Medicare and the Elderly

Prescription Drug Coverage and Effects on Drug Expenditures among Elderly Medicare Beneficiaries

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Objective. To identify determinants of drug coverage among elderly Medicare beneficiaries and to investigate the impact of drug coverage on drug expenditures with and without taking selection bias into account.

Data Sources/Study Setting. The primary data were from the 2000 Medicare Current Beneficiary Survey (MCBS) Cost and Use file, linked to other data sources at the county or state-level that provided instrumental variables. Community-dwelling elderly Medicare beneficiaries who completed the survey were included in the study ($N = 7,525$). A probit regression to predict the probability of having drug coverage and the effects of drug coverage on drug expenditures was estimated by a two-part model, assuming no correlation across equations. In addition, the discrete factor model estimated choice of drug coverage and expenditures for prescription drugs simultaneously to control for self-selection into drug coverage, allowing for correlation of error terms across equations.

Principal Findings. Findings indicated that unobservable characteristics leading elderly Medicare beneficiaries to purchase drug coverage also lead them to have higher drug expenditures on conditional use (i.e., adverse selection), while the same unobservable factors do not influence their decisions whether to use any drugs. After controlling for potential selection bias, the probability of any drug use among persons with drug coverage use was 4.5 percent higher than among those without, and drug coverage led to an increase in drug expenditures of \$308 among those who used prescription drugs.

Conclusions. Given significant adverse selection into drug coverage before the implementation of the Medicare Prescription Drug Improvement and Modernization Act, it is essential that selection effects be monitored as beneficiaries choose whether or not to enroll in this voluntary program.

Key Words. Prescription drugs, Medicare, adverse selection

Innovations in medical technology, especially pharmaceuticals, have improved health outcomes and quality of life and have replaced surgeries and other invasive treatments. This shift has been one of the main drivers of the

rapid growth of spending for prescription drugs during recent years. Rapid growth of prescription drug expenditures is likely to disproportionately influence the elderly because they are more dependent upon them than any other group, due to high prevalence of chronic conditions that require long-term medications.

Lack of drug coverage among Medicare beneficiaries has been a formidable barrier to effective medication therapy and may lead to adverse consequences. People without drug coverage face greater financial burdens with higher out-of-pocket drug expenses, so they not only fill fewer prescriptions than those with coverage (Davis et al. 1999; DHHS 2000; Stuart, Shea, and Briesacher 2000; Poisal and Murray 2001), but they are also less likely to have access to a broad array of therapies, including newer, more costly medications and clinically essential medications (Blustein 2000; Adams, Soumerai, and Ross-Degnan 2001; Federman et al. 2001). It is too early to know how the Medicare Prescription Drug Improvement and Modernization Act (MMA), implemented in 2006, will affect use of services.

The literature on factors associated with drug spending suggests that insurance plays a significant role in the drug utilization decisions of Medicare beneficiaries. Although previous research reports that Medicare beneficiaries with coverage use more outpatient prescription medications than those without it, additional studies controlling for potential self-selection into insurance are critical to estimate the causal effect of drug coverage. Beneficiaries who anticipate large drug expenditures might be more likely to seek drug coverage than those who do not expect to spend much on drugs. The goal of the current study is to test the hypothesis that beneficiaries with prescription drug coverage will spend more on prescription drugs than those without drug coverage, adjusting for self-selection into drug coverage on the basis of both observables and unobservables.

PREVIOUS RESEARCH

Previous studies provide substantial evidence that drug coverage is associated with use of prescription drugs. However, evidence from cross-sectional data

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analyses, unless from a randomized control design, does not necessarily mean that there is a causal relationship between drug coverage and drug use. Persons who anticipate high expenditures for drugs may purchase coverage to help reduce the costs of prescription drugs, which may lead to selection bias. There is a substantial body of research on selection into Medicare supplemental insurance, but the findings are mixed and do little to clarify the issue of possible adverse selection into prescription drug coverage. Only one study examined adverse selection into drug coverage and found no evidence of adverse selection (Lillard, Rogowski, and Kington 1997), but the data for this study are quite old (1968–1990). A few multivariate studies suggest that drug coverage increases use of prescription drugs among elderly Medicare beneficiaries (Stuart and Grana 1998; Lillard, Rogowski, and Kington 1999). However, none of these drew this conclusion by fully controlling for the potential selection bias.

Using survey data from the RAND Elderly Health Supplement to the 1990 Panel Study of Income Dynamics, Lillard, Rogowski, and Kington (1999) examined the effect of insurance coverage on prescription use and expenditures and found that prescription drug coverage significantly increased the probability of use of any drug, but not of total expenditures among those who used prescription drugs. They conducted a series of tests of the exogeneity of private insurance and of drug coverage for each drug utilization equation and found that insurance coverage for prescription drugs increased the probability of use, but not of total expenditures, among those who used prescription drugs. The joint model of insurance coverage, drug coverage, and the drug use equations was estimated using instrumental variables for insurance coverage and drug coverage. One limitation to this study is that possible correlation between insurance coverage and the demand equations is allowed only at the couple level (i.e., married persons). In addition, the instrument for drug coverage—whether the source of the private insurance is the employer—may not be appropriate because drug coverage and employer-sponsored insurance can be determined simultaneously, in that people may choose an insurance plan because of its drug coverage.

Stuart and Grana (1998) analyzed survey data on medication usage for 23 common health problems reported by a large sample of Pennsylvania elderly in 1990 and found that elderly persons with supplemental coverage were between 6 percent and 17 percent more likely to use prescription medicine than were persons with Medicare coverage alone. This study included an endogeneity test of the insurance variable using a two-stage Hausman specification and found no evidence of a selection effect. However, the Hausman

test is a relatively low-power test and may not detect endogeneity if the impact is small. In addition, the study's findings could not be generalized to the entire elderly Medicare population because it focused on a particular regional area.

Several studies show that supplemental drug coverage generally leads to increased medication use for certain therapeutic classes (Blustein 2000; Adams, Soumerai, and Ross-Degnan 2001; Federman et al. 2001). In addition, the insurance effect is further supported by evidence that restricting coverage or higher cost-sharing can lead to decreased use of medications (Soumerai et al. 1987, 1991; Soumerai, McLaughlin, and Ross-Degnan 1994; Tamblyn et al. 2001; Joyce et al. 2002) while expanding reimbursable limits of drug benefit leads to an increase in medication use (Balkrishnan et al. 2001). Although these studies indicate that insurance coverage for prescription drugs is associated with increased use of prescription drugs, this increase cannot necessarily be interpreted as an insurance effect because it is not estimated controlling for potential selection bias.

CONCEPTUAL FRAMEWORK

To examine the relationship between drug coverage and the utilization of prescription drugs, an economic model of individual choices was developed. Individuals make three choices in this context: whether to purchase drug coverage, whether to use prescription drugs, and how many drugs to use.

Demand for Drug Coverage

Most people prefer to avoid financial risk resulting from high drug costs for treating illness and will seek to insure against it. Obviously, people differ in the amount of risk they prefer to confront, or, more importantly, in the amount they are willing to spend to reduce or eliminate financial risk (Phelps 1997, p. 33). Individuals are more likely to purchase drug coverage if they are more risk averse. The demand for prescription drug coverage is influenced by other factors as well. Holding everything else (including price) constant, people are expected to be more likely to purchase drug coverage include those in poor health, with higher incomes, and with stronger preferences for taking drugs.

Choice of drug coverage can also be influenced by the supply of health insurance that provides drug coverage for Medicare beneficiaries. Moreover, beneficiaries in areas with high health maintenance organizations (HMO) penetration are more likely to enroll in Medicare HMO plans (which usually provide drug benefits) compared with those in areas with low penetration,

other things being equal. The percent of Medicare HMO¹ enrollees among eligible beneficiaries may reflect the supply of Medicare HMO plans.

Demand for Drugs

All else equal, an individual demands more prescription drugs as the price gets lower, when he/she earns higher income (for a normal good) and/or when the person is in poor health and/or when the person's preference for prescription drugs is high. As prescription drug coverage pays for part or all of the prescriptions the enrollee receives, this has the effect of reducing the price that people pay for drugs at the time they purchase it. Thus, the out-of-pocket price of prescription drugs would be lower for a person with drug coverage and quantity demanded would be greater. Other things being constant, we expect the demand for prescription drugs increases as the price of drug falls as a result of prescription drug coverage.

When travel costs, the actual time spent, or the value of time rises, the patient is also less likely to get prescription drugs. Lower supply of health care services such as hospitals, physicians, and pharmacists in the local area is a proxy for greater time as well as direct travel costs for prescription use.

In this conceptual model, underlying health status and an individual's preference may influence both a beneficiary's choice of drug coverage and drug spending. Thus, a beneficiary's likelihood of purchasing drug coverage may be correlated with the level of demand for prescription drugs in unobservable ways, resulting in selection bias that may induce substantial bias in estimating the effects of drug coverage on drug expenditures.

To correct for selection bias, the estimation approach requires appropriate identifying variables (IVs) that influence the choice of drug coverage but do not directly affect drug spending (only indirectly, through coverage). The conceptual model illustrates that the price of drug coverage and the supply of the health insurance plans can be used as IVs. The model also assumes that the supply of health care services affects drug utilization, but not the choice of drug insurance coverage.

METHODS

Data Sources

The primary data were from the 2000 Medicare Current Beneficiary Survey (MCBS) "Cost and Use" file. MCBS is a multipurpose survey sponsored by the Centers for Medicare and Medicaid Services (CMS) that provides information on health care use and expenditures including detailed self-reported

utilization data such as filled prescriptions in the prescription event file. To assist in reporting data on prescription medicines, respondents are asked to bring to the interview bottles, tubes, and prescription receipts provided by the pharmacy (CMS, www.cms.hhs.gov/mcbs).

In addition, county-level information was gathered from CMS, including adjusted average per capita cost (AAPCC) rate, Medicare HMO penetration rates measured by percent of Medicare HMO enrollees among eligible beneficiaries, and the number of Medicare HMO plans. Moreover, state-level data including premiums for Medigap plan from a large health insurance plan, percent of union members, income eligibility for supplemental security income (SSI) and presence of Medically Needy program were also used.

County-level health care supply variables were obtained from the Bureau of Health Professions' Area Resource File 2001 (ARF). All of the area-level data were merged with the MCBS data for multivariate analyses.

Study Sample

Medicare beneficiaries who were aged 65 and older, community dwelling (except for Puerto Rico), enrolled in Medicare Part A and B through the entire year and completed the Medicare Beneficiary Survey were included in analyses. Those with end-stage renal disease, or who died any time during the year, were excluded. We excluded 28.2 percent of the starting sample for these reasons. From the remaining 8,542 respondents, 550 (6.4 percent of the sample) were excluded because state-level data for the proxy measures of the price of drug coverage were not available. Those included persons who resided in three states where Medigap plans differ from nationally standardized plans: Massachusetts ($n = 106$), Minnesota ($n = 87$), and Wisconsin ($n = 292$); and 65 persons from Mississippi, where the SSI standard was not available, were also excluded.² In addition, persons were excluded due to missing values for individual characteristics and/or health care supply variables ($n = 467$, 5.5 percent of the sample).³ The final data set had 7,525 observations.

Variable Specification

Supplementary Appendix A presents all variables that are included in analyses and provides a description, level of aggregation, and data source for each. Table 1 provides descriptive statistics for all independent variables.

Dependent Variable

Drug Coverage. Whether or not a sample member purchases drug coverage is a dependent variable in the choice model, and an independent variable in the drug utilization equations. Drug coverage is an indicator variable, which takes a value of 1 when a person had drug coverage, otherwise 0. Prescription drug coverage is identified if (i) a beneficiary reports drug coverage through supplemental insurance including Medicaid, Medicare HMO, employer-sponsored insurance, Medigap policies or other public plans, or (ii) if there is any payment for drug expenses by these supplemental plans although the person did not report drug coverage.⁴

Drug Spending. Drug spending is defined as per capita total drug expenditures for a year. For establishing payment amounts, the actual transaction price for each prescribed drug is used. MCBS uses an imputation process when household respondents were unable to provide price and third-party payment information. A variety of methods were developed to determine a reasonable transaction price when respondents know the amount they paid out of pocket but do not know the total transaction price (see Poisal et al. 1999).⁵

Independent Variables

Out-of-Pocket Premiums for Drug Coverage. Because out-of-pocket premiums for drug coverage were not available in the data set, the following proxy measures were used:

AAPCC. The AAPCC rate is the Medicare capitated payment amount for Medicare HMOs in the beneficiary's county, and serves as a proxy for Medicare HMO benefits. As Medicare HMOs are able to offer more comprehensive benefits in counties with higher AAPCCs (Barents Group LLC 1997), it is expected that a higher AAPCC results in more comprehensive benefits, including prescription drugs, and a greater likelihood of Medicare HMO enrollment (Rice et al. 2002).

Medigap Policy Premium. The average monthly premiums of Medigap policies that provide drug benefits (Plans H, I, and J) at the state level from a large health insurance plan were included.

Medicaid Eligibility. Before 2006, Medicaid always provided a prescription drug benefit with zero premiums. The state income standard for SSI, which is an income supplement program designed to help aged, blind, and

Table 1: Characteristics of Elderly Medicare Beneficiaries

<i>Variable</i>	<i>% or Mean (SD)</i>
Individual level	
Age (years)	
65–69	19.2
70–74	29.3
75–79	24.7
80–84	15.5
≥ 85	11.4
Sex	
Male	41.1
Female	58.9
Race/ethnicity	
White	88.5
Black	8.2
Other	3.3
Education	
Less than high school	32.2
High school	29.2
More than high school	38.6
Marital status	
Married	54.0
Widowed	35.8
Divorced–separated	7.2
Never married	3.1
Family income	
≤ \$10,000	17.2
\$10,001– ≤ \$20,000	31.6
\$20,001– ≤ \$40,000	33.1
≥ \$40,001	18.1
Drug coverage	
Yes	71.9
No	28.1
Residence in metropolitan area	
Nonmetropolitan	25.4
Metropolitan	74.6
Self-rated health status	
Excellent	15.0
Very good	28.9
Good	34.1
Fair	16.6
Poor	5.4
ADL	
0	73.6
1	12.1
2	5.6
3	3.4

continued

Table 1. *Continued*

<i>Variable</i>	<i>% or Mean (SD)</i>
4	2.3
5	1.9
6	1.1
IADL	
0	64.8
1	17.6
2	6.3
3	3.4
4	3.5
5	2.4
6	2.0
Functional limitations	
0	21.6
1	22.2
2	17.8
3	13.8
4	12.3
5	12.4
Comorbid conditions	
0	7.7
1	16.3
2	22.1
3	20.5
4	15.3
≥ 5	18.2

<i>Insurance Market and Health Care Supply Variables at County or State Level</i>	<i>Mean (SD)</i>
AAPCC rate*	\$514.0 (5.66)
Medicare HMO penetration*	16.82% (1.17)
Number of Medicare HMO plans*	3.81 (0.25)
% Union members among currently working people [†]	13.57 (0.52)
Average monthly premiums for Medigap plan (H, I, & J) [†]	\$184.38 (2.0)
Federal poverty level for SSI standard [†]	71.93% (0.51)
Presence of medically needy program [†]	0.70 (0.04)
Average retail price of prescription drugs [†]	\$54.64 (0.40)
Active medical doctors per 1,000 population*	2.42 (0.10)
Hospitals per 1,000 population*	0.022 (0.015)
Pharmacists per 1,000 population*	0.74 (0.02)

Note: Weighted $N = 23,666,347$.

*County-level data.

[†]State-level data.

ADL, activities of daily living; IADL, instrumental activities of daily living; AAPCC, adjusted average per capita cost; HMO, health maintenance organizations; SSI, supplemental security income.

disabled people and in most cases uses the same standard as Medicaid (Ettner 1997), is included along with an indicator for the presence of a Medicaid medically needy program in the state.

Proportion of Workers Represented in Unions. Employer-sponsored insurance coverage usually provides a drug benefit with relatively low premiums and, thus, the availability of employer-sponsored health insurance coverage is an important determinant of drug coverage (Lillard, Rogowski, and Kington 1997). Because the percent of workers represented in unions is usually positively associated with offers of health benefits by employers, this variable is used as a proxy for employer-sponsored insurance.

Health Status. Health status measures include self-rated health status, number of personal activities of daily living (ADL) limitations, number of instrumental activities of daily living (IADL) limitations, number of functional imitations, and number of comorbid conditions.

Sociodemographic Variables. Sociodemographic characteristics hypothesized to affect both drug coverage and drug use include age, sex, race/ethnicity, education, marital status, family income,⁶ and metropolitan residence status.

Supply of Managed Care Plans. The number of Medicare HMO plans available and Medicare HMO penetration in each county are included to control for supply of insurance plans.

Supply of Health Care Services. The numbers of active physicians, hospitals, and pharmacists per 1,000 persons at the county level are used to measure health care supply.

Average Price of Prescription Drug. This is measured as the average price charged for retail prescriptions filled by retail pharmacies,⁷ including new prescriptions and refills of both brand and generic drugs but excluding those filled by mail order.

Empirical Model and Estimation Methods

The sample for MCBS is drawn from the selection of 107 geographic primary sampling units (PSUs) and the sampling weight was applied to represent the

United States. Both descriptive and multivariate analyses account for the clustered nature of the MCBS.

Purchase of Drug Coverage

Defining I^* as the latent index underlying individual's choice of drug coverage, the drug coverage equation is specified as

$$I^* = Z\gamma + \varepsilon_1 \quad \varepsilon_1 \sim N(0, 1). \quad (1)$$

If $I^* > 0$, an individual has drug coverage ($I = 1$), otherwise not ($I = 0$). Z is a vector of exogenous characteristics such as demographic, health status, and Medicare health insurance market characteristics, which may influence an individual's choice of drug coverage. The error term, ε_1 , is assumed to be normally distributed with mean zero and variance normalized to 1. The probability of having drug coverage is estimated using a probit model.

Prescription Drug Spending

The decisions whether to use prescription drugs and how much to use are modeled as a function of drug coverage, individual characteristics and supply factors:

$$y^* = X_1\alpha_1 + I\beta_1 + \varepsilon_2 \quad (2)$$

$$y|y^* \geq 0 = X_2\alpha_2 + I\beta_2 + \varepsilon_3 \quad (3)$$

where y^* is the latent propensity of using prescription drug and $y_1 = 1$ if $y^* > 0$ and 0 otherwise. Drug expenditures (y) are observed only if $y^* > 0$. Thus, equation (3) specifies drug expenditures in a given year conditional on prescription drug use. X_1 and X_2 are overlapping vectors of demographic, health status, and health care supply variables. ε_2 and ε_3 are the error terms.

Estimation Methods

This study employs two approaches for modeling the relationship between drug coverage and drug use: the "naïve" two-part model⁸ and the discrete factor model (DFM).

Naïve Model: Two-Part Model. By assuming that the error terms (ε_1 , ε_2 , and ε_3) are normally distributed and uncorrelated with each other, the model can be estimated by a two-part model. A probit estimation is used for equation (2)—any drug use; and ordinary least squares (OLS) estimation for equation

(3)–drug expenditures conditional on the use of any drugs. Conditional drug expenditures had a skewed distribution, so this outcome was log transformed to achieve a distribution closer to normality.

The estimates from the probit regression were transformed into a relative risk, defined as the mean of the ratio of predicted probability of any drug use if all persons in the sample were given drug coverage to predicted probability of drug use if no one in the sample had drug coverage. The estimates from the conditional drug expenditures equation were retransformed (Duan 1983) to derive the predictive margin, defined as the mean difference in the expected conditional drug expenditures if everybody in the sample had drug coverage versus if nobody did. As the residuals were distributed normally but exhibited heteroskedasticity, an appropriate retransformation algorithm was used to calculate the predictive margin.

Finally, the estimates were combined to calculate the net overall effect on the unconditional outcome. The expected drug expenditure for the entire sample (nonusers as well as users) was obtained by multiplying the predicted probability of having any drug use by the predicted conditional expected outcome for each person. We then calculated the mean predictive margin for the unconditional outcome, defined as the expected differences in drug utilization with and without drug coverage. Ninety-five percent confidence intervals were derived for all estimates using bias-corrected empirical bootstrapping with replacement (1,000 repetitions).

DFM. A three-equation approach assumes a common but unobservable factor across equations (Heckman and Singer 1984) (i.e., a DFM), and estimates three equations simultaneously by allowing correlation between error terms in equations (1)–(3) (Goldman 1995; Goldman, Leibowitz, and Buchanan 1998). It is preferable to use a single equation or a two-equation simultaneous estimation approach because it provides the strong control for selection bias and relaxes the joint normality assumption of the selection model. The likelihood function of the DFM is described in Supplementary Appendix B. The DFM estimates were then used to calculate relative risks for any drug use and predictive margins for unconditional drug expenditures, using the approach described above for the two-part model.

Tests for IVs. Two tests of the validity of the instrumental variables were performed. A Wald test was used to test the “non-zero average causal effect” assumption (i.e., to determine whether the IVs were jointly associated with

the potentially endogenous variable, in this case drug coverage). To test whether the IVs could be excluded from both drug use equations, each utilization equation was re-run including one instrument at a time, while still excluding the other instruments. If the instrument was significantly associated with drug expenditures even after controlling for drug coverage, then it could not be excluded from the expenditure equation. Without at least one unique identifier that affects selection into drug coverage but does not utilization outcome, the result from the test for selection bias is not valid.

RESULTS

Purchase of Drug Coverage

The results from a probit analysis indicate that the presence of comorbid conditions and an individual's residence in a metropolitan area are important positive predictors of drug coverage (Table 2). In contrast, individuals aged 70 or older and nearly poor people whose annual family income fell between \$10,001 and \$20,000 were less likely to have drug coverage. One possible reason why poor people were more likely to have drug coverage is because they were likely to be eligible for Medicaid programs that provide drug coverage. The positive correlation of drug coverage and the number of comorbid conditions could mean that those who need coverage most are the most likely to purchase it (i.e., adverse selection).

With regard to environmental characteristics beyond the individual's control, the number of Medicare HMO plans at the county level and the percentage of union members at the state level were strongly associated with drug coverage. This suggests that the supply of Medicare HMO plans and the percentage of union members, which is usually highly associated with employer-sponsored insurance, are important predictors of drug coverage. Therefore, the purchase of drug coverage may be influenced by where the beneficiary lives.

Results from the discrete factor estimation (Table 2) were consistent with those from the regular probit analysis in terms of the direction and significance of individual characteristics in predicting drug coverage. Curiously, the AAPCC rate and Medicare HMO penetration were significant determinants of drug coverage in the DFM, while they were not significant in the probit model. This difference may be a result of different estimation approaches—unlike the probit model, the DFM controls for unobservable characteristics that are commonly related to drug utilization.

Table 2: Determinants of Prescription Drug Coverage

<i>Variable</i>	<i>Probit Model</i>		<i>Discrete Factor Model</i>	
	<i>Coefficient</i>	<i>SE</i>	<i>Coefficient</i>	<i>SE</i>
AAPCC rate	0.0002	0.0005	0.0004	0.0003
No. of Medicare HMO plans	0.02	0.01	0.018*	0.008
% of union members	0.015*	0.006	0.014*	0.003
Average Medigap premiums (Plan H, I, and J)	− 0.00013	0.002	0.00013	0.0008
Presence of Medicaid medically needy program	− 0.077	0.07	− 0.06	0.04
SSI standard	− 0.0016	0.003	− 0.0018	0.002
Medicare HMO penetration	0.01*	0.003	0.01*	0.002
Age (years)				
65–69 (referent)	—	—	—	—
70–74	− 0.14*	0.06	− 0.14*	0.05
75–79	− 0.20*	0.06	− 0.21*	0.05
80–84	− 0.36*	0.06	− 0.37*	0.06
≥ 85	− 0.45*	0.06	− 0.46*	0.06
Sex				
Male (referent)	—	—	—	—
Female	− 0.09*	0.04	− 0.11*	0.04
Race/ethnicity				
White (referent)	—	—	—	—
Black	0.13	0.07	0.13*	0.61
Other	0.31*	0.04	0.38*	0.11
Education				
Less than high school (referent)	—	—	—	—
High school	− 0.04	0.05	− 0.064	0.04
More than high school	0.034	0.05	0.022	0.04
Marital status				
Married (referent)	—	—	—	—
Widowed	0.009		0.024	0.04
Divorced–separated	− 0.067		− 0.08	0.07
Never married	− 0.12		− 0.18	0.09
Family income				
≤ \$10,000 (referent)	—	—	—	—
\$10,001– ≤ \$20,000	− 0.11	0.05	− 0.14*	0.05
\$20,001– ≤ \$40,000	0.09	0.06	0.04	0.05
≥ \$40,001	0.03	0.08	0.012	0.06
Residence in metropolitan area				
Nonmetropolitan (referent)	—	—	—	—
Metropolitan	0.2*	0.09	0.22*	0.04
Self-rated health status				
Excellent/very good/good (referent)	—	—	—	—
Fair/poor	0.04	0.05	0.039	0.04
ADL				
0 (referent)	—	—	—	—
≥ 1	0.07	0.05	0.094*	0.05

continued

Table 2. *Continued*

<i>Variable</i>	<i>Probit Model</i>		<i>Discrete Factor Model</i>	
	<i>Coefficient</i>	<i>SE</i>	<i>Coefficient</i>	<i>SE</i>
IADL				
0 (referent)	—	—	—	—
≥ 1	− 0.04	0.04	− 0.068	0.04
Functional limitation				
0 (referent)	—	—	—	—
1–2	0.07	0.05	0.075	0.05
3–5	0.07	0.06	0.084	0.06
Comorbid conditions				
0 (referent)	—	—	—	—
1	0.31*	0.07	0.31*	0.07
2	0.36*	0.07	0.36*	0.07
3	0.5*	0.07	0.48*	0.07
4	0.61*	0.07	0.58*	0.07
≥ 5	0.65*	0.08	0.62*	0.07

* $p < .05$.

ADL, activities of daily living; IADL, instrumental activities of daily living; AAPCC, adjusted average per capita cost; HMO, health maintenance organizations.

Impact of Drug Coverage on Drug Expenditures

Naïve Two-Part Model. Supplementary Appendix C shows the full set of parameter estimates from estimating the probit model for the probability of observing a positive value of drug expenditures (the first part) and the OLS model using the sub-sample of positive observations (the second part). The estimates suggest that holding all else constant, the mean probability of any drug use would be 10 percent higher (RR = 1.10, CI: 1.07, 1.12) if all beneficiaries had drug coverage than if they did not have drug coverage (Table 3). Drug coverage is associated with significant increases in conditional and unconditional drug expenditures of \$421 (CI: \$350, \$500) and \$461 (CI: \$388, \$534), respectively (Table 3).

DFM. The impact of drug coverage on drug utilization—any drug use and conditional use of drugs—was still significant after controlling for selection bias in the DFM estimation. The magnitudes of drug coverage effects from the DFM were smaller than those from the single-equation results. The average predicted probability of any drug expenditures was 4.5 percent higher with drug coverage than without, and drug coverage led to an increase in

Table 3: Predicted Margins of Any Drug Use and Drug Spending by Drug Coverage

<i>Dependent Variable</i>	<i>Predicted Mean</i>	<i>(CI)</i>
Any drug use		
Drug coverage = 0	0.88	(0.87, 0.89)
Drug coverage = 1	0.95	(0.94, 0.95)
Relative risk	1.10	(1.07, 1.12)
Conditional drug spending		
Drug coverage = 0	1,120	(1,062, 1,184)
Drug coverage = 1	1,541	(1,495, 1,591)
Difference	4,21	(350, 500)
Unconditional drug spending		
Drug coverage = 0	1,034	(978, 1,094)
Drug coverage = 1	1,495	(1,450, 1,542)
Difference	461	(388, 534)

Note: 95% confidence intervals (CIs) are shown in parentheses and were derived by 1,000 bootstrap replications.

unconditional drug expenditures of \$308 for those who use prescription drugs after controlling for possible selection bias.

The main parameters of interest from DFM are selection effects represented by ρ_2 and ρ_3 . The DFM analysis demonstrated significant adverse selection into drug coverage (i.e., $\rho_3 > 0$), which indicates that selection appears to mainly affect conditional drug expenditures rather than use of any drug (i.e., $\rho_2 < 0$) (Table 4). This implies that the same unobservable characteristics leading patients to purchase drug coverage also lead them to have higher drug expenditures once they have filled prescriptions, but the unobservable factors do not influence their decisions whether to use any drugs. For example, persons who expect high drug expenditures because of

Table 4: Parameter Estimates for the Discrete Factor Model

	<i>Parameter</i>	<i>Estimate</i>	<i>SE</i>
Points of support for the distribution of θ	θ_1	- 0.06	0.02
	θ_2	0.07	0.005
Selection effects for any drug use	ρ_2	- 3.74	0.90
Selection effects for drug spending	ρ_3	2.16	0.40
Probabilities of θ_1 and θ_2 , respectively	P_1	0. 53	—
	P_2	0.47	—
Variance of uncorrelated error terms, ε_1^* , ε_2^* , and ε_3^*	σ	1.07	—
Variance of θ	$\text{Var}(\theta)$	1.18	—

Note: ρ_2 and ρ_3 ($p < .05$).

unmeasured adverse health status, high preference for medication treatment, or other unobserved factors are more likely to purchase drug coverage.

Tests for IVs

With the exception of Medicare HMO penetration rate, all of the IVs proved to be excludable from both utilization equations (i.e., any use of drug and conditional level of drug) in the empirical tests. HMO penetration was significantly associated with any use of drugs at the 5 percent level ($p = .016$), although it was not significantly associated with the conditional level of drug use. It is difficult to explain why Medicare HMO penetration might be a significant predictor of any use of drugs, but not the conditional level of drug use. Possibly HMOs reduce conditional use because they cut back on the high-end use, although HMOs often increase the probability of any use as well.

The Wald test determined that the six potential IVs, including proxy measures for prescription drug coverage and health insurance market variables (except HMO penetration, as it was not excludable), were jointly significant in the drug coverage choice equation ($\chi^2(6) = 26.53$, $p = .0002$), indicating that they passed the test of the nonzero average causal effect.

SUMMARY AND CONCLUSIONS

Drug Coverage and Drug Spending

This study found a strong effect of drug coverage on drug spending even after controlling for selection bias. Drug coverage was associated with increases of 9.6 percent in the probability of any prescription use and \$461 in annual drug spending per person using the two-part model, compared with 4.5 percent and \$308 from the DFM. These effects of drug coverage on drug spending could have resulted from a demand for more prescriptions and/or for more expensive drugs by consumers with drug coverage. Other contributing factors are the physician's prescribing practices, which may be influenced by a patient's coverage status such that patients with coverage are prescribed either more drug therapy, or more costly drugs. It is difficult to distinguish the extent to which the decision to consume more prescription drugs is driven by consumers or physicians. Moreover, it is unclear whether more drug use with coverage indicates that persons with coverage received needed medication treatment in appropriate manner, or that they were treated excessively in terms of dosage, duration, or expensive drugs.

Although drug coverage significantly increased drug spending, comorbid conditions seemed to be the most important factor determining use of prescription drugs and leading to high drug spending. Those with five or more comorbid conditions have a 54 percent higher probability of using prescription drugs and spend more than three times as much on drug costs compared with those without any comorbidities.

Adverse Selection

This study investigated self-selection into drug coverage using simultaneous equations methods among elderly Medicare beneficiaries. There has been concern that the observed differences in drug expenditures between those with and without coverage may be attributable to self-selection, but no previous studies have investigated self-selecting behavior in purchasing drug coverage. Our estimates indicate adverse selection into drug coverage for conditional drug expenditures but not for any drug use. This finding has important implications for implementation of the MMA, as discussed below.

Study Limitations

There are several limitations to this study. First, payment amounts based on imputed drug prices may not accurately reflect actual payment. In particular, the price data will not include the discounts negotiated by insurance companies or pharmacy benefits managers, thereby potentially attenuating the measured differences between purchasers.

Second, there is possible underreporting of the actual costs for prescription drugs. Survey respondents may not recall relatively small, routine expenses for drugs compared with large medical expenses such as hospitalization. In developing the field procedures for the MCBS, the MCBS respondent is asked each round (every 4 months) about all health care events, charges, and payments since the previous interview to avoid this problem (Poissal et al. 1999). In addition to asking to retain the prescription bottle, the package, and any receipts, interviewers are furnished a list of all prescription drugs reported in the previous interview so they can ask whether the respondent has taken any of those drugs during the reporting period (Poissal et al. 1999). Despite these substantial efforts, underreporting of prescription drugs may still exist and is a particular problem for one-time drugs. However, in general measurement error is likely to bias findings towards the null hypothesis as long as it is not systematic. Another possible underreporting bias exists

for drug coverage, which was identified by source-of-payment data and self-reports.

Third, as the MCBS data do not provide detailed information regarding the generosity of prescription drug benefits, the differential effect of more versus less generous drug coverage cannot be investigated. We did, however, have information on the source of drug coverage as a proxy for generosity. In sensitivity analyses using single-equation methods to estimate the separate effects of different sources of drug coverage, employment-based health insurance appeared to be most generous, while other sources of drug coverage had similar effects.

Finally, as MCBS did not have any information regarding compliance of prescription drugs, we cannot know whether patients took the prescribed medication or had stopped taking medications due to adverse effects or cost.

Policy Implications

This study found that inequities exist in prescription drug coverage among elderly Medicare beneficiaries. It also found that, after controlling for possible selection bias, drug coverage significantly increases both the probability of receiving prescription drugs and the level of drug use. In addition, a simultaneous equations method demonstrates a significant self-selection into drug coverage. These findings raise policy-relevant questions with respect to the new prescription drug benefit that was implemented as a part of the MMA in 2006.

Given the choices offered to beneficiaries, the MMA may not eliminate the potential for selection. Two types of selection may occur. As this study found, elderly Medicare beneficiaries who anticipate high drug costs tend to choose drug coverage under the MMA (i.e., adverse selection). Conversely, there is possibility of favorable selection as the insurers have a powerful incentive to select and retain healthy people to increase their profits.

This study addressed significant insurance effects of drug coverage even after controlling for possible selection bias. The predicted values of drug spending suggest that providing drug coverage to elderly Medicare population through the MMA will generate a substantial increase in drug expenditures.

Results from this study demonstrate a large income effect on drug expenditures after controlling for prescription drug coverage. The substantial increase of drug expenditures with income suggests that low-income people either use fewer prescription drugs or use cheaper drugs compared with high-income people. This may imply that low-income people receive a lower level of drugs than what they need, although we were not able to examine this issue

directly. This raises a critical issue because the new standard drug benefit package contains a gap in coverage for people whose spending on prescription drugs falls between \$2,250 and \$5,100 and the legislation requires each individual to pay up to \$3,600 in out-of-pocket expenses before catastrophic coverage can begin. Both the benefit gap and the requirement of high out-of-pocket spending for the catastrophic coverage will pose significant barriers for low-income people who may not be able to afford it.

Both the descriptive and the multivariate analyses point to a strong association between comorbid health conditions and drug spending. As persons with more chronic conditions are likely to be poor due to high costs for health care including prescription drugs, they may be dually vulnerable due to high drug expenditures that are not fully covered and insufficient premium subsidies for drug benefit. The problem of possible underuse of effective medications due to a patient's inability to afford them is frequently discussed. More effort is needed to identify beneficiaries who are least likely to fill needed prescriptions after the MMA provides the new drug coverage to Medicare beneficiaries and to find ways to provide them with adequate financial access to necessary drugs. The government should improve the drug benefit structures to reduce financial barriers to necessary medication treatment. More discussions between physicians and patients on drug affordability could lead to the prescribing of less costly drugs in the formulary, or help guide patients to available assistance programs offered by government programs, community organizations, and drug manufacturers.

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NOTES

1. Throughout the article, we refer to Medicare HMOs since they were the dominant form of Medicare managed care under the Medicare+Choice program until 2006. In 2006, PPOs were also introduced under the new Medicare Advantage program.

2. The SSI standard was also unavailable for Hawaii, but there were no observations meeting the inclusion criteria.
3. When we ran the single-equation models including dummy variables for missing values for individual characteristics ($n = 307$), the coefficients of drug coverage and other independent variables were almost identical to the results from the model excluding missing values. We therefore reported the complete-case estimates only, based on Allison's (2001) suggestion that these estimates are preferred to the estimates based on using "missing data dummies."
4. If drug coverage is identified by self-report, 61 percent of beneficiaries had drug coverage. Drug coverage is indicated by 70.4 percent of sample when drug coverage is identified by whether a person either reports drug coverage or there is third-party payment for prescription drugs.
5. In 2000, about one third of drug reports were used and 56 percent relied on imputed prices because respondents did not know total transaction price even though they knew the amount they paid out of pocket. The remaining 10 percent were classified as coming from unknown payment source. We obtained detailed information about imputed drug price for 2000 MCBS data through personal communication with a person who working on MCBS data (Dr. John Poisal).
6. The income measure in the MCBS Cost and Use module is the self-reported total income for the panelist and spouse only. Income from other related and nonrelated household members is not asked during the interview. Thus, controlling for marital status suffices to normalize the income measure.
7. Retail pharmacies include independent pharmacies, chain pharmacies, food stores, and mass merchandisers found in 814 defined regional zones (Kaiser Family Foundation, www.statehealthfacts.org).
8. One-part model alternatives to the two-part model (OLS without a log transformation of the dependent variable and γ) yielded very similar estimates for the effect of drug coverage.

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SUPPLEMENTARY MATERIAL

The following supplementary material for this article is available online:

Appendix A. Description of Variables and Data Source.

Appendix B. Likelihood Function of the Discrete Factor Model (DFM).

Appendix C. Any Drug Use and Log of Drug Expenditures: Two-Part Model.

Appendix D. Any Drug Use and Log of Drug Expenditures: Discrete Factor Model.

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