NBER WORKING PAPER SERIES

PRESCRIPTION DRUG COVERAGE AND ELDERLY MEDICARE SPENDING

Baoping Shang
Dana P. Goldman

Working Paper 13358
http://www.nber.org/papers/w13358

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2007

This research was supported by the Hagopian dissertation award and the Bing Center for Health Economics. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

© 2007 by Baoping Shang and Dana P. Goldman. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Prescription Drug Coverage and Elderly Medicare Spending
Baoping Shang and Dana P. Goldman
NBER Working Paper No. 13358
September 2007
JEL No. I0

ABSTRACT

The introduction of Medicare Part D has generated interest in the cost of providing drug coverage to the elderly. Of paramount importance -- often unaccounted for in budget estimates -- are the salutary effects that increased prescription drug use might have on other Medicare spending. This paper uses longitudinal data from the Medicare Current Beneficiary Survey (MCBS) to estimate how prescription drug benefits affect Medicare spending. We compare spending and service use for Medigap enrollees with and without drug coverage. Because of concerns about selection, we use variation in supply-side regulations of the individual insurance market -- including guaranteed issue and community rating -- as instruments for prescription drug coverage. We employ a discrete factor model to control for individual-level heterogeneity that might induce bias in the effects of drug coverage. Medigap prescription drug coverage increases drug spending by $170 or 22%, and reduces Medicare Part A spending by $350 or 13% (in 2000 dollars). Medigap prescription drug coverage reduces Medicare Part B spending, but the estimates are not statistically significant. Overall, a $1 increase in prescription drug spending is associated with a $2.06 reduction in Medicare spending. Furthermore, the substitution effect decreases as income rises, and thus provides support for the low-income assistance program of Medicare Part D.

Baoping Shang
RAND Corporation
1776 Main Street
P.O. Box 2138
Santa Monica, CA 90407-2138
baoping_shang@rand.org

Dana P. Goldman
RAND Corporation
1776 Main Street
P.O. Box 2138
Santa Monica, CA 90407-2138
and NBER
dgoldman@rand.org

1 Introduction

The primary objective of the Medicare Prescription Drug, Improvement, and Modernization Act (MMA) was to provide seniors with affordable coverage for their prescription medications through the new Medicare Part D prescription drug benefit. After the MMA was signed—but before Part D was implemented—there was a very public controversy about the cost of the program. In March 2004, the Medicare Chief Actuary testified before the House Ways and Means Committee that he was ordered by the (Centers for Medicare & Medicaid Services) CMS Administrator to suppress his estimates of the 10-year cost of the program, which were substantially greater than original Congressional Budget Office estimates.

In fact, soaring costs have not materialized. According to the 2007 Medicare Trustees report, the average 2007 plan bid was about 10 percent lower than in 2006. These savings likely reflect a variety of factors, including vigorous plan competition, increased generic use, and a general slowing of spending relative to earlier in the decade. And there are even more reasons to be optimistic, since these estimates do not reflect the increasingly important role prescription drugs play in improving health outcomes by replacing surgery and other invasive treatments, and quickening recovery for patients who receive these treatments. Official estimates of the costs of Part D do not take these savings into account, in part because the magnitude and degree of such savings remain an open question among the elderly and disabled population. While not designed to provide estimates of the cost savings in Part D, this paper does provide insight into the potential of Part D to improve the fiscal outlook for both Parts A and B.

Medicare only partially covers medical services for seniors, and prescription drugs were not covered before 2006.[1] Supplemental Medicare was designed to fill this gap. Beneficiaries can get prescription drug benefits from their former employers or from Medicaid or other public programs, by enrolling in Medicare managed care[2], or by purchasing Medigap[3]. Although many beneficiaries had some source of drug coverage, 38% still had no coverage at all in 1999 (Laschober et al., 2002).

Economic theory suggests that when a drug benefit lowers the price of prescription drugs, it should increase the use of prescription drugs and complements of prescription drugs and decrease the use of substitutes of prescription drugs. It is unclear, however, whether prescription drugs and other medical services, including inpatient care and outpatient care, are substitutes or complements. On the one hand, people with prescription drug coverage may be more likely to have doctor visits to get the drugs they need, and inpatient care and outpatient care are often combined with prescription drugs in the treatment of many illnesses. In that sense, prescription drugs and other medical services are complements. On the other hand, some diseases can be treated by either prescription drugs or inpatient and outpatient care, and prescription drugs can improve health outcomes, reduce illness, and, thus, reduce the demand for medical care. In that sense, prescription drugs and other medical services are substitutes. Therefore, the absence of prescription drug coverage and the presence of generous coverage on inpatient and outpatient care would result in inefficient overall health care utilization: the

[1]Medicare did cover physician-administered drugs and a small number of self-administered drugs. Examples of Medicare-covered self-administered drugs include blood clotting factors, epoetin alfa for dialysis patients, immunosuppressive drugs after a Medicare-covered transplant, certain oral cancer drugs, and certain oral anti-emetic drugs.
[2]Most Medicare managed care plans have prescription drug benefit.
[3]Medigap is the short name for “Medicare Supplement Insurance” that is designed to fill some of the “gaps in coverage” left by Medicare.

underuse of prescription drugs and the overuse of inpatient and outpatient care (Goldman and Philipson, 2007). Furthermore, to the extent that these cross-price elasticities vary by income, then overall efficiency could be improved by further subsidizing the poor.

Few randomized studies have examined the effects of prescription drug benefits or cost-sharing on prescription drug use and the use of other medical services. The RAND Health Insurance Experiment (HIE) found the cost-sharing response to prescription drugs (ε=-0.27) is similar to that for all ambulatory medical services (Newhouse, 1993) in the non-elderly population. However, in the HIE, the pharmacy benefits perfectly co-varied with other medical benefits (by design), whereas the real question is how changes in pharmacy benefits, holding medical benefits constant, affect spending. Several observational studies have tried to disentangle these effects using quasi-experimental designs. Goldman et al (2007) recently reviewed 132 studies on the effects of cost-sharing. The evidence clearly demonstrates that increased cost-sharing is associated with lower pharmaceutical use. These effects can be quite large—even for chronic medications—suggesting there will be long-term health consequences. However, the direct evidence on the link between cost-sharing and health is rather limited. Most studies examine important proxies for health (and medical spending) such as emergency department use and hospitalizations. The findings from studies focusing solely on the chronically-ill are unambiguous: for patients with congestive heart failure (Cole et al., 2006), lipid disorders (Gibson et al., 2006 and Goldman et al., 2006), diabetes (Mahoney, 2005), and schizophrenia (Soumerai et al., 1994), greater use of inpatient and emergency medical services are associated with higher copayments or cost-sharing for prescription drugs or benefit caps. These findings are corroborated by the one paper that looked at clinical outcomes for a population with benefit caps (Hsu et al., 2006).

By contrast, studies that look at the effects of cost-sharing more broadly (on all drugs or a wide range of classes)—are ambiguous in their findings. Some find that higher cost-sharing is associated with adverse outcomes (Lingle et al., 1987), particularly among vulnerable populations such as the elderly and poor (Tamblyn et al., 2001 and Soumerai et al., 1991). But most find that—when the population is not limited to certain chronic illnesses—the effects of prescription drug cost containment policies are mostly benign. For example, studies by Fairman et al. (2003), Motheral and Fairman (2001), Johnson et al. (1997) and Smith and Kirking (1992) find that increased co-payments were not associated with more outpatient visits, hospitalizations, or emergency department visits. On the other hand, Gaynor et al. (2006) found that cost-sharing for prescription drugs reduces both use of, and spending on, prescription drugs, increases spending on outpatient care, and increases spending on inpatient care for those who are users of impatient care.

One of the reasons for the discrepancy in the findings is that any observational study must account for the endogeneity of prescription drug coverage, and most do not do an adequate job. Lillard et al. (1999) used an instrumental variable approach (instrumental variables include employment history for employer-sponsored benefits, measures of permanent income and wealth, the urbanicity of area of residence, lagged health status and lagged measures of presence of private health insurance for Medigap coverage) to estimate the effect of drug benefits on drug spending. Yang et al. (2004) used a discrete factor model to control for unobserved individual heterogeneity and Khan et al. (2007) adopted an individual fixed-effects model. These two studies found that prescription drug benefits either have no effects on non-drug medical spending or slightly increase non-drug medical spending. None of these studies, however, fully distinguish different sources of drug benefits. But even more importantly, none of these studies controls for the generosity of the medical benefits in estimating the effects of prescription drugs. Because health insurance with a drug benefit is more likely to have more generous non-drug benefits, the cross-price effect is subject to underestimation when the generosity of the medical benefits is not held constant.

In this paper, we use the Medicare Current Beneficiary Survey (MCBS) to examine spending of Medicare beneficiaries with Medicare coverage and a Medigap supplemental plan with or without a drug benefit. While the Medigap prescription drug coverage may not be broadly representative, this study design has the appealing feature that the medical benefits are completely known and are relatively homogeneous across plan types. Thus, the quasi-experimental design is one in which medical benefits are held constant, but drug coverage is allowed to vary. We use state reforms in the individual health insurance market[4] as instrumental variables and a discrete factor model to address the endogeneity of Medigap drug coverage. Finally, we interact prescription drug benefits with income to examine how the effects of drug coverage vary by income. We find that a $1 increase in prescription drug spending is associated with a $2.06 reduction in Medicare spending. Furthermore, the substitution effect decreases as income rises, and thus provides support for the low-income assistance program of Medicare Part D.

[4] Sometimes it is also called non-group health insurance market.

2 Data

The MCBS is a nationally representative sample of aged, disabled, and institutionalized Medicare beneficiaries. The MCBS attempts to interview each respondent 12 times over three years, regardless of whether he or she resides in the community or a facility or transitions between community and facility settings. The disabled (under 65 years of age) and oldest-old (85 years of age or older) are over-sampled. The first round of interviewing was conducted in 1991. Originally, the survey was a longitudinal sample with periodic supplements and indefinite periods of participation. In 1994, the MCBS switched to a rotating panel design with limited periods of participation. Each fall, a new panel is introduced, with a target sample size of 12,000 respondents, and each summer a panel is retired. Institutionalized respondents are interviewed by proxy. The MCBS contains comprehensive self-reported information on the health status, health care use and expenditures, health insurance coverage, and socioeconomic and demographic characteristics of the entire spectrum of Medicare beneficiaries. We use data from the 1992-2000 MCBS in the analysis.

Measuring Spending

Our primary dependent variables are Medicare Part A spending[5], Medicare Part B spending[6], and prescription drug spending by Medicare beneficiaries. Medicare Part A and Part B spending is based on Medicare claims data, linked to the MCBS. Medicare

[5]Medicare Part A covers care in hospitals as an inpatient, critical access hospitals (small facilities that give limited outpatient and inpatient to people in rural areas), skilled nursing facilities, hospice care, and some home health care.
[6]Medicare Part B covers doctor's services, outpatient hospital care, and some other medical services that Part A does not cover, such as the services of physical and occupational therapists, and some home health care. Medicare Part B helps pay for these covered services and supplies when they are medically necessary.

Part A and Part B spending in different years is adjusted using the Consumer Price Index and reported in 2000 dollars. Prescription drug spending is based on respondent self-reports and may be underreported. The CMS Office of the Actuary compared self-reporting of expenses associated with physician office visits with Medicare claims records and found underreporting of 33%. This result has led the Congressional Budget Office (CBO) and others to assume drug expenditures are underreported by a similar amount. However, because drugs are more salient (and regular) than physician office visits, they are less likely to be underreported. Subsequent analyses by CMS staff suggest drug expenses are probably underreported by 10–15%. This estimate is based on examining records from people who were known to have accurate self-reported data—that is, people who reported the same patterns of Part A and B utilization as indicated by the claims records. Using this sub-sample, CMS developed an imputation scheme for drug expenses. A comparison of imputed expenditures for the entire MCBS sample with actual reported expenditures yielded the 10–15% estimate. As such, we assume that total drug expenses are underreported by 15% in all our analyses (Goldman et al., 2002).

Measuring Insurance Coverage

Medicare and Medicaid coverage is based on administrative records. In addition, up to five plans are reported based on questions about plan type (private employer-sponsored, Medigap, private unknown, private HMO or Medicare HMO), start and end date, number of people covered, annual premium, prescription drug benefit, and nursing home care. Because the exact benefit structure is unavailable, all insurance measures are dummy variables.

Measuring Health

We focus on major disease conditions, functional status, and risk factors that are known to be strongly associated with prescription drug and medical spending. Conditions include diabetes, cancer (excluding skin cancer), heart disease (myocardial infarction, heart attack, angina, coronary heart disease, congestive heart failure, or other heart condition), hypertension, stroke, lung disease (emphysema, asthma, or chronic obstructive pulmonary disease), Alzheimer's disease, and osteoarthritis. Functional status is typically measured by limitations in Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs) in empirical studies. ADLs are defined as any difficulty dressing, eating, bathing, getting in/out of chair, walking, and using toilet or being bedridden. IADLs are defined as any difficulty using the phone, doing light housework, doing heavy housework, making meals, shopping, or managing money. Risk factor measures include current smoking and obesity (defined as BMI over 30). Self-reported overall health is rated from 1 to 5 (1= excellent, 2=very good, 3=good, 4=fair, and 5=poor). Other variables included in our analysis are age, gender, race, education, metropolitan area (urban), and income.

We dropped beneficiaries from our data who were under 65, had partial or no Medicare coverage, were in Medicare HMOs or Medicaid, resided in nursing home facilities, were currently employed, or had multiple supplemental insurances. All the remaining beneficiaries in our data had a Medigap plan with or without a prescription drug benefit as their only supplemental insurance. The Omnibus Budget Reconciliation Act (OBRA) of 1990 requires that Medigap plans be standardized in as many as ten different benefit packages offering varying levels of supplemental coverage. All policies sold since July 1992 (except in three exempted states: Massachusetts, Minnesota, and Wisconsin)[1] have conformed to one of these ten standardized benefit packages, known as plans A to J. Plans H, I and J have prescription drug benefits. A high-deductible option is also available for plans F and J. Policies sold prior to July 1992 are not required to comply with these ten standard packages. Medigap plans with and without prescription drug benefits, on average, have similar coverage for non-drug medical care (Table 1).

Table 2 shows the descriptive statistics of the beneficiaries in our data by Medigap plan type (with and without prescription drug benefits). Compared to those with prescription drug benefits, Medicare beneficiaries without drug benefits tend to be older, less educated, less likely to be in an urban area, and poorer. They are sicker in term of both self-reported overall health and histories of chronic diseases, with significantly higher prevalence of diabetes, cancer, and stroke. They have less prescription drug spending but more Medicare Part A spending.

The observed differences between those with prescription drug benefits and those without prescription drug benefits seem to indicate potential self-selection, but the direction is unclear. Richer and more educated beneficiaries are more likely to have prescription drug coverage and tend to have higher prescription drug spending; the sicker are less likely to have prescription drug coverage but they also tend to have higher prescription drug spending. The literature provides strong evidence of the presence of moral hazard in the Medigap market. The results on self-selection, however, are mixed. Wolfe and Goddeeris (1991) estimated health care utilization for Medicare beneficiaries and found that those with large past expenditures were more likely to hold private supplemental insurance. Ettner (1997) found that respondents who purchase private supplemental insurance use more physician services and have higher Medicare reimbursement, even after controlling for moral hazard. Hurd and McGarry (1997) found there was little relationship between observed health measures and the propensity to hold or purchase private insurance and argued that the differences in health care services reflect moral hazard rather than adverse selection. There is little direct evidence, but the literature seems to suggest adverse selection into prescription drug benefits (Pauly and Zeng, 2006).

The observed difference in health measures can also be the result of the improvement in health because of increased prescription drug use for people who had prescription drug benefits. If that is the case, the model with health measures as covariates would underestimate the reduction in Medicare Part A and Medicare Part B spending and overestimate the increase in prescription drug spending as a result of prescription drug benefits.

3 Empirical Specification

Medicare beneficiaries make their choice between Medigap plans with and without prescription drug benefits by maximizing their indirect utility. The utility index d^* is a function of sociodemographic characteristics, health status, exogenous shocks on Medigap market, and an individual unobserved component:

$$d^* = \alpha_0 + \alpha_1 X + \alpha_2 Z + \varepsilon_1$$

We do not directly observe d*. Instead, we observe individuals with drug benefits when $d^*>0$ and without drug benefits when $d^*\leq 0$.

$$d = \begin{cases} 1 \text{ if } d^* > 0 \\ 0 \text{ if } d^* \le 0 \end{cases}$$

Here, X denotes individual sociodemographic characteristics and health status; Z denotes exogenous shocks; and d is a dummy variable for prescription drug benefits. Sociodemographic characteristics include age, gender, race (white or nonwhite), marital status, college education or higher, urbanicity, and income. Health measures include ever-smoked, obesity, general health index[7], and chronic diseases, including cancer, heart disease, hypertension, stroke, lung disease, Alzheimer's disease, and osteoarthritis. We also include Adjusted Average Per Capita Cost (AAPCC) by county to control for regional difference in medical care costs. In addition, we include state and year fixed effects in our model.

The distribution of medical expenses has two characteristics (Duan, Manning, Morris and Newhouse 1982). First, there are many zero expenses. Second, the remaining positive expenses are highly skewed, but the positive expenses are approximately log-normally distributed through most of their range. The econometric and statistical literatures provide a number of models for dealing with this kind of data. We adopt a typical two-part structure in modeling spending. The first part models the probability of having positive spending and the second part uses a log-linear specification to model spending conditional on positive spending. The any spending equation is:

$$p^* = \beta_0 + \beta_1 X + \beta_2 d + \beta_3 d * Income + \varepsilon_2$$

[7]The construction of the health index is similar to Dor et al. (2003). The health index is a summary of self-reported overall health (1–5), number of IADL (0–6) and number of ADL (0–6). All three components are coded so that lower values indicate better health.

$$p = \begin{cases} 1 \text{ if } p^* > 0 \\ 0 \text{ if } p^* \leq 0 \end{cases}$$

Log spending conditional on positive spending:

$$\ln(Y \mid Y > 0) = \gamma_0 + \gamma_1 X + \gamma_2 d + \gamma_3 d * Income + \varepsilon_3$$

Here, Y denotes Medicare Part A spending, Medicare Part B spending, or prescription drug spending. We also include a variable for whether people have nursing home coverage to control for the generosity of their insurance coverage.

Identification

We use state reforms in the individual health insurance market as instrumental variables to address the endogeneity of prescription drug benefits. These state reforms were aimed at reducing the number of uninsured and increasing the availability and affordability of individual health insurance. These reforms include rate rating, pre-existing condition restrictions, guaranteed issues, guaranteed renewal, reinsurance, and minimum loss ratio and were mostly passed in the early to mid-1990s. Here, we focus on the two most dramatic measures: guaranteed issue and rate rating:

- *Guaranteed issue* requires health plans to offer coverage to all individuals, regardless of their health status or claims experience.
- *Rate rating* includes rating bands, very tight rating bands, and community rating. Rating bands restrict health plans' use of experience, health status, or duration of coverage in setting premium rates for individuals. Very tight rating bands allow very limited adjustment for experience, health status, and

duration. Community rating prohibits health plans' use of experience, health status, or duration of coverage in setting premium rates for individual coverage. Some community rating laws also prohibit the use of demographic factors in setting premium rates for individual coverage.

The impacts of these reforms are mixed. In states that adopted the most comprehensive reforms — guaranteed issue often combined with such other reforms as guaranteed renewability, rate rating, and strict limits on exclusions for pre-existing conditions — insurance became more widely available, although comprehensive reforms generally resulted in some carrier departures from individual health insurance markets and less choice of insurance products (Swartz, 2000). That is, fewer policies were available for people to purchase. Studies indicate that access to individual insurance policies for people at high risk clearly increased in the comprehensive reforms states of New Hampshire, New York, New Jersey, Vermont, and Washington.[8] The research thus provides some evidence that guaranteed issue of all policies assumes the availability of policies to anyone regardless of risk factors, such as health status and prior use of health services.

Community rating generally resulted in higher premiums on average, lower premiums for high-risk individuals, and higher premiums for low-risk enrollees (Swartz, 2000; Hall, 2000; and Kirk, 2000). States with more comprehensive reforms experienced a decrease in overall coverage rates (Zuckerman and Rajan, 1999; Percy, 2000; Sloan and Conover, 1998; and Marsteller et al., 1998). However, Buchmueller and DiNardo (2002),

[8]Institute for Health Policy Solutions, "State Experiences with Community Rating Reforms," Prepared for the Kaiser Family Foundation, September 1995; Maine Department of Professional and Financial Regulation, "White Paper: Maine's Individual Health Insurance Market," Prepared by the Staff of the Maine Bureau of Insurance, January, 2001

looking at how coverage rates changed in a comprehensive reform state, New York, compared to two states that did not enact such reforms, Pennsylvania and Connecticut, found that New York's community rating law was not responsible for changing the rate of coverage but was responsible for changing the nature of individual insurance from largely indemnity to HMO coverage.

In New York, the risk pool changed — average number of claims per policyholder and average age of policyholders increased (Hall, 2000). In New Jersey, the evidence suggests a more complicated picture, one in which age of enrollees increased but the health status of enrollees remained relatively good. Swartz and Garnick (2000) compared self-reported health status, age, and other risk characteristics of enrollees in individual policies compared with the state's uninsured and employer-covered populations after the New Jersey reforms were implemented. They found that enrollees with individual coverage were more likely to be older than the uninsured but also more likely to be healthier. Lo Sasso and Lurie (2003) analyzed data from the Bureau of Census Survey of Income and Program Participation (SIPP) and concluded that community rating reforms make healthy people less likely to be insured and unhealthy people more likely to be insured by individual polices; as a result, the enrollees with individual policies in community rating states were sicker.

Although these reforms may not have achieved their goal of reducing the number of uninsured and making health insurance more affordable, they nevertheless generate some exogenous shocks to the individual health insurance markets from both the supply side and the demand side. Past studies have exclusively focused on the effects of state reforms on coverage rate, premiums, and change in risk pool and found that sicker individuals are more likely to purchase health insurance in states with reforms. The empirical evidence is consistent with economic theory that sicker individuals would buy more insurance with more risk pooling, and we speculate it would be also true that sicker individuals are more likely to purchase health plans with more comprehensive coverage, such as plans with prescription drug benefits. While federal regulations in the Medigap market are very limited[9], state reforms in the individual health insurance market further limit health plans' ability of risk adjustment — denying coverage and/or setting high premiums for the sicker elderly. Elderly who did not get Medigap coverage can purchase it later and can postpone the decision of purchasing a Medigap plan. Elderly also can easily switch to another Medigap plan as they wish after the initial enrollment period.

In this paper, we will explore the fact that state reforms reduced coverage rates through both the demand side and supply side and that state reforms changed the risk pool of enrollees. Guaranteed issue and rate rating are unlikely to operate independently because, with guaranteed issue but not rate rating, health plans can simply charge prohibitive premiums to drive risky individuals out of the market. Likewise, with rate rating but not guaranteed issue, health plans can just refuse to offer a policy to potentially risky individuals. In states with guaranteed issue requirements, some kind of rate rating

[9]Federal law provides Medicare beneficiaries with guaranteed access to Medigap policies offered in their state of residence during an initial six-month enrollment period, which begins on the first day of the month in which an individual is 65 or older and is enrolled in Medicare Part B. During this initial open-enrollment period, an insurer cannot deny Medigap coverage for any plan types they sell to eligible individuals, place conditions on the policies, or charge a higher price because of past or present health problems. Additional federal Medigap protections include guaranteed issue rights, which provide beneficiaries over age 65 with access to plans A, B, C, or F in certain circumstances, such as when their employer terminates retiree health benefits or their Medicare + choice plan leaves the program or stops serving their areas. Individuals must apply for a Medigap plan no later than 63 days after their prior health coverage ends for these guarantees to apply. During the guaranteed-issue periods, no pre-existing conditions exclusion period may be applied.

was also enacted. Therefore, there are three types of states in our analysis: states with both guaranteed issue and rate rating; states with only rate rating; and states with neither.

For state reforms to be valid instruments, two conditions have to be met. First, they need to be a strong predictor of prescription drug coverage. Second, they need to be independent of unobserved determinants of health care spending. The first condition is testable, and we report the Wald statistics for joint significance of state regulations in predicting individual prescription drug coverage. The second condition cannot be tested directly. Although these reforms were primarily targeting the individual health insurance market for people under age 65 to reduce the number of uninsured, it may be a proxy for something else at the state level that is correlated with both state reforms and determinants of individual health care spending. We include state and year fixed effects in the model. Furthermore, if this is the case, then it should hold not only for Medigap coverage, but also for employer-sponsored coverage.

Table 3 shows the predictive power of state reforms on prescription drug benefits for both Medigap and employer-sponsored coverage. States reforms strongly predict prescription drug coverage for Medigap, but not for employer-sponsored coverage. So, while state reforms, on average, reduce the amount of insurance purchased in the Medigap market, they appear not to be approximating other state-level variables that also affect employer-sponsored drug benefits.

We further regress state reforms on lagged Medicare Part A spending, Medicare Part B spending, and prescription drug spending to see if states with reforms have different health care spending trends from states without reforms. Table 4 shows that past spending trends do not predict state reforms. It is also worth noting that the effects of state reforms on prescription drug benefits in our analysis are identified across states and over time because state reforms were enacted after 1992, the first period of our data.

Unobserved Individual Heterogeneity

The error terms in the three equations discussed earlier are likely to be correlated with each other, and we estimate them jointly to allow for this correlation. We adopt a modified version of the model in Mroz (1999), Goldman, Leibowitz, and Buchanan (1998), and Goldman et al. (2001) and assume all error terms have an unobservable heterogeneity component η:

$$\varepsilon_1 = \eta_1 + \upsilon_1$$

$$\varepsilon_2 = \eta_2 + \upsilon_2$$

$$\varepsilon_3 = \eta_3 + \upsilon_3$$

We assume that υ_1, υ_2 υ_3 and $\eta' s$ are independent, that υ_1 and υ_2 are standard normal errors and that υ_3 has mean zero and variance σ^2. Because the prescription drug benefit equation and any spending equation are binary choice models, the variances are not identified.

Miss-specifying a continuous distribution for unobserved individual heterogeneity would result in inconsistent parameter estimates. Discrete factor models have been widely used in the study of the effects of endogenous dummy variables on a continuous outcome with unobserved individual heterogeneity (Bhattacharya et al., 2003; Cutler, 1995; Goldman, 1995; Goldman, Leibowitz and Buchanan, 1998). Mroz (1999) found that when the true model has bivariate normal disturbances, estimators using discrete factor approximations compare favorably to efficient estimators in terms of both precision and bias; these approximation estimators dominate all the other estimators examined when the disturbances are non-normal. A discrete factor model also significantly simplifies the likelihood function and reduces the computational burden of the estimation.

We adopt a semi-parametric approach to model the correlation among error terms and assume that η_1, η_2 and η_3 can each take one of three values ($\eta_{11}, \eta_{12}, \eta_{13}$), ($\eta_{21}, \eta_{22}, \eta_{23}$), ($\eta_{31}, \eta_{32}, \eta_{33}$) with probability p_1, p_2 and p_3=1- p_1 - p_2 , respectively. This implies that there are three types of people. Being each type has different effects on drug coverage and health care utilization, ($\eta_{11}, \eta_{12}, \eta_{13}$) for drug coverage, ($\eta_{21}, \eta_{22}, \eta_{23}$) for probability of any health care spending, and ($\eta_{31}, \eta_{32}, \eta_{33}$) for health care spending conditional on positive spending. For example, there is a p_1 probability for someone to be type 1, which would imply realization of η_{11} for drug coverage, η_{21} for probability of any spending, and η_{31} for spending conditional on positive spending. Reasons for the differences among three types of people can be contributed to unobserved health characteristics, risk preference, discount rate, life-style preference, etc.

Since all three equations have intercept terms, we normalize the mean of each heterogeneity component to be zero[10]. This model allows non-zero covariance across three error terms with the following variance-covariance structure:

$$\begin{bmatrix} 1+\sum_{k=1}^{3} p_k(\eta_{1k})^2 & \sum_{k=1}^{3} p_k\eta_{1k}\eta_{2k} & \sum_{k=1}^{3} p_k\eta_{1k}\eta_{3k} \\ & 1+\sum_{k=1}^{3} p_k(\eta_{2k})^2 & \sum_{k=1}^{3} p_k\eta_{2k}\eta_{3k} \\ & & \sigma^2+\sum_{k=1}^{3} p_k(\eta_{3k})^2 \end{bmatrix}$$

Then, it is straightforward to write the likelihood function for individual i by integrating over the distribution of the unobserved error components:

$$\begin{aligned} l_i = \sum_{k=1}^{3} p_k\{ & (\Phi[\alpha_0+\alpha_1 Z+\alpha_2 X+\eta_{1k}])^d \times (1-\Phi[\alpha_0+\alpha_1 Z+\alpha_2 X+\eta_{1k}]]^{1-d}) \\ & \times (\Phi[\beta_0+\beta_1 X+\beta_2 d+\beta_3 d*Income+\eta_{2k}])^{(Y>0)} \\ & \times (1-\Phi[\beta_0+\beta_1 X+\beta_2 d+\beta_3 d*Income+\eta_{2k}])^{1-(Y>0)}) \\ & \times [\frac{1}{\sigma}\phi(\frac{\ln Y-\gamma_0-\gamma_1 X-\gamma_2 d-\gamma_3 d*Income-\eta_{3k}}{\sigma})]^{(Y>0)}\} \end{aligned}$$

And the log likelihood function is:

$$\ln L = \sum_{i=1}^{N} w_i \ln(l_i)$$

N is the sample size and w_i is the individual weight. Robust standard errors are reported for our coefficient estimates.

[10]For example, the third support in the prescription drug benefit equation can be written as a function of the other two supports and probabilities of each support:

$$\begin{aligned} & E(\eta_1)=0 \\ & \Rightarrow p_1\eta_{11}+p_2\eta_{12}+(1-p_1-p_2)\eta_{13}=0 \\ & \Rightarrow \eta_{13}=-(p_1\eta_{11}+p_2\eta_{12})/(1-p_1-p_2) \end{aligned}$$

Simulation

Because we adopt a two-part model structure for our spending equations, it is difficult to interpret the magnitude of the parameter estimates directly. Furthermore, the net effect is unclear when the coefficient on the first part of the two-part model has the opposite sign from the coefficient on the second part. We simulate the average effects of prescription drug benefits on prescription drug spending, on Medicare Part A spending, and on Medicare Part B spending. The probability of having positive spending is straightforward except we need to integrate over the discrete factor:

$$\begin{aligned}\hat{P}(Y>0) &= \int \hat{P}(Y>0 \mid \eta_2)\,dF(\eta_2) \\ &= \int \Phi(\hat{\beta}_0 + \hat{\beta}_1 X + \hat{\beta}_2 d + \hat{\beta}_3 d * Income + \eta_2)\,dF(\eta_2) \\ &= \sum_{j}^{3} p_j * \Phi(\hat{\beta}_0 + \hat{\beta}_1 X + \hat{\beta}_2 d + \hat{\beta}_3 d * Income + \hat{\eta}_{2,j})\end{aligned}$$

We use the non-parametric smearing estimates (Duan et al., 1983) to retransform the spending conditional on positive spending from log term to normal term.

$$\begin{aligned}\hat{E}(Y \mid Y>0) &= \int \exp(\hat{\gamma}_0 + \hat{\gamma}_1 X + \hat{\gamma}_2 d + \hat{\gamma}_3 d * Income + \varepsilon_3)\,d\hat{F}_n(\varepsilon_3) \\ &= \frac{1}{\sum w_i} \sum_{i=1}^{N} w_i * \exp(\hat{\gamma}_0 + \hat{\gamma}_1 X + \hat{\gamma}_2 d + \hat{\gamma}_3 d * Income + \hat{\varepsilon}_{3,i}) \\ &= \exp(\hat{\gamma}_0 + \hat{\gamma}_1 X + \hat{\gamma}_2 d + \hat{\gamma}_3 d * Income) * \frac{1}{\sum w_i} \sum_{i=1}^{N} w_i * \exp(\hat{\varepsilon}_{3,i})\end{aligned}$$

This calculation is done by percentiles (1^{st}, 5^{th}, 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}, 95^{th}, 99^{th}) of the residuals to better account for heteroscedasticity, and the predicted values well re-produce the mean spending.

Then, the expected spending is:

$$\hat{E}(Y) = \hat{P}(Y > 0) * \hat{E}(Y \mid Y > 0)$$

4 Results

Table 5 reports the results from simple two-part models, which adjust for observed differences between elderly with drug benefits and elderly without drug benefits. We then use state reforms in the individual insurance market as instrumental variables to address potential self-selection and a discrete factor model to account for unobserved individual heterogeneity. Results are shown in Tables 6-8 for prescription drug spending, Medicare Part A spending, and Medicare Part B spending, respectively. In our model, we include interactions between state reforms and health (age and health index) to model changes in health status mix among Medigap enrollees in states with reforms.

In the insurance choice model, state regulations and its interactions with age significantly predict prescription drug benefits with p-values around 0.0001. Guaranteed issue and rate rating together increase the likelihood of prescription drug benefits for younger elderly and reduce the likelihood of prescription drug benefits for older elderly (Figure 1). The likely explanation is that when health plans are prohibited from using health status and history of claims in their decisions about offering insurance and in setting premium, age is the best available alternative to sort the elderly by their health status. Rate rating alone reduces the likelihood of prescription drug benefits, but it does not vary much with age, which is consistent with the view that, with rate rating but not guaranteed issue, health plans simply deny offering insurance to sicker elderly, and, therefore, there is no need to use age as an indicator of health status. Interactions between health and regulations seem to suggest that the less healthy are more likely to have prescription drug benefits in states with regulations, but the effects are small.

The effects of prescription drug benefits on the probability of having any prescription drug spending increase with income, and the effects of prescription drug benefits on prescription drug spending conditional on positive spending decrease with income. Medicare beneficiaries with prescription drug benefits are less likely to have positive drug spending (when income is less than $34,000), but incur more drug spending conditional on positive spending (when income is less than $333,000). These two effects are either too small or cancel each other out and the net effects of prescription drug benefits on prescription drug spending do not appear to vary much with income (Figure 2), although prescription drug spending itself increases with income. The discrete factor estimates do not indicate a clear direction of self-selection in terms of unobservables.

The effects of prescription drug benefits on the probability of having any Medicare Part A spending increase with income and the effects of prescription drug benefits on Medicare Part A spending conditional on positive spending decrease with income. Medicare beneficiaries with prescription drug benefits are less likely to have positive Medicare Part A spending (when income is less than $80,600) and incur less Medicare Part A spending conditional on positive spending. The net effects of prescription drug benefits on Medicare Part A spending decrease with income (Figure 3). The results imply that a $10,000 dollar increase in income is associated with $47 decrease in the substitution effect between prescription drugs and Medicare Part A. The discrete factor estimates show that 70.3% of beneficiaries who are more likely to have prescription drug benefits, are more likely to have positive Medicare Part A spending, and incur more Medicare Part A spending conditional on positive spending. 25.1% of beneficiaries who are less likely to have prescription drug benefits, are less likely to have positive Medicare Part A spending, and incur less Medicare Part A spending conditional on positive spending. This indicates adverse selection into prescription drug benefit in terms of unobservables in the sense that those with prescription drug benefits consume more medical care covered by Medicare Part A than those without.

The effects of prescription drug benefits on the probability of having any Medicare Part B spending and on Medicare Part B spending conditional on positive spending increase with income. Medicare beneficiaries with prescription drug benefits are less likely to have positive Medicare Part B spending (when income is less than $36,000) and incur less Medicare Part B spending conditional on positive spending (when income is less than $66,000). The net effects of prescription drug benefits on Medicare Part B spending decrease with income (Figure 4). The results imply that a $10,000 dollar increase in income is associated with $35 decrease in the substitution effect between prescription drugs and Medicare Part B. The coefficients on drug benefits and its interactions with income are jointly insignificant. As in the drug spending model, discrete factor estimates do not indicate clear direction of self-selection in terms of unobservables.

Table 9 shows the simulated effects of prescription drug benefits on prescription drug spending, Medicare Part A spending, and Medicare Part B spending from the simple two-part model and from the discrete factor model. The simple two-part model adjusts for observables and the results show that prescription drug benefits increase drug spending by $157, reduces Medicare Part A spending by $135, and increases Medicare Part B spending by $31.

When both observables and unobservables are accounted for, prescription drug benefits increase drug spending by $148 or 22%. After adjusting for the underreporting of prescription drug spending in MCBS, our estimates suggest that prescription drug benefits increase drug spending by $148*(1+15%) = $170; prescription drug benefits decrease Medicare Part A spending by $350 or 13%; and prescription drug benefits decrease Medicare Part B spending by $74 or 4% although the estimates are statistically insignificant.

5 Discussion

Among patients with Medigap insurance, those in worse health—both observed and unobserved in the MCBS—self-select into prescription drug coverage. After controlling for this selection, our results indicate that prescription drugs and medical services covered by Medicare Part A and Medicare Part B are substitutes. Furthermore, these substitution patterns are underestimated when one does not control for this adverse selection. Each $1 increase in drug spending is associated with a steady-state $2.06 decrease in Medicare Part A spending and $0.44 decrease in Medicare Part B spending. Thus, it appears that Medicare beneficiaries may have been overinsured with respect to medical services, and underinsured with respect to prescription drugs. Medicare beneficiaries without drug benefits had the incentive to substitute prescription drugs with cheaper (to them, but not to Medicare) Medicare covered services (Medicare Part A and

Part B). This suggests that Medicare Part D could potentially remove the incentive and improve the overall efficiency of health care utilization among the elderly.

We find that the substitution effect decreases with income; therefore, prescription drug benefits would result in more cost savings among the poor. The simple explanation is that prescription drug spending increases with income and the substitution effect decreases with prescription drug use. The increase in prescription drug use from prescription drug benefits for people with higher income is more likely to be from increased use of non-essential drugs; therefore, it has less effect on health and inpatient and outpatient care. Our results suggest that providing prescription drug benefits to the poor would result in more cost savings and, thus, provide support for the low-income assistance program of Medicare Part D.

Prior studies on the Medicare population found that prescription drug benefits either have no effect on Medicare Part A and Part B spending or increase Medicare Part A and Part B spending. There are two potential problems with these studies. First, they included beneficiaries with various types of drug coverage in their analysis and, therefore, could not adequately address the self-selection into these different types of drug coverage. For example, beneficiaries who have public drug coverage, mainly Medicaid drug coverage, are less healthy, less educated, and poor, and beneficiaries who have HMO drug coverage are relatively healthy.

Second, the generosity of non-drug coverage matters because of the non-zero cross-price elasticities; and in many previous studies the populations have very different medical benefits as well as drug benefits. Our study focuses on beneficiaries that have

Medigap supplemental coverage with or without drug coverage and adopts a discrete factor model with instrumental variables to address the self-selection problem. Our results are consistent with studies using quasi-experimental designs on the non-elderly population (Goldman et al., 2004; Gaynor et al., 2006) and elderly population (Tamblyn et al., 2001). The no finding by Motheral et al. (2001) may be explained by the fact that switching from a two-tier prescription co-pay system to a three-tier prescription co-pay system only reduces prescription drug spending by about 10% and the study population still has a rather generous prescription drug benefit after the change.

Gaynor et al. (2006) also found dynamics in the response to cost-sharing increase. Their estimates imply that a $1 increase in prescription drug spending would result in a $0.23 decrease in outpatient spending in the first year after the prices changes and a $0.41 decrease in the second year after the price changes. They found that prescription drug prices have no significant effect on inpatient care in general but found large positive price effects for individuals who had positive inpatient care. Our estimates should be interpreted as the substitution effect at the steady state. Our estimate for the substitution effect between prescription drugs and outpatient care (Medicare Part B) is virtually identical to the estimate from Gaynor et al. (2006) in the second year after the price changes. Our finding of a significant substitution effect between prescription drugs and Medicare Part A (inpatient care) is consistent with their story that there is large substitution effect between prescription drugs and inpatient care for sick individuals, since Medicare beneficiaries are on average much sicker than working age adults. As prescription drugs become increasingly integral to medical treatment of many illnesses, looking at drug spending in isolation from the rest of health care spending and the efforts simply to reduce drug spending may result in inefficient overall health care utilization.

Reference

Bhattacharya, Jayanta, Dana Goldman and Neeraj Sood (2003), "The Link between Public and Private Insurance and HIV-related Mortality," Journal of Health Economics 22: 1105-1122

Buchmueller, Thomas and John DiNardo (2002), "Did Community Rating Induce an Adverse Selection Death Spiral? Evidence from New York, Pennsylvania and Connecticut," American Economic Review, 92(1): 280-294

Catlin, Aaron, Cathy Cowan, Stephen Heffler, Benjamin Washington (2007), "National Health Spending in 2005: The Slowdown Continues," Health Affairs 26(1): 142-153

Cole JA, Norman H, Weatherby LB, Walker AM (2006), "Drug copayment and adherence in chronic heart failure: effect on cost and outcomes," Pharmacotherapy 26(8):1157-1164

Congressional Budget Office (2004), "A detailed Description of CBO's Cost Estimate for the Medicare Prescription Drug Benefit," July

Cutler, David M. (1995), "The Incidence of Adverse Medical Outcomes under Prospective Payment," Econometrica 63 (1): 29-50

Dor, Avi, Joseph J. Sudano and David W. Baker (2003), "The Effects of Private Insurance on Measures of Health: Evidence from the Health and Retirement Study," NBER Working Paper 9774

Duan, Naihua (1983), "Smearing Estimate: a Nonparametric retransformation Method," Journal of the American Statistical Association 78(383): 605-610

Ettner, Susan (1997), "Adverse Selection and the Purchase of Medigap Insurance by the Elderly", Journal of Health Economics 16(5): 543-562

Fairman KA, Motheral BR, Henderson RR (2003), "Retrospective, long-term follow-up study of the effect of a three-tier prescription drug copayment system on pharmaceutical and other medical utilization and costs," Clinical Therapy 25(12): 3147-3161

Gaynor Martin, Jian Li and William Vogt (2006), "Is Drug coverage A Free Lunch? Cross-price Elasticities and the Design of Prescription Drug Benefits," NBER Working paper 12758

Gibson TB, Mark TL, Axelsen K, Baser O, Rublee DA, McGuigan KA (2006), "Impact of statin copayments on adherence and medical care utilization and expenditures," American Journal of Managed Care 12(special issue): 11-19

Goldman, Dana P. (1995), "Managed Care as a Public Cost-containment Mechanism," The RAND Journal of Economics 26 (2): 277-295

Goldman, Dana P., Geoffrey F. Joyce, and Jesse Dylan Malkin (2002) "The Costs of A Medicare Prescription Drug Benefit," Topics in Economic Analysis & Policy: Vol. 2: No. 1, Article 3

Goldman DP, J. Bhattacharya, DF McCaffrey, N. Duan, AA Leibowitz, GF Joyce, SC Morton (2001), "Effects of Insurance on Mortality in an HIV-Positive Population In Care." Journal of the American Statistical Association 96(445): 883-893

Goldman, Dana, Geoffrey Joyce, et al. (2004), "Pharmacy Benefits and the Use of Drugs by the Chronically Ill," Journal of the American Medical Association 291(19): 2344-2350

Goldman, Dana, Arleen Leibowitz and Joan Buchanan (1998), "Cost-Containment and Adverse Selection in Medicaid HMOs," Journal of the American Statistical Association 93(441): 54-62.

Goldman, Dana and Tomas Philipson (2007), "Integrated Insurance Design in the Presence of Multiple Medical Technologies," American Economic Review 97(2): 427-432

Goldman DP, Joyce GF, Karaca-Mandic P (2006), "Varying pharmacy benefits with clinical status: the case of cholesterol-lowering therapy," American Journal of Managed Care 12(1):21-28

Hall, Mark (1998), "An Evaluation of Ohio's Health Insurance Market Reforms," Wake Forest University School of Medicine

Hall, Mark (2000), "An Evaluation of New York's Reform Law," Journal of Health, Politics, Policy and Law 25(1); 71-99

Hsu J, Price M, Huang J, et al. (2006), "Unintended consequences of caps on Medicare drug benefits," New England Journal of Medicine 354(22):2349-2359

Hurd, Michael and McGarry, Kathleen (1997), "Medical Insurance and the Use of Health Care Services by the Elderly", Journal of Health Economics 16(2): 129-154

Johnson RE, Goodman MJ, Hornbrook MC, Eldredge MB (1997), "The effect of increased prescription drug cost sharing on medical care utilization and expenses of elderly health maintenance organization members," Medical Care 35(11): 1119-1131

Kirk, Adele (2000), "Riding the Bull: Experience with Individual Market Reform in Washington, Kentucky, and Massachusetts," Journal of Health Politics, Policy and Law 25(1): 133-173

Khan, Nasreen, Robert Kaestner and Swu Jane Lin (2007), “Prescription Drug Insurance and Its Effect on Utilization and Health of the Elderly,” NBER Working Paper 12848

Laschober, Mary, Michelle Kitchman, Patricia Neuman and Allison Strabic (2002), “Trends in Medicare Supplemental Insurance and Prescription Drug Coverage, 1996-1999,” Health Affairs – Web Exclusive

Lichtenberg, Frank (1996), “Do (More and Better) Drugs Keep People Out of Hospitals?” American Economic Review 86: 384-8

Lillard, Lee A., Jeannette Rogowski and Raynard Kington (1999), “Insurance Coverage for Prescription Drugs: Effects on Use and Expenditures in the Medicare Population,” Med Care 37: 926-936

Lingle, EW Jr, Kirk KW, Kelly WR (1987), “The impact of outpatient drug benefits on the use and costs of health care services for the elderly,” Inquiry 24(3): 203-211

Lo Sasso, Anthony and Lthai Lurie (2003), “The Effects of State Policies on the Market for Private Non-Group Health Insurance,” Unpublished manuscript

McWilliams, Michael J., Alan M. Zaslavsky, Ellen Meara and John Z. Ayanian (2003), “Impact of Medicare Coverage on Basic Clinical Services for Previously Uninsured Adults,” JAMA 290 (6): 757-764

Mahoney JJ (2005), “Reducing patient drug acquisition costs can lower diabetes health claims,” American Journal of Managed Care 11(5) (supplement): 170- 176

Motheral, Brenda, and Kathleen A. Fairman (2001), “Effects of a Three-tier Prescription Copay on Pharmaceutical and Other Medical Utilization,” Medical Care 39 (12): 1293-1304

Mroz, Thomas A. (1999), “Discrete Factor Approximation in Simultaneous Equation Models: Estimating the Impact of a Dummy Endogenous Variable on a Continuous Outcome,” Journal of Econometrics 92: 233-274

Newhouse, Joe (1993), “Free for All? Lessons from the Rand Health Insurance Experiment,” London, England: Harvard University Press

Pauly, Mark and Yuhui Zeng (2004), “Adverse Selection and the Challenges to Stand-Alone Prescription Drug Insurance,” Frontiers in Health Policy Research, Volume 7, Article 3

Percy, Allison (2000), “Community Rating and Regulatory Reform in the Small Group and Individual Health Insurance Markets,” Unpublished Manuscript

Sloan, Frank and Christopher Conover (1998), “Effects of State Reforms on Health Insurance Coverage of Adults,” Inquiry 35: 280-293

Smith DG, Kirking DM (1992), “Impact of consumer fees on drug utilization,” Pharmacoeconomics 2(4): 335-342

Soumerai SB, McLaughlin TJ, Ross-Degnan D, Casteris CS, Bollini P (1994), “Effects of a limit on Medicaid drug-reimbursement benefits on the use of psychotropic agents and acute mental health services by patients with schizophrenia,” New England Journal of Medicine 331(10): 650-655

Soumerai, Stephen, Dennis Ross-Degnan, Jerry Avorn, Thomas McLaughlin and Igor Choodnovskiy (1991), “Effects of Medicaid Drug-payment Limits on Admission to Hospitals and Nursing Homes,” The New England Journal of Medicine 15(325): 1072-1077

Swartz, Katherine and Deborah Garnick (2000), “Regulating Markets: Lessons from New Jersey,” Journal of Health Politics, Policy and Law 25 (1): 45-70

Tamblyn, Robyn, Rejean Laprise, James A. Hanley et al. (2001), “Adverse Events Associated With Prescription Drug Cost-sharing Among Poor and Elderly Persons,” JAMA 285 (4): 421-429

Wolfe, John and John Goddeeris (1991), “Adverse Selection, Moral Hazard, and Wealth Effects in the Medigap Insurance Market”, Journal of Health Economics, 10(4): 433-459

Yang, Zhou, Donna B. Gilleskie and Edward C. Norton (2004), “Prescription Drugs, Medical Care, and Health Outcomes: A Model of Elderly Health Dynamics,” NBER Working Paper 10964

Zuckerman, Stephen and Shruti Rajan (1999), “An Alternative Approach to Measuring the Effects of Insurance Market Reforms,” Inquiry 36: 44-56

Table 1: Medigap Plan Options[11]

Benefit	A	B	C	D	E	F	G	H	I	J
Basic Benefits	X	X	X	X	X	X	X	X	X	X
Skilled Nursing Co-Insurance			X	X	X	X	X	X	X	X
Part A Deductible		X	X	X	X	X		X	X	X
Part B Deductible			X			X				X
Part B Excess						X 100%	X 80%		X 100%	X 100%
Foreign Travel Emergency			X	X	X	X	X	X	X	X
At-Home Recovery				X			X		X	X
Basic Drugs								X $1250 Limit	X $1250 Limit	X $3000 Limit
Preventive Care					X					X

All plans include the Basic Benefits:

- Hospitalization: Part A coinsurance ($210 per day from 61st to 90th day and $420 from 91st to 150th day) plus coverage for 365 additional days after Medicare benefits end.
- Medical Expenses: Part B coinsurance (generally 20% of Medicare-approved expenses)
- Blood: First three pints of blood each year

Plans F and J also have an option called a high deductible Plan F and high deductible Plan J. These high deductible plans pay the same or offer the same benefits as Plans F and J after one has paid a calendar year $1,650 deductible. Benefits from high deductible plans F and J will not begin until out-of-pocket expenses are $1,650.

Out-of-pocket expenses for this deductible are expenses that would ordinarily be paid by the policy. These expenses include the Medicare deductibles for Part A and Part B, but do not include, in plan J, the plan's separate prescription drug deductible or, in plans F and J, the plans' separate foreign travel emergency deductible.

[11] Source: http://insurance.mo.gov/consumer/senior/medsupp/options.htm
http://www.medicare.gov/Publications/Pubs/pdf/02110.pdf

Table 2: Descriptive Statistics

Variable	With drug benefit	Without drug benefit	Difference	
Age	75.142	75.611	-0.469	***
Male	0.385	0.387	-0.002	
Nonwhite	0.035	0.035	-0.000	
Married	0.565	0.567	-0.002	
College or above	0.139	0.097	0.043	***
Urban	0.674	0.647	0.027	***
Income/1,000	30.543	25.364	5.179	***
Self-reported health				
Excellent	0.195	0.167	0.028	***
Very good	0.297	0.287	0.010	
Good	0.292	0.323	-0.031	***
Fair	0.158	0.162	-0.003	
Poor	0.057	0.061	-0.004	
Number of IADLs	0.531	0.509	0.022	
Number of ADLs	0.593	0.630	-0.036	
Diabetes	0.135	0.152	-0.016	**
Cancer	0.185	0.205	-0.020	***
Heart disease	0.382	0.385	-0.003	
Stroke	0.090	0.106	-0.015	***
Alzheimer’s	0.019	0.019	-0.000	
Hypertension	0.533	0.540	-0.007	
Arthritis	0.579	0.581	-0.002	
Lung disease	0.135	0.137	-0.002	
Died	0.033	0.033	-0.000	
Current smoking	0.109	0.115	-0.005	
Obese	0.151	0.153	-0.002	
Nursing home coverage	0.237	0.180	0.057	***
Log AAPCC	5.917	5.921	-0.004	
Prescription drug spending	817	678	139	***
Medicare Part A spending	2,537	2,775	-238	
Medicare Part B spending	1,852	1,788	65	
N	3,394	15,218		

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%

Table 3: Prescription Drug Benefit and State Reforms in Individual Insurance Market

Variable	Medigap Drug Benefit Coefficient		Medigap Drug Benefit Std. Error	Employer-Sponsored Drug Benefit Coefficient		Employer-Sponsored Drug Benefit Std. Error
Age	-0.005	**	0.003	0.003	***	0.003
Male	-0.004		0.032	0.031	**	0.032
Nonwhite	-0.012		0.066	0.066	**	0.059
Married	-0.057	**	0.028	0.028	***	0.029
College and above	0.182	***	0.041	0.041		0.038
Urban	0.098	**	0.038	0.038	***	0.041
Income/1,000	0.001	***	0.000	0.000		0.000
Guaranteed Issue and rate rating	-0.086		0.060	0.060		0.065
Rate rating only	-0.363	***	0.133	0.133		0.148
Health Index	-0.001		0.004	0.005		0.005
Diabetes	-0.030		0.043	0.035		0.037
Cancer	-0.064	**	0.036	0.031		0.033
Heart Disease	0.033			0.026	**	0.028
Stroke	-0.107	***		0.040		0.046
Hypertension	0.006			0.025	*	0.027
Lung Disease	0.002			0.035		0.039
Arthritis	0.021			0.026	**	0.027
Alzheimer's	0.092			0.080		0.097
Current Smoking	-0.056			0.041		0.043
Obese	-0.020			0.036		0.038
Died	0.046		0.064	0.064		0.071
AAPCC (log)	-0.055		0.078	0.078	***	0.089
Year fixed-effects	Yes			Yes		
State fixed-effects	Yes			Yes		
Constant	-0.735	**	0.347	0.346	***	0.367

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%

Note: The sample for employer-sponsored drug benefit includes Medicare beneficiaries who had employ-sponsored supplemental coverage with/without drug benefit.

Table 4: Spending Trends and State Reforms

	Guaranteed-issue and rate-rating		Rate-rating only	
Part A spending, one year lag	0.004	0.003	0.003	0.003
	0.004	0.004	0.003	0.003
Part B spending, one year lag	-0.017	-0.018	-0.009	-0.010
	0.018	0.016	0.013	0.014
Drug spending, one year lag	0.001	-0.015	0.044	0.015
	0.045	0.042	0.029	0.036
Part A spending, two year lag		0.009		-0.002
		0.006		0.005
Part B spending, two year lag		-0.003		0.012
		0.018		0.016
Drug spending, two year lag		0.014		0.041
		0.049		0.047
State fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
P value for joint F statistic	0.805	0.455	0.411	0.776

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%

Note: The analysis here was performed in the state level. We computed the state average Medicare Part A, Medicare Part B and prescription drug spending by year for our study sample. For states with reforms, we dropped the years after the reforms were implemented. Linear probability models were used in the analysis.

Table 5: Estimates from Simple Two-Part Model

Variable	Any Drug Spending		Log Drug Spending		Any Part A Spending		Log Part A Spending		Any Part B Spending		Log Part B Spending	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Age	0.010 **	0.004	-0.009 ***	0.003	0.012 ***	0.003	-0.033 ***	0.004	0.014 ***	0.005	-0.024 ***	0.003
Male	-0.238 ***	0.046	-0.150 ***	0.036	0.079 **	0.034	0.065	0.048	-0.192 ***	0.049	-0.018	0.038
Nonwhite	-0.215 **	0.097	-0.082	0.076	-0.093	0.073	0.124	0.100	-0.160 *	0.090	-0.111	0.078
Married	0.097 **	0.043	0.004	0.031	-0.013	0.031	-0.035	0.044	0.128 ***	0.044	0.028	0.034
College or above	0.018	0.061	0.079	0.049	0.012	0.048	-0.009	0.080	0.192 ***	0.071	0.041	0.051
Urban	0.045	0.060	-0.084 **	0.041	-0.042	0.041	-0.012	0.060	-0.035	0.062	-0.070	0.047
Income/1,000	0.001	0.001	0.001 ***	0.000	-0.001	0.001	0.000	0.001	0.002	0.001	0.001 **	0.000
Health Index	0.076 ***	0.010	0.080 ***	0.005	0.116 ***	0.005	0.050 ***	0.006	0.045 ***	0.009	0.116 ***	0.005
Diabetes	0.397 ***	0.070	0.354 ***	0.033	0.218 ***	0.036	0.048	0.048	0.368 ***	0.072	0.266 ***	0.039
Cancer	0.301 ***	0.053	0.099 ***	0.033	0.213 ***	0.031	0.073 *	0.042	0.490 ***	0.060	0.493 ***	0.035
Heart Disease	0.552 ***	0.046	0.457 ***	0.027	0.354 ***	0.027	0.152 ***	0.041	0.414 ***	0.044	0.452 ***	0.030
Stroke	0.065	0.076	0.098 **	0.039	0.218 ***	0.038	0.000	0.051	0.108	0.078	0.092 **	0.043
Hypertension	0.719 ***	0.041	0.572 ***	0.029	0.086 ***	0.028	0.022	0.041	0.363 ***	0.041	0.078 **	0.031
Lung Disease	0.458 ***	0.070	0.354 ***	0.036	0.171 ***	0.036	-0.066	0.049	0.287 ***	0.068	0.282 ***	0.043
Arthritis	0.221 ***	0.038	0.081 ***	0.028	0.047 *	0.028	-0.064	0.040	0.282 ***	0.040	0.188 ***	0.031
Alzheimer’s	-0.115	0.141	-0.164 **	0.075	0.061	0.084	-0.083	0.088	-0.145	0.145	-0.305 ***	0.095
Current Smoking	-0.155 ***	0.054	-0.127 ***	0.044	-0.093 **	0.047	-0.106	0.074	-0.322 ***	0.055	-0.168 ***	0.054
Obese	0.008	0.056	0.047	0.035	-0.028	0.039	-0.191 ***	0.062	-0.174 ***	0.055	-0.014	0.045
Died	-0.775 ***	0.082	-0.842 ***	0.065	1.588 ***	0.070	0.439 ***	0.059	-0.105	0.102	0.683 ***	0.064
Nursing Home Coverage	0.048	0.045	0.019	0.031	0.048	0.033	0.037	0.050	0.076	0.047	0.069 **	0.035
AAPCC (Log)	0.167 *	0.120	0.259 ***	0.088	0.113	0.084	0.655 ***	0.125	0.330 ***	0.123	0.997 ***	0.095
Prescription Drug Benefit	-0.153 **	0.067	0.230 ***	0.040	-0.082 *	0.042	-0.017	0.053	-0.125 *	0.072	-0.005	0.045
Interaction with income/1,000	0.004 **	0.002	0.000	0.001	0.002 **	0.001	0.000	0.001	0.003	0.002	0.001	0.001
Year Fixed-effects	Yes		Yes		Yes		Yes		Yes		Yes	
State Fixed-effects	Yes		Yes		Yes		Yes		Yes		Yes	
Constant	-1.516 ***	0.450	4.256 ***	0.363	-3.394 ***	0.362	7.031 ***	0.555	-2.592 ***	0.489	1.389 ***	0.408

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%

Table 6: Discrete Factor Estimates on Prescription Drug Spending

Variable	Drug Benefit			Any Spending			Spending | Any		
	Coefficient		Std. Error	Coefficient		Std. Error	Coefficient		Std. Error
Age	-0.003		0.003	0.010	**	0.004	-0.012	***	0.002
Male	-0.005		0.031	-0.294	***	0.042	-0.086	***	0.022
Nonwhite	-0.013		0.066	-0.238	***	0.093	-0.046		0.045
Married	-0.053	*	0.028	0.099	**	0.039	0.010		0.019
College and above	0.179	***	0.041	0.010		0.060	0.080	***	0.032
Urban	0.099	***	0.038	0.013		0.055	-0.030		0.026
Income/1,000	0.001	***	0.000	0.001		0.001	0.001	***	0.000
Guaranteed-issue and rate rating	1.065	***	0.328						
Rate-rating only	-1.504	*	0.793						
Age*Guaranteed-issue	-0.015	***	0.004						
Age*Rate-rating	0.013		0.010						
Health Index* Guaranteed-issue	0.000		0.012						
Health Index*Rate-rating	0.035		0.027						
Health Index	-0.002		0.005	0.091	***	0.010	0.067	***	0.003
Diabetes	-0.033		0.035	0.463	***	0.066	0.254	***	0.020
Cancer	-0.063	**	0.031	0.328	***	0.048	0.083	***	0.020
Heart Disease	0.033		0.026	0.650	***	0.042	0.316	***	0.017
Stroke	-0.109	***	0.040	0.078		0.069	0.089	***	0.024
Hypertension	0.004		0.026	0.871	***	0.038	0.313	***	0.020
Lung Disease	0.002		0.035	0.523	***	0.066	0.260	***	0.022
Arthritis	0.022		0.026	0.236	***	0.035	0.061	***	0.018
Alzheimer's	0.098		0.081	-0.165		0.128	-0.113	**	0.054
Current Smoking	-0.056		0.041	-0.173	***	0.052	-0.104	***	0.031
Obese	-0.021		0.036	0.032		0.054	0.005		0.022
Died	0.048		0.065	-0.909	***	0.099	-0.609	***	0.054
Nursing Home Coverage				0.076	*	0.046	-0.003		0.021
AAPCC (log)	-0.048		0.078	0.236	**	0.113	0.209	***	0.057
Prescription Drug Benefit				-0.145	**	0.068	0.221	***	0.031
Interaction with income/1,000				0.004	**	0.002	-0.001		0.000
Year Fixed-effects	Yes			Yes			Yes		
State Fixed-effects	Yes			Yes			Yes		
Constant	-0.989	***	0.347	-1.287	***	0.500	5.043	***	0.241
First Support	0.071		0.073	3.842	***	0.571	-3.080	***	0.077
Second Support	-0.081	*	0.043	3.016	***	0.694	-1.168	***	0.059
Third Support	0.017	†		-0.971	†		0.461	†	
Probability of First Support	0.041	***							
Probability of Second Support	0.194	***							
Probability of Third Support	0.765	‡							
Standard Error							0.712	***	0.010

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%

†: Computed as the following: $\eta_{13} = -(p_1\eta_{11} + p_2\eta_{12})/(1 - p_1 - p_2)$

‡: Computed as the following: $p_3 = 1 - p_1 - p_2$

Table 7: Discrete Factor Estimates on Medicare Part A Spending

Variable	Drug Benefit Coefficient		Drug Benefit Std. Error	Any Spending Coefficient		Any Spending Std. Error	Spending | Any Coefficient		Spending | Any Std. Error
Age	-0.003		0.003	0.015	***	0.003	-0.032	***	0.004
Male	-0.004		0.031	0.091	**	0.037	0.059		0.040
Nonwhite	-0.011		0.066	-0.104		0.077	0.087		0.085
Married	-0.055	**	0.028	-0.014		0.034	-0.068	*	0.039
College and above	0.179	***	0.041	0.014		0.053	0.017		0.066
Urban	0.098	**	0.038	-0.054		0.046	0.010		0.052
Income/1,000	0.001	***	0.000	-0.001		0.001	0.000		0.000
Guaranteed-issue and rate rating	1.069	***	0.330						
Rate-rating only	-1.518	*	0.799						
Age*Guaranteed-issue	-0.015	***	0.004						
Age*Rate-rating	0.013		0.011						
Health Index* Guaranteed-issue	0.000		0.012						
Health Index*Rate-rating	0.035		0.027						
Health Index	-0.001		0.005	0.153	***	0.011	0.064	***	0.006
Diabetes	-0.034		0.035	0.238	***	0.040	0.038		0.042
Cancer	-0.065	**	0.031	0.256	***	0.039	0.073	**	0.037
Heart Disease	0.034		0.026	0.416	***	0.033	0.127	***	0.034
Stroke	-0.109	***	0.040	0.279	***	0.049	0.020		0.045
Hypertension	0.005		0.026	0.091	***	0.031	0.036		0.034
Lung Disease	0.001		0.036	0.195	***	0.043	-0.061		0.041
Arthritis	0.023		0.026	0.056	*	0.031	-0.027		0.035
Alzheimer's	0.099		0.081	0.142		0.106	-0.079		0.076
Current Smoking	-0.056		0.041	-0.118	**	0.052	-0.059		0.062
Obese	-0.019		0.036	-0.023		0.043	-0.103	**	0.049
Died	0.047		0.065	3.010	***	0.552	0.585	***	0.058
Nursing Home Coverage				0.060		0.038	0.029		0.042
AAPCC (log)	-0.048		0.078	0.110		0.096	0.655	***	0.108
Prescription Drug Benefit				-0.202	**	0.092	-0.029		0.050
Interaction with income/1,000				0.003	*	0.001	-0.000		0.001
Year Fixed-effects	Yes			Yes			Yes		
State Fixed-effects	Yes			Yes			Yes		
Constant	-0.995	***	0.348	-4.477	***	0.475	6.566	***	0.477
First Support	0.063		0.049	0.868	***	0.194	0.354	***	0.060
Second Support	0.016		0.171	0.186		0.224	-3.212	***	0.168
Third Support	-0.180	†		-2.463	†		-0.406	†	
Probability of First Support	0.703	***							
Probability of Second Support	0.046	***							
Probability of Third Support	0.251	‡							
Standard Error							0.925	***	0.013

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%

†: Computed as the following: $\eta_{13} = -(p_1\eta_{11} + p_2\eta_{12})/(1 - p_1 - p_2)$

‡: Computed as the following: $p_3 = 1 - p_1 - p_2$

Table 8: Discrete Factor Estimates on Medicare Part B Spending

Variable	Drug Benefit		Any Spending		Spending | Any	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Age	-0.003	0.003	0.015 ***	0.004	-0.025 ***	0.002
Male	-0.004	0.031	-0.242 ***	0.045	0.058 **	0.028
Nonwhite	-0.011	0.066	-0.178 **	0.085	-0.072	0.063
Married	-0.055 **	0.028	0.147 ***	0.042	-0.010	0.025
College and above	0.180 ***	0.041	0.200 ***	0.066	0.002	0.037
Urban	0.098 **	0.038	-0.028	0.057	-0.065 *	0.036
Income/1,000	0.001 ***	0.000	0.002 **	0.001	0.000	0.000
Guaranteed-issue and rate rating	1.051 ***	0.328				
Rate-rating only	-1.513 *	0.795				
Age*Guaranteed-issue	-0.015 ***	0.004				
Age*Rate-rating	0.013	0.011				
Health Index* Guaranteed-issue	0.000	0.012				
Health Index*Rate-rating	0.033	0.027				
Health Index	-0.002	0.005	0.052 ***	0.010	0.112 ***	0.004
Diabetes	-0.031	0.035	0.404 ***	0.068	0.197 ***	0.031
Cancer	-0.064 **	0.031	0.563 ***	0.057	0.396 ***	0.026
Heart Disease	0.033	0.026	0.475 ***	0.042	0.334 ***	0.023
Stroke	-0.110 ***	0.040	0.128 *	0.071	0.045	0.034
Hypertension	0.007	0.026	0.402 ***	0.038	0.012	0.023
Lung Disease	0.001	0.035	0.346 ***	0.065	0.210 ***	0.031
Arthritis	0.021	0.026	0.342 ***	0.037	0.077 ***	0.024
Alzheimer’s	0.097	0.081	-0.180	0.140	-0.229 ***	0.078
Current Smoking	-0.057	0.041	-0.369 ***	0.052	-0.074 *	0.042
Obese	-0.021	0.036	-0.181 ***	0.053	0.017	0.032
Died	0.046	0.065	-0.040	0.113	0.665 ***	0.057
Nursing Home Coverage			0.084 *	0.049	0.054 *	0.028
AAPCC (log)	-0.050	0.078	0.454 ***	0.119	0.803 ***	0.070
Prescription Drug Benefit			-0.124	0.078	-0.064	0.056
Interaction with income/1,000			0.003	0.002	0.001	0.001
Year Fixed-effects	Yes		Yes		Yes	
State Fixed-effects	Yes		Yes		Yes	
Constant	-0.970 ***	0.347	-2.906 ***	0.745	2.859 ***	0.309
First Support	-0.064	0.047	0.345 **	0.502	-0.841 ***	0.048
Second Support	-0.005	0.061	7.494	9.570	-3.394 ***	0.060
Third Support	0.035 †		-0.732 †		0.778 †	
Probability of First Support	0.332 ***					
Probability of Second Support	0.058 ***					
Probability of Third Support	0.610 ‡					
Standard Error					0.910 ***	0.015

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%

†: Computed as the following: $\eta_{13} = -(p_1\eta_{11} + p_2\eta_{12})/(1 - p_1 - p_2)$

‡: Computed as the following: $p_3 = 1 - p_1 - p_2$

Figure 1: State Reforms and Prescription Drug Benefit

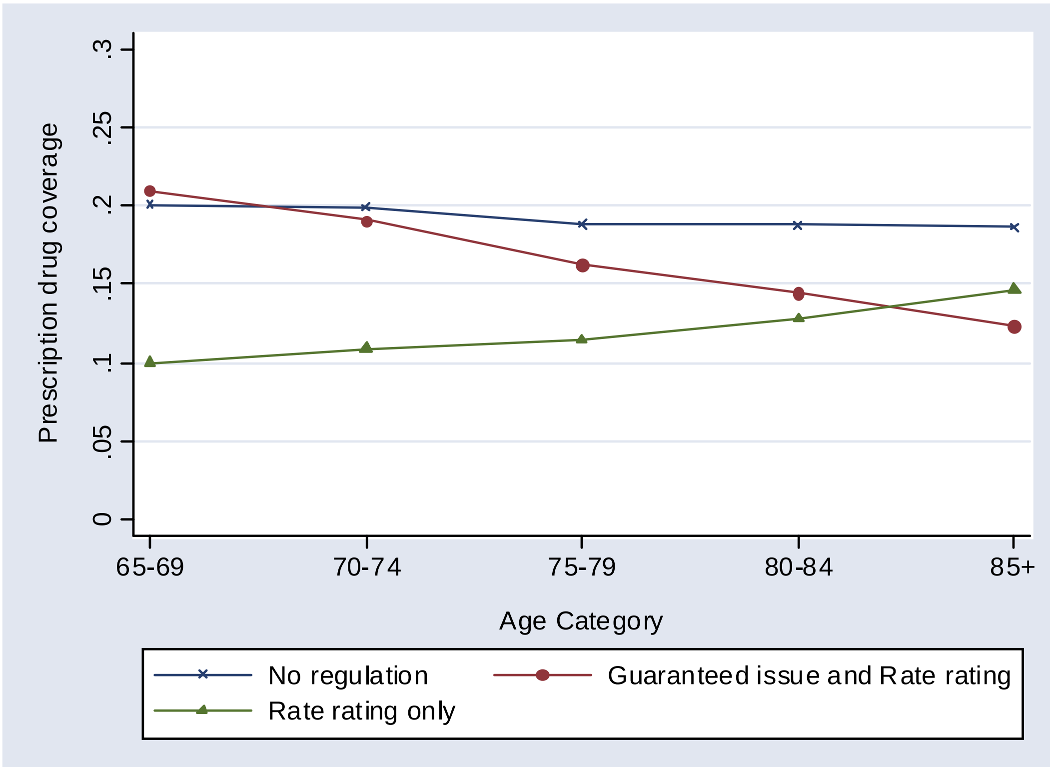

Figure 2: Increase in Prescription Drug Spending by Income

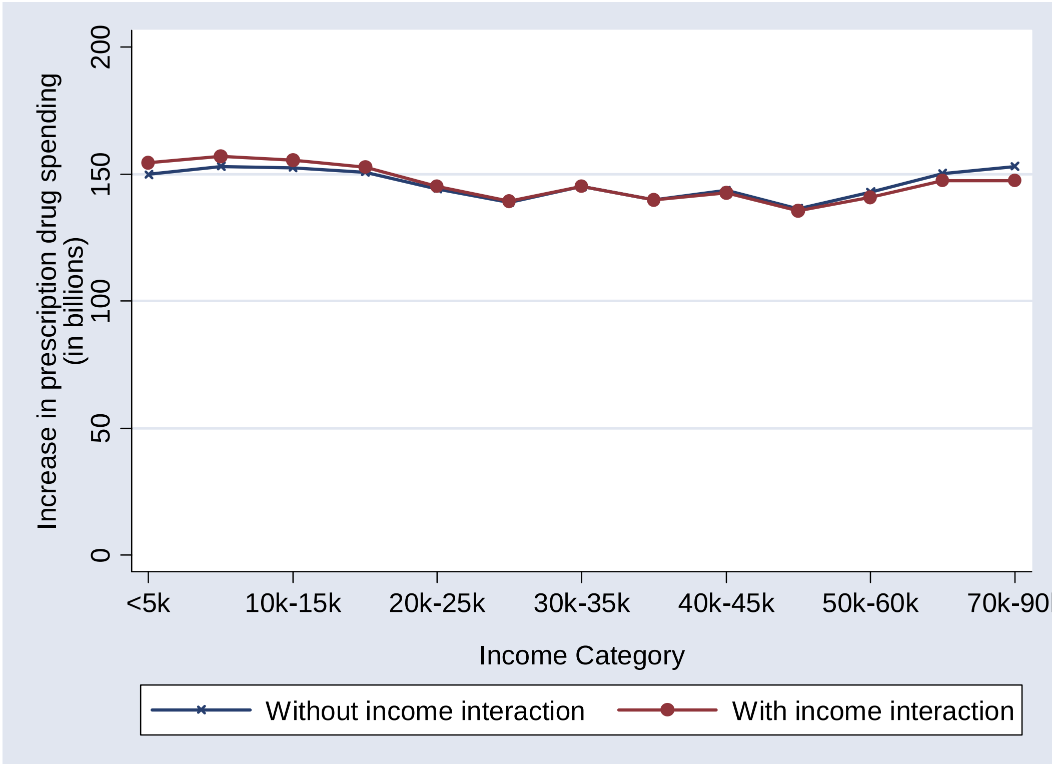

Figure 3: Cost Savings in Medicare Part A by Income

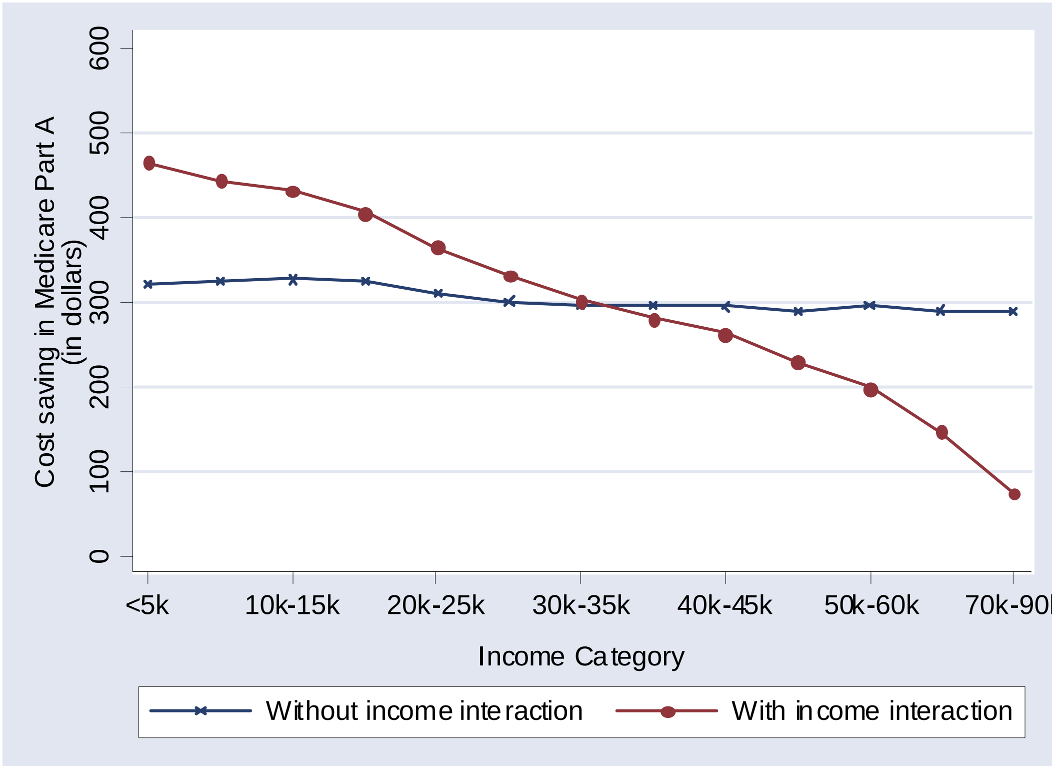

Figure 4: Cost Savings in Medicare Part B by Income

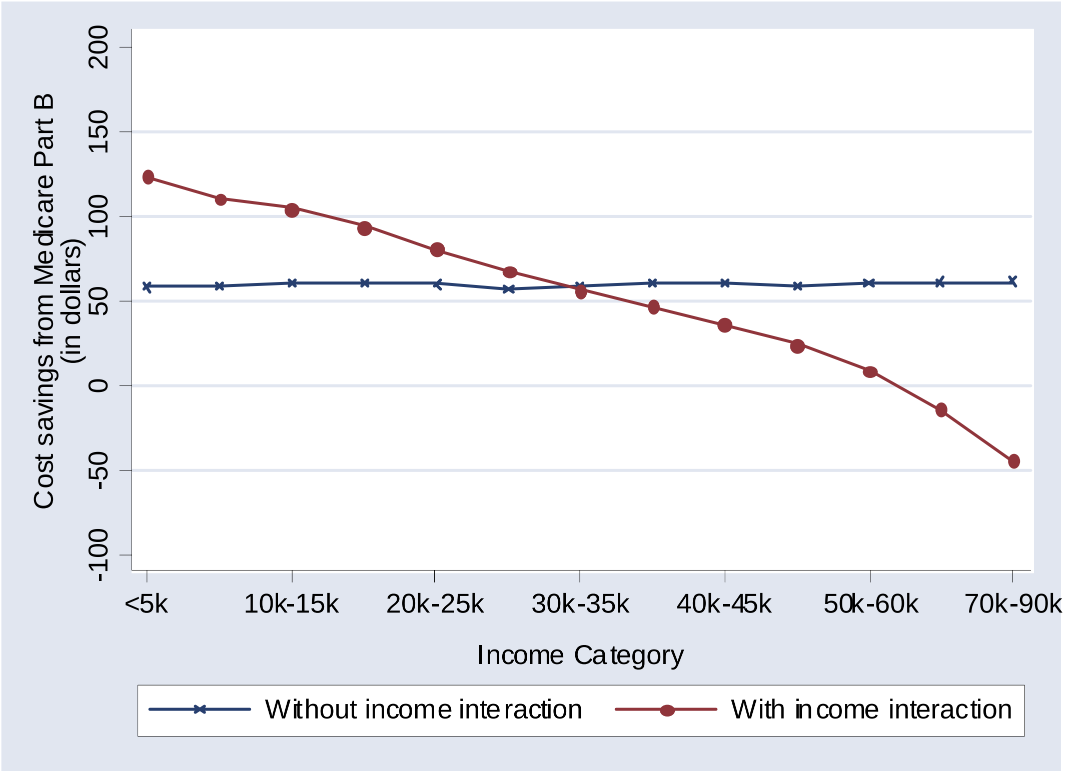

Table 9: Simulated Effects

	Model	With drug benefit	Without drug benefit	Difference
Prescription drug spending	Simple two-part model	$830	$673	$157
	Discrete factor with Income interaction	$821	$673	$148
Medicare Part A spending	Simple two-part model	$2,602	$2,737	-$135
	Discrete factor with Income interaction	$2,422	$2,772	-$350
Medicare Part B spending	Simple two-part model	$1,817	$1,786	$31
	Discrete factor with Income interaction	$1,729	$1,803	-$74