drugs from these studies varies significantly from small effects, which would imply few health benefits, to large effects, which would suggest greater improvements in health. The literature on the effects of prescription drug insurance on health of the elderly is even smaller. In short, there is insufficient research available to inform policy makers as to the likely effects of the MMA.

The purpose of this study is to add to this literature by examining the relationship between prescription drug insurance and the health of the elderly population. While an evaluation of the MMA itself would be preferable, such analyses are still hampered by data availability. It will be several years before large-scale studies can be undertaken. Here we provide evidence that will be informative and serve as a bridge until more explicit evaluations of MMA can be conducted. Our 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, and we 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 elderly health that can plausibly be given a causal interpretation.

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PRIOR LITERATURE

There are several studies of the effect of prescription drug insurance on use of prescription drugs among the elderly, although only a few used a representative sample of elderly people (Lillard, Rogowski, and Kington 1999; Yang, Gilleskie, and Norton 2004; Shea, Terza, and Stuart 2007). Virtually all previous studies, despite using different methods and focusing on different populations, reported that prescription drug insurance was associated with greater use of prescription drugs. However, estimates of the magnitude of the effect of prescription drug insurance on prescription use varied considerably. For example, Lillard et al. (1999) found that insurance coverage increased the probability of any drug use by 12.2 percent for those with private insurance whereas Shea et al. (2007) reported that prescription drug insurance was associated with approximately a 30 percent increase in the probability of any prescription use and a 50 percent increase in the number of prescriptions filled.

While the magnitude of the effect of prescription drug insurance on use may be uncertain, few would argue with the conclusion that prescription drug insurance is associated with an increase in use of prescription drugs. More uncertain is the effect of prescription drug use on health. Presumably, the goal of prescription drug insurance is to provide greater financial access to prescription drugs that are necessary to improve health. However, evidence on this point is scarce and inconsistent (Goldman, Joyce, and Zheng 2007). Briesacher et al. (2005), Soumerai et al. (1991), and Johnson et al. (1997) did not find any effect of prescription drug insurance or a change in prescription copayment on hospitalization. Chandra, Gruber, and McKnight (2007) reported that increase in copayments for physician and prescription drugs increased the probability of hospitalization by 6 percent. Finally, Yang et al. (2004) found that prescription drug coverage decreased mortality slightly.

This brief review of the literature reveals that there is little evidence of the effect of prescription drug insurance on the health of the elderly. Much of what does exist focuses on hospitalization and whether prescription drugs are a substitute for hospitalization. Moreover, the wide disparity in estimates of the effect of prescription drug insurance on use of prescription drugs does not provide sufficient evidence to predict the effects of drug insurance on health. It is clear that additional studies are warranted, specifically, studies that use a nationally representative sample, that examine a wider range of outcomes than hospitalization or mortality, and that pay special attention to the non-random nature of prescription drug insurance.

CONCEPTUAL FRAMEWORK—DEMAND FOR PRESCRIPTION DRUG INSURANCE

Economic theory assumes that people are risk averse. 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 and Zeckhauser 2000).

This simple model of insurance has important implications for empirical analyses of the effect of prescription drug insurance on health. It suggests that those with insurance will differ from those without insurance. Those with insurance are likely to be at greater risk of illness (need of prescription drugs) and/or be more risk averse. So prescription drug use would likely differ between those with and without insurance even if there was no insurance. A second implication 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 (see Table 1). Consequently, 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.

EMPIRICAL STRATEGY

Given the simple model described above, the fundamental identification problem in estimating the effect of prescription drug insurance on health is that the same person is never simultaneously observed with and without prescription drug insurance. Therefore, there is a possibility of nonrandom selection into insurance coverage. To address this issue, we use a multivariable regression model with controls for person-specific fixed effects.¹ Longitudinal data provide a potential solution to the selection problem because over time people move into and out of prescription drug insurance. Thus, we can observe the same person with and without insurance, 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 insurance. The time aspect of this approach, however, introduces the possibility that

Table 1: Average Sample Characteristics, Weighted

Individual Characteristics (1)	Variable Description (2)	Entire Sample (3)	No Drug Insurance (4)	Any Drug Insurance (5)	Public (6)	Employer- Sponsored (7)	Medicare HMO (8)	Medigap (9)
Sex (proportion)	Female* [‡]	0.59	0.57	0.59	0.70	0.54	0.57	0.63
Race (proportion)	White* [‡]	0.88	0.90	0.87	0.69	0.93	0.88	0.96
	African American* [‡]	0.08	0.08	0.08	0.19	0.05	0.07	0.03
	Other* [‡]	0.03	0.02	0.04	0.12	0.01	0.05	0.01
Age (years)	Age* [‡]	75.34	75.82	75.06	76.22	74.37	74.96	75.78
Income (\$)	Income* [‡]	25,511	22,886	27,028	12,672	33,402	25,597	29,805
Urban (proportion)	Urban* [‡]	0.74	0.66	0.79	0.73	0.80	0.95	0.67
Marital status (proportion)	Married [†]	0.56	0.56	0.56	0.31	0.67	0.57	0.55
	Widowed* [‡]	0.33	0.34	0.33	0.50	0.25	0.31	0.36
	Divorced/separated [†]	0.07	0.07	0.07	0.13	0.05	0.08	0.05
	Not married [†]	0.04	0.03	0.04	0.06	0.03	0.03	0.04
Education (proportion)	No high school* [‡]	0.37	0.40	0.36	0.65	0.26	0.31	0.28
	High school [†]	0.33	0.34	0.33	0.21	0.37	0.36	0.36
	Some college* [‡]	0.15	0.14	0.15	0.08	0.17	0.19	0.18
	College plus* [‡]	0.14	0.12	0.16	0.06	0.21	0.14	0.18
Smoking status (proportion)	Never smoked [†]	0.40	0.40	0.40	0.44	0.38	0.35	0.44
	Former smoker* [‡]	0.48	0.47	0.49	0.43	0.52	0.53	0.45
	Current smoker* [‡]	0.12	0.13	0.11	0.13	0.10	0.12	0.11
Prescription drug utilization	Any prescription* [‡]	0.89	0.85	0.90	0.92	0.90	0.90	0.88
	# of prescriptions* [‡]	19.85	17.21	21.39	27.14	19.85	19.06	19.74
Hospitalization	Hospitalization* [‡]	0.17	0.16	0.17	0.22	0.16	0.15	0.16
Health status	Poor health [†]	0.21	0.21	0.22	0.37	0.17	0.16	0.18
	Functional disability [†]	1.34	1.29	1.37	2.36	1.05	1.03	1.24
	# Chronic conditions* [‡]	2.96	2.82	3.03	3.58	2.90	2.80	2.83
	# Doctors visits	2.98	2.87	3.05	3.95	2.98	1.78	3.17
Number of observations		66,905	25,035 (37%)	41,870 (63%)	10,600 (16%)	19,656 (29%)	6,329 (9%)	5,285 (8%)

Source: MCBS Survey Cost and Use File, 1992–2000.

*The difference was found to be statistically significant between no drug insurance and any drug insurance group using t -test or χ^2 test at $p < .05$. The standard errors are adjusted for complex survey design using replication weights.

[†]The difference was found to be statistically significant between different sources of drug insurance using χ^2 or one-way ANOVA at $p < .05$.

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 effects analysis. First, there should be sufficient variation in prescription drug coverage within individuals over time. To assess the extent of variation in our data, we analyzed transitions into and out of prescription drug insurance. To the best of our knowledge, this is the first analysis of this type for the elderly. In our sample of 22,741 elderly individuals with at least 2 years of information between 1992 and 2000, 29 percent never had any drug coverage; 55 percent were always covered; and 17 percent lost or gained drug coverage. Among those who changed insurance status, 51 percent gained coverage; 34 percent lost coverage; and 15 percent had multiple transitions (e.g., lost and gained). Those who obtained coverage were distributed fairly uniformly between employer coverage (27 percent), Medicare HMO coverage (23 percent), Medigap (29 percent), and Medicaid or other public (21 percent). For those who lost coverage, most lost employer-sponsored coverage (34 percent) and Medigap (42 percent). We also observed switching between insurance plans, so while 17 percent of the sample switch between insured and uninsured state, a greater proportion switched if we count switches between types of coverage. In sum, there is evidence of significant within-person variation in prescription drug insurance, and as we show below, fixed effects estimates of the effect of insurance are sufficiently precise to rule out small effects.

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 in a limited way the plausibility of this assumption, we conducted a “pseudo” analysis or falsification analysis. The key aspect of this analysis is that we can provide evidence as to the validity of the assumptions underlying the fixed effects research design. We present the details of these analyses below, but note here that the results of this analysis strongly supported the fixed effects research design. In sum, while we cannot definitively test the assumption underlying the fixed effects approach, we believe the evidence we will present supports the plausibility of this approach.

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

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

where the dependent variable (Y), self-reported poor health status 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 factors that might be related to health. These could include differences in health across geography or technological advances in medicine over time that improved health. The vector X represents time varying individual characteristics that might affect health 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 parameters to be estimated and ϵ is the error term.

To further bolster the plausibility of our research design, in some models we included the number of chronic conditions. This was motivated by the recent work of Shea et al. (2007) who reported that after conditioning on measures of health, there was little evidence of selection into insurance. This result is consistent with the theory that suggests that changes in health status would be one of the most important causes of selection. Obviously, we cannot condition on health as broadly as Shea et al. (2007) because health is the dependent variable in equation (1). We do not intend to regress health on itself. Here we included a narrower measure of health, the number of chronic conditions and a measure of utilization (doctor visits) that should reflect health. It is unlikely that prescription drug insurance (drug use) is a cause of the onset of chronic conditions, although drug use may decrease the morbidity associated with chronic conditions (which we can measure). Instead, any correlation between the number of chronic conditions and prescription drug insurance reflects a change in health that will cause a change in insurance, self-reported health, and functional disability. It is this potential change in health that we want to control for. Including number of chronic conditions and number of doctor visits in the model controls for unmeasured changes in health that may affect both prescription drug insurance and the measures of health that we use as dependent variables. If estimates of the effect of prescription drug insurance on these measures of health are largely insensitive to the inclusion of these variables, which themselves are significant predictors of our health outcomes, we believe this is further evidence in support of our research design.

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 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 effects 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 (Cameron and Trivedi 1998; Allison and Waterman 2000).² In both cases (OLS and Poisson), we construct what are commonly referred to as robust standard errors (Wooldridge 2002).³ 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 MCBS—Cost and Use file from CMS. MCBS is a nationally representative, continuous, survey of aged, disabled and institutionalized Medicare beneficiaries (CMS 2000). The MCBS sample of approximately 12,000 individuals is drawn from the Medicare enrollment file. 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.

For the purpose of this analysis, data from 1992 to 2000 were used. The sample was restricted to noninstitutionalized elderly without end-stage renal disease and who had at least 2 complete years of information. We also excluded individuals from four U.S. 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 66,905 person-year observations representing 22,741 unique individuals.

MCBS respondents report up to five sources of non-Medicare insurance and prescription drug coverage. The respondent reported the start and stop dates of the insurance and whether this source of insurance provided prescription drug coverage. Based on this information, we assigned a person to insured or uninsured category for each month in the survey. If they had prescription drug insurance for at least 6 months in a year, we assigned them to the insured category. Then, for those with prescription drug insurance, we assigned them the insurance category for which they have the most months of coverage. Individuals who reported multiple coverage's in a month were

assigned to the more generous source in the following hierarchical order: public, employer-sponsored, Medicare HMO, Medigap, and no drug coverage.⁴ As an alternative, we also constructed measures of the proportion of months with each type of prescription drug insurance (or no insurance). Results using this alternative measure were virtually the same as those presented below.

We used several measures of health. Several clinical trials indicate that prescription drugs improve health perceptions and health related quality of life (Croog et al. 1986; Testa et al. 1993; Hjalmarson et al. 2000; Reza et al. 2002; Bech, Moses, and Gomis 2003). In addition, health perceptions about oneself have been shown to correlate strongly with clinical outcomes and mortality (DeSalvo et al. 2005; Rodriguez-Artalejo et al. 2005). Therefore, we use self-reported general health status as one of the health outcomes. A dichotomous variable representing poor health was constructed in which poor health was coded if self-reported health was fair or poor.

Studies have also indicated that prescription drugs improve functional disability: ability to perform activities of daily living (ADL) and instrumental activities of daily living (IADL) (Hamilton et al. 2001; Feldman et al. 2003; Canete et al. 2006). Given this evidence, ADL and IADL were used as measures of health. ADL include eating, dressing, bathing, walking, transferring into and out of a chair, and using the toilet. IADL include making meals, using the phone, going shopping, managing money, and doing light or heavy housework. We used scores on six-items of ADL and IADL as dependent variable. Finally, a composite measure of functional disability was constructed that sums ADL and IADL. 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. Cook et al. (2006) showed that each item is a sensitive measure of functional disability and, therefore, can be used individually.

We also examined the effect of prescription drug coverage on probability of hospitalizations. Assuming a beneficial effect of prescription insurance coverage on health, one would expect lower hospitalizations rate for covered individuals, compared with those without prescription coverage. We constructed a dichotomous measure of hospitalization.

All analyses control for age, sex, race, education, urban residence, income, marital status, and smoking status. All analyses include state and year fixed effects. As previously mentioned, in some models we included number of chronic conditions and number of doctor visits.⁵

RESULTS

Descriptive Analysis

The average characteristics of the entire sample and by drug coverage category are presented in Table 1, which reports weighted estimates.⁶ The average age of the sample was 75 years; 59 percent were women and 11 percent were nonwhite. Almost every respondent was married at least once in their life and 29 percent had at least some college education. Average annual income was \$25,511 (2000 dollars). Almost every individual in the sample reported having at least one prescription. Sixty-three percent of the sample had prescription drug insurance with the majority of the coverage provided by employers. In terms of health, 21 percent of the elderly respondents reported poor or fair health.

Table 1 also shows differences in characteristics 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 socioeconomic 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. Elderly in public programs were more likely to be women, low-income, and reported no high-school degree. These differences suggest that there is some selection on observed characteristics particularly among those with public insurance.

Figures in Table 1 suggest that those with prescription drug insurance have greater use of drugs. Part of the greater use of prescription drugs may be due to differences in health. Generally, elderly without insurance coverage reported worse health than individuals with employer, HMO, or Medigap insurance coverage. Those with public insurance were least healthy. These individuals had significantly worse health compared with all others, even those without drug insurance as evident from substantially higher hospitalization, number of chronic conditions and doctors' visit for this group.

Regression Analysis

Tables 2–4 display estimates of the effect of drug insurance on health, as measured by self-reported poor health status, functional disability, and hospitalization. Table 2 shows the effect of prescription drug insurance on probability of being in poor health. Each column of Table 2 represents a different regression model. Column 2 is the basic model without controls for number of

Table 2: OLS Estimates of the Effect of Prescription Drug Insurance on Self-Reported Poor Health Status

(1) <i>Type of Prescription Drug Insurance</i>	(2) <i>Basic Model</i>	(3) <i>Add Chronic Conditions and Doctor Visits</i>	(4) <i>Fixed Effects</i>	(5) <i>Fixed Effects Add Chronic Conditions and Doctor Visits</i>
Public (Medicaid/PAP/VA)	0.106 [0.008]**	0.057 [0.007]**	0.033 [0.014]*	0.027 [0.014]
Employer-sponsored	0.004 [0.005]	-0.010 [0.005]*	0.001 [0.008]	-0.001 [0.008]
Medicare HMO	-0.016 [0.007]*	-0.005 [0.007]	-0.009 [0.010]	-0.008 [0.010]
Medigap	0.006 [0.007]	-0.001 [0.007]	0.001 [0.008]	0.001 [0.008]
Mean of dependent variable for uninsured	0.22	0.22	0.22	0.22
Number of observations	66,337	66,181	66,337	66,181
Any drug insurance (no public sample)	0.001 [0.005]	-0.007 [0.004]	0.000 [0.006]	-0.000 [0.006]
Number of observations (no public sample)	54,397	54,290	54,397	54,290

Source: MCBS Survey Cost and Use File, 1992–2000.

Reference category is uninsured.

Covariates included in the model are: female, age (age 65, age 66, . . . , age 79, age 80–84, age 85–90, age 90 or more), race categories (white, African-American, other race), marital status (married, widowed, divorced or separated, not married), income categories (less than \$10,000, \$10,000–\$15,000, \$15,000–\$20,000, \$20,000–\$30,000, \$30,000–\$40,000, \$40,000–\$50,000, \$50,000 or more), education categories (no high school, high school, some college, college or more), rural, smoking status (current smoker, former smoker, never smoked), year fixed effects, state fixed effects.

Column 3 and 5 includes indicator for number of chronic conditions categories (0, 1, 2, 3, 4, 5 or more), and number of outpatient visits categories (0, 1, 2–3, 4–5, 6 or more).

Time invariant covariates drop out in fixed effect models.

Robust standard errors in brackets.

*Significant at $p < .05$.

**Significant at $p < .01$.

chronic conditions, doctor visits, or person-specific fixed effects. Column 3 adds number of chronic conditions and doctor visits as covariates. Columns 4 and 5 are similar to columns 3 and 4, except now we have included person-specific fixed effects.

Estimates in Table 2 from models without person-specific fixed effects suggest that public prescription drug insurance was associated with a higher probability of poor health and that HMO coverage was associated with a lower probability of being in poor health. Those with public coverage were

Table 3: Poisson Estimates of the Effect of Prescription Drug Insurance on Functional Disability (ADL Plus IADL Score)

(1) <i>Type of Prescription Drug Insurance</i>	(2) <i>Basic Model</i>	(3) <i>Add Chronic Conditions and Doctor Visits</i>	(4) <i>Fixed Effects</i>	(5) <i>Fixed Effects Add Chronic Conditions and Doctor Visits</i>
Public (Medicaid/PAP/VA)	0.403 [0.023]**	0.221 [0.024]**	0.005 [0.029]	− 0.019 [0.029]
Employer-sponsored	0.038 [0.025]	− 0.024 [0.024]	− 0.005 [0.026]	− 0.005 [0.026]
Medicare HMO	− 0.091 [0.037]*	− 0.061 [0.035]	− 0.073 [0.035]*	− 0.068 [0.035]
Medigap	0.043 [0.034]	0.024 [0.032]	− 0.021 [0.027]	− 0.014 [0.027]
Mean of dependent variable for uninsured	1.45	1.43	1.43	1.43
Number of observations	66,392	66,234	39,547	39,405
Any drug insurance (no public sample)	0.037 [0.022]	− 0.006 [0.021]	− 0.029 [0.021]	− 0.025 [0.021]
Number of observations (No public sample)	54,446	54,338	30,426	30,336

See notes to Table 2.

10.6 percentage points (50 percent) more likely to report poor health and those with HMO coverage were 1.6 percentage points (7 percent) less likely to report poor health than those with no prescription drug insurance. Adding the number of chronic conditions and doctor visits to the model (column 3) resulted in some notable changes that are consistent with intuition. Estimates associated with public insurance became less positive (5.7 percentage points), which reflects the fact that this group tends to be sicker, and estimates associated with Medicare HMO coverage became less negative (− 0.5 percentage points) and statistically insignificant, which reflects the fact that this group tends to be healthier. The estimate associated with employer-sponsored coverage in column 3 is small (1.0 percentage point), negative, and statistically significant.

Controlling for person-specific fixed effects (column 4) further reduced the estimate of the effect of public coverage (0.033) and reduced the estimate of the effect of employer-sponsored coverage, which is now no longer significant. In general, adding the number of chronic conditions and doctor visits to the fixed effects model had no major effect on the estimates of drug insurance (column 5) except it further reduced the effect of public coverage to the point where it is relatively small (2.7 percentage points) and statistically insignificant.

Table 4: OLS Estimates of the Effect of Prescription Drug Insurance on Hospitalizations

(1) <i>Type of Prescription Drug Insurance</i>	(2) <i>Basic Model</i>	(3) <i>Add Chronic Conditions and Doctor Visits</i>	(4) <i>Fixed Effects</i>	(5) <i>Fixed Effects Add Chronic Conditions and Doctor Visits</i>
Public (Medicaid/PAP/VA)	0.057 [0.006]**	0.013 [0.006]*	0.021 [0.016]	0.013 [0.015]
Employer-sponsored	0.007 [0.004]	− 0.002 [0.004]	0.007 [0.009]	0.006 [0.009]
Medicare HMO	− 0.003 [0.006]	0.017 [0.006]**	0.007 [0.012]	0.016 [0.011]
Medigap	0.008 [0.006]	0.000 [0.006]	0.010 [0.010]	0.015 [0.010]
Mean of dependent variable for uninsured	0.17	0.17	0.17	0.17
Number of observations	66,455	66,293	66,455	66,293
Any drug insurance (no public sample)	0.006 [0.004]	0.002 [0.003]	0.007 [0.007]	0.012 [0.007]
Number of observations (no public sample)	54,491	54,379	54,491	54,379

See notes to Table 2.

As can be seen in Table 1, those covered by Medicaid are older, poorer, and sicker than those who are uninsured or covered by other types of insurance. To investigate whether estimates of the effects of other coverage are sensitive to the exclusion of those on Medicaid, we re-estimated all models dropping those ever on Medicaid. For this sample, we combine those with employer-sponsored coverage, Medigap, and Medicare HMO coverage into one category—the insured. Estimates obtained using this sample of elderly are reported in the second panel of Table 2. Focusing on columns 4 and 5, estimates of the effect of insurance (any drug insurance) are almost zero. Overall, estimates in Table 2 suggest that prescription drug insurance is not significantly related to self-reported poor health status.

Table 3 present estimates of the effect of drug insurance on functional disability (ADL plus IADL). These tables have a similar presentation structure as Table 2. Here, we only discuss the fixed effects estimates, but note that controlling for fixed effects makes a substantial difference and reflects the selection into insurance status. Further, controlling for the number of chronic conditions and doctor visits has little effect on the fixed effects estimates. Fixed effect estimates in Table 3 are generally small and statistically insignificant. The lone exception is prescription drug coverage through a Medicare HMO,

which is associated with approximately 7 percent fewer functional disabilities. The average score (ADL plus IADL) for uninsured people was 1.43; therefore, drug coverage through a Medicare HMO would be expected to decrease the score by 0.10. Appendices SA2 and SA3 present estimates of the effect of drug insurance on individual IADL and ADL items that control for the number of chronic conditions and doctor visits. A similar beneficial effect of HMO coverage was observed for individual ADL and IADL items. Those with HMO coverage experienced reduced disability in bathing, dressing, getting out of a chair, and heavy housework. Estimates from a model in which those ever on Medicaid were dropped indicate that any prescription drug coverage is usually associated with a slight (3 percent) improvement in functional disability, although only one estimate (getting out of a chair) was statistically significant.

Table 4 presents estimates of the effect of drug coverage on hospitalization. Estimates in column 2 indicate that elderly with public insurance were 5.7 percentage points (33 percent) more likely to have a hospitalization than those without insurance. This is a large effect, which is due to nonrandom selection. Adding number of chronic conditions and doctor visits to the model (column 3) markedly reduced the effect of public insurance coverage on hospitalization and fixed effects estimates indicated that public prescription drug insurance had no statistically significant effect on hospitalization. Fixed effect estimates for other types of insurance, and all nonpublic insurance coverage combined, are small relative to the mean and statistically insignificant. Overall, estimates in Table 4 suggest that prescription drugs and hospitalization, if related, are weakly complementary treatments.

ANALYSES OF SUBPOPULATIONS (RESULTS NOT PRESENTED)

We also examined whether prescription drug coverage had a different effect for low-educated elderly (< 12 years of education), older elderly (71 years or older), and elderly with at least three chronic conditions. These three groups are in poorer health than the general population and the low-educated are also financially disadvantaged. Prescription drug coverage might be more beneficial to these groups compared with other groups who are healthier and who have greater means to purchase prescription drugs in the absence of insurance.

Results for the low-educated group were similar to the analysis using the entire sample. For the older elderly and elderly with three or more chronic conditions, prescription drug insurance had a slightly larger beneficial effect

than it did for the general population. In models in which those on Medicaid were dropped, prescription drug insurance (all categories combined) was associated with a 4 percent improvement in functional disability for older elderly and elderly with three or more chronic conditions. The estimate for the group of older elderly was statistically significant at the 10 percent level. These results are consistent with the evidence reviewed by Goldman, Joyce, and Zheng (2007), who concluded that among certain chronically ill elderly, prescription drug insurance was associated with improved health outcomes.

Additional Specification Tests of Fixed Effects Assumption (Falsification Analysis)

The fixed effects analysis assumes that in the absence of any change in prescription drug insurance changes in 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 estimated models identical to those in Tables 2–4, using all observations for nonswitchers and only observations on switchers in years before switching. We randomly assigned those who were true switchers a pseudo-switch year—a year in which they supposedly gained prescription drug coverage. If switchers and nonswitchers 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 (self-reported poor health status, functional disability, and hospitalization). While this result does not address potential contemporaneous changes in health and insurance, they provide evidence that absent any change in insurance status, the health of those insured and uninsured followed the same trend before switching. These results, along with those from models that included the number of chronic conditions and doctor visits, provide strong evidence that the fixed effects design is valid.⁷

The evidence presented suggests that changes in insurance status are plausibly exogenous conditional on measured covariates and controls for time-invariant person-specific effects. While we do not know with certainty the causes of these transitions, there are possible exogenous explanations. One factor is the expansion of Medicaid eligibility thresholds and Pharmaceutical Assistance Programs (PAP) (Bruen et al. 1999; Schneider, Fennel, and Keenan 1999; Stone and Yacker 2002; Bruen, Wiener, Thomas 2003). 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. Expansion of Medicare managed care might account for some of the changes in coverage. Between 1996 and 1999, enrollment in

Medicare HMOs, which often provided prescription drug coverage, increased by 5 percentage points (Laschober et al. 2002). However, the 1997 Balanced Budget Act decreased payments to Medicare HMOs and, as a result, many HMOs either terminated or reduced the benefits provided (Booske, Lynch, and Riley 2002; Pizer and Frakt 2002). Those who lost Medicare HMO coverage and who lived in areas of low managed care penetration were more likely to enroll in Medigap plans (Booske et al. 2002). For those who gained employer coverage, data from the 1999 and 2000 MCBS (information not available in other years) indicated that some did so through their spouses or by starting employment. A Kaiser/Hewitt 2002 Retiree Health Survey reported that many employers had increased drug copayments, which could result in employees' withdrawing from those plans (Kaiser Family Foundation 2002). Overall, there are plausible explanations for the statistical finding that switches in prescription drug insurance appear to be exogenous.

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 in terms of elderly health, as there is little research examining the effects of prescription drug coverage on health (Goldman, Joyce, and Zheng 2007). In this study, we have tried to address this shortfall.

The results of this study indicated that prescription drug insurance was not associated with significant (statistically or clinically) changes in self-reported health or functional disability among the general population of elderly. The lone exception was for prescription drug insurance obtained through a Medicare HMO. In this case, prescription drug coverage was associated with slight improvement in functional disability. Nor did we find consistent evidence that prescription drug insurance decreased the prevalence of hospitalization. In fact, if anything we found the opposite. Similar results were obtained for a sample of low-educated people. Among older (70 years or more) elderly and elderly with three or more chronic conditions, there was somewhat more evidence of a beneficial effect of prescription drug insurance. For these two subgroups, prescription drug insurance was associated with a 4 percent improvement in functional disability.

What explains these results? First, in a companion paper (Khan and Kaestner 2007) we found that prescription drug coverage had relatively small effects on prescription drug use in the general population. Prescription drug insurance was associated with between a 6 and 14 percent increase in the number of prescriptions. Similar results are reported by Huh, Rice, and Ettner (2007). Therefore, it may be expected that prescription drug insurance would have few health benefits. Alternatively, the absence of effect could be due to inappropriate pharmacotherapy either because of unnecessary utilization or nonadherence to therapy on the part of consumers (Zhan et al. 2001; Budnitz et al. 2006). Finally, we acknowledge that study limitations may explain these findings. While we believe that the research design was reasonable and that evidence supported its validity, we cannot completely rule out the possibility that our estimates are biased by selection effects. In addition, the use of more targeted measures of health such as reduction in HbA_{1c} for diabetic patients or blood pressure for hypertensive patients may lead to different conclusions.

The analysis has implications for Medicare Part D. It is believed that efficacy of prescription drugs depends on proper prescribing and compliance to medication. Indeed, prior research supports that intervention by health care providers improves clinical, economic, and humanistic outcomes (Bunting and Cranor 2006). Our finding of a small effect of drug coverage on health suggests that simply providing drug insurance might not be sufficient to improve health. Other interventions such as those provided by medication therapy management programs as a part of MMA (e.g., monitoring medication use, coordinating therapy, providing education and training on drug use) might be necessary for all elderly.

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NOTES

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 effects model. It does not fully eliminate the influence of unmeasured personal characteristics (see Allison and 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 χ^2 goodness of fit statistics to its degrees of freedom.
4. 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. However, later years indicate that the vast majority of those on Medicaid have drug coverage.
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 5 months but had no coverage for the other 7 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.
6. Number of chronic conditions was defined as the sum of self-reports of the presence of the following diseases: cardiovascular, diabetes, arthritic, respiratory, neurological, psychiatric, and neoplastic disorders.
7. The standard errors, presented were calculated using the balanced repeated replication weights provided with the data.
8. To assess whether insurance status transitions were correlated with time-varying measured characteristics, we estimated fixed effects regression models using separate samples of those who gained coverage and those who lost coverage. The dependent variable was whether the person had prescription drug coverage. Estimates from these analyses indicated that insurance status transitions were not correlated with time-varying measured characteristics including doctor visits or number of chronic conditions.

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SUPPLEMENTARY MATERIAL

The following supplementary material is available for this article online:

Appendix SA1: Author matrix.

Appendix SA2. OLS Fixed Effect Estimates of the Effect of Prescription Drug Insurance on Individual Items of ADL.

Appendix SA3. OLS Fixed Effect Estimates of the Effect of Prescription Drug Insurance on Individual Items of IADL.

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