# Prescription Drug Coverage and Medicare Spending among U.S. Elderly* 

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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 to estimate how prescription drug benefits affect Medicare spending. We compare spending and service use for Medigap enrollees with and without drug coverage. Owing to 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. We find Medigap prescription drug coverage significantly increases drug spending and reduces Medicare Part A spending. Medigap prescription drug coverage reduces Medicare Part B spending, but the estimates are not statistically significant. Furthermore, the substitution effect decreases as income rises, and thus provides support for the low-income assistance program of Medicare Part D.
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## Introduction

The primary objective of the Medicare Prescription Drug, Improvement, and Modernization Act (MMA) was to provide seniors in the United States 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 programme. In March 2004, the Medicare Chief Actuary testified before the House Ways and Means Committee of United States Congress that he was ordered by the (Centers for Medicare \& Medicaid Services) CMS Administrator to suppress his estimates of the ten-year cost of the programme, which were substantially greater than original Congressional Budget Office (CBO) estimates.

[^0]In fact, soaring costs have not materialised. According to the 2007 Medicare Trustees report, the average 2007 plan bid was about 10 per cent 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. Although 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. ${ }^{1}$

Medicare only partially covers medical services for seniors, and prescription drugs were not covered before $2006 .{ }^{2}$ Supplemental Medicare ${ }^{3}$ was designed to fill this gap. Beneficiaries could get prescription drug benefits from their former employers or from Medicaid or other public programmes, by enrolling in Medicare managed care, ${ }^{4}$ or by purchasing Medigap. ${ }^{5}$ Although many beneficiaries had some source of drug coverage, 38 per cent still had no coverage at all in 1999. ${ }^{6}$

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.

[^1]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 utilisation: the underuse of prescription drugs and the overuse of inpatient and outpatient care. ${ }^{7}$ Furthermore, to the extent that these cross-price elasticities vary by income, then overall efficiency could be improved by further subsidising the poor.

The RAND Health Insurance Experiment (HIE) found the cost-sharing response to prescription drugs ( $\varepsilon=-0.27$ ) is similar to that of all ambulatory medical services ${ }^{8}$ in the non-elderly population. However, in the HIE, the pharmacy benefits perfectly covaried 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 quasiexperimental designs. Goldman et al. ${ }^{9}$ 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 hospitalisations. The findings from studies focusing solely on the chronically ill are unambiguous: for patients with congestive heart failure, ${ }^{10}$ lipid disorders, ${ }^{11}$ diabetes ${ }^{12}$ and schizophrenia, ${ }^{13}$ 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. ${ }^{14}$

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 found that higher cost-sharing is associated with adverse outcomes, ${ }^{15}$ particularly among vulnerable populations such as the elderly and poor. ${ }^{16,17}$ But most found 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., ${ }^{18}$ Motheral and Fairman, ${ }^{19}$ Johnson et al. ${ }^{20}$ and Smith and Kirking ${ }^{21}$ found that increased co-payments are not associated with more outpatient visits, hospitalisations

[^2]or emergency department visits. On the other hand, Gaynor et al. ${ }^{22}$ found that, for working age adults, 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 inpatient 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. ${ }^{23}$ 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. ${ }^{24}$ used a discrete factor model to control for unobserved individual heterogeneity and Khan et al. ${ }^{25}$ 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 distinguishes different sources of drug benefits. But even more importantly, none of these studies controls for the generosity of 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 medical benefits is not held constant. Stuart et al. ${ }^{26}$ found prescription drug coverage reduces inpatient and total Medicare spending using a propensity score approach, but the effects are statistically insignificant. One likely reason is the small sample size. Stuart et al. ${ }^{27}$ used drug coverage as instrument for drug use and found that increase in drug use is associated with reduction in hospital costs among Medicare beneficiaries. However, drug coverage could be endogenous even with the inclusion of strong control variables in the model.

Ideally, we can conduct a randomised control trial in which both the control group and treatment group have the same coverage for inpatient and outpatient care while only the treatment group has prescription drug coverage. Spending for prescription drugs, inpatient care and outpatient care from the two groups can be compared to estimate the effects of prescription drug coverage on prescription drug spending, inpatient spending and outpatient spending. 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. Although the Medigap prescription drug coverage may not be broadly representative, this study design has the appealing feature that medical benefits are completely known and are relatively homogeneous across plan types. Thus, the quasiexperimental 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

[^3]market $^{28}$ 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 US $\$ 1$ increase in prescription drug spending is associated with a US $\$ 2.06$ reduction in Medicare spending. Furthermore, the substitution effect decreases as income rises, and thus provides support for the low-income assistance programme of Medicare Part D.

## Data

The MCBS is a nationally representative sample of aged, disabled and institutionalised 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. Institutionalised respondents are interviewed by proxy. The MCBS contains comprehensive self-reported information on the health status, health care utilisation 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, Medicare Part B spending 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 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 selfreporting of expenses associated with physician office visits with Medicare claims records and found underreporting of 33 per cent. This result has led the 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 $10-15$ per cent. 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 utilisation 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 $10-15$ per cent estimate. As such,

[^4]we assume that total drug expenses are underreported by 15 per cent in all our analyses. ${ }^{29}$

## Measuring insurance coverage

Medicare and Medicaid coverage are based on administrative records. In addition, up to five plans are reported based on questions about plan type (private employersponsored, Medigap, private unknown, private HMO or Medicare HMO), start and end date, number of people covered, annual premium, prescription drug coverage, and nursing home coverage. 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 arthritis. 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 the toilets or being bedridden. IADLs are defined as any difficulty using the phone, doing light housework, doing heavy housework, making meals, shopping and 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 no or 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 standardised 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) have conformed to one of these ten standardised 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 nondrug medical care (Table 1).

[^5]Table 1 Medigap plan options

| 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 facility coinsurance ${ }^{\text {a }}$ |  |  | X | X | X | X | X | X | X | X |
| Part A deductible ${ }^{\text {a }}$ |  | X | X | X | X | X | X | X | X | X |
| Part B deductible ${ }^{\text {a }}$ |  |  | X |  |  | X |  |  |  | X |
| Part B balance billing ${ }^{\text {b }}$ |  |  |  |  |  | X | X |  | X | X |
| Foreign travel emergency |  |  | X | X | X | X | X | X | X | X |
| Home health care |  |  |  | X |  |  | X |  | X | X |
| Prescription drugs |  |  |  |  |  |  |  | X | X | X |
|  |  |  |  |  |  |  |  | US\$1,250 limit | US\$1,250 limit | US\$3,000 limit |
| Preventive care ${ }^{\text {c }}$ |  |  |  |  | X |  |  |  |  | X |
| Percentage enrolled, $1999{ }^{\text {d }}$ | 4 | 13 | 26 | 6 | 2 | 37 | 2 | 2 | 2 | 4 |

[^6]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 terms 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 risk 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 risk selection,

Table 2 Descriptive statistics

| Variable | With drug benefits | Without drug benefits | 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 |  |  |  |
| $\quad$ 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 | $0.057^{* * *}$ |
| AAPCC (Log) | 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 | 1588 | 65 |
| $N$ | 3,394 | 15,218 |  |

*Significant at 10 per cent; ${ }^{* *}$ Significant at 5 per cent; ${ }^{* * *}$ Significant at 1 per cent.
however, are mixed. Wolfe and Goddeeris ${ }^{30}$ estimated health care utilisation for Medicare beneficiaries and found that those with large past expenditures were more likely to hold private supplemental insurance. Ettner ${ }^{31}$ 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 ${ }^{32}$ 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 also evidence of advantageous selection into Medigap, and factors other than health status such as

[^7]income, education, cognitive ability and health plan attributes appear to be important in the demand for health insurance. ${ }^{33}$ There is little direct evidence, but the literature seems to suggest adverse selection into prescription drug benefits. ${ }^{34}$

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.

## Empirical specification

We assume that Medicare beneficiaries make their choice between Medigap plans with and without prescription drug benefits by maximising 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 $d^{*} \leqslant 0$.

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

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 current smoking, obesity, a general health index ${ }^{35}$ and chronic diseases, including cancer, heart disease, hypertension, stroke, lung disease, Alzheimer's disease and arthritis. We also include Adjusted Average Per Capita Cost (AAPCC) by county to control for regional differences in medical care costs. In addition, we include State and year fixed effects in our model.

The distribution of medical expenses has two characteristics. 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

[^8]dealing with this kind of data. We adopt a typical two-part structure in modelling 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:
\[

$$
\begin{gathered}
p^{*}=\beta_{0}+\beta_{1} X+\beta_{2} d+\beta_{3} d^{*} \text { Income }+\varepsilon_{2}, \\
p= \begin{cases}1, & \text { if } p^{*}>0 \\
0, & \text { if } p^{*} \leqslant 0\end{cases}
\end{gathered}
$$
\]

Log spending conditional on positive spending:

$$
\ln (Y \mid Y>0)=\gamma_{0}+\gamma_{1} X+\gamma_{2} d+\gamma_{3} d^{*} \text { Income }+\varepsilon_{3} .
$$

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 rating restrictions, pre-existing condition restrictions, guaranteed issue, 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 rating restrictions:

- Guaranteed issue requires health plans to offer coverage to all individuals, regardless of their health status or claims experience.
- Rating restrictions include 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.
Table 3 lists the reform States, types of reforms enacted and the year of implementation. 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, rating restrictions and strict limits on exclusions for pre-existing conditions - insurance became more widely available, although comprehensive reforms

Table 3 Summary of state health reforms

| State | Rating bands | Community rating | Guaranteed issue |
| :--- | :---: | :---: | :---: |
| IA | 1995 |  | 1995 |
| ID | 1994 | 1994 | 1994 |
| KY | $1993^{\text {b }}$ |  | $1994^{\text {a }}$ |
| LA |  | 1996 | 1996 |
| MA | 1992 | 1993 | 1993 |
| ME |  |  |  |
| MN |  | 1995 | 1994 |
| ND | 1999 | 1992 | 1992 |
| NH |  | $1995^{\text {c }}$ |  |
| NJ | 1992 | 1992 |  |
| NM | 1996 | 1993 | 1993 |
| NV | 1995 |  | 1996 |
| NY |  | 1992 | 1995 |
| OH | 1995 | 1993 | 1992 |
| OR |  |  | 1993 |
| SD |  |  |  |
| UT |  |  |  |
| VT |  |  |  |
| WA |  |  |  |
| WV |  |  |  |

${ }^{\text {a }}$ Guaranteed issue was appealed in 1999.
${ }^{\mathrm{b}}$ The law was not enforced.
${ }^{\text {c }}$ The Law was signed in 1998, but it was largely a formality.
generally resulted in some carrier departures from individual health insurance markets and less choice of insurance products. ${ }^{36}$ That is, fewer policies were available for people to purchase. There is suggested evidence that access to individual insurance policies for people at high risk increased in the comprehensive reforms States of New Hampshire, New York, New Jersey, Vermont and Washington. ${ }^{37}$ The research thus provides some evidence that guaranteed issue of all policies assures 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. ${ }^{36,38,39}$ States with more comprehensive reforms experienced a decrease in overall coverage rates. ${ }^{40}$ However, Buchmueller and DiNardo, ${ }^{41}$ looking at how coverage rates

[^9]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 policy-holder and average age of policy-holders increased. ${ }^{38}$ 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 ${ }^{36}$ compared self-reported health status, age and other risk characteristics of enrollees in individual policies 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 ${ }^{42}$ analysed 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. The empirical evidence is consistent with economic theory that sicker individuals would buy more insurance with more risk pooling, ${ }^{43}$ 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. Although federal regulations in the Medigap market are limited, ${ }^{44}$ State reforms in the individual health insurance market restrict 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 enrolment period.

[^10]As suggested by past studies, State reforms such as guaranteed issue and rating restrictions could potentially change coverage rates through both the demand side and the supply side, and also change the risk pool of enrollees. Guaranteed issue and rating restrictions are unlikely to operate independently because, with guaranteed issue but not rating restrictions, health plans can simply charge prohibitive premiums to drive risky individuals out of the market. Likewise, with rating restrictions but not guaranteed issue, health plans can just refuse to offer a policy to potentially risky individuals. ${ }^{45}$ In States with guaranteed issue requirements, some kind of rating restrictions were also enacted. Therefore, there are three types of States in our analysis: States with both guaranteed issue and rating restrictions; States with only rating restrictions; 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.

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 $\mathrm{Mroz}^{46}$ and Goldman et al. ${ }^{47,48}$ and assume all error terms have an unobservable heterogeneity component $\eta$ :

$$
\begin{aligned}
& \varepsilon_{1}=\eta_{1}+v_{1}, \\
& \varepsilon_{2}=\eta_{2}+v_{2}, \\
& \varepsilon_{3}=\eta_{3}+v_{3} .
\end{aligned}
$$

[^11]Table 4 Spending trends and State reforms

|  | Guaranteed-issue and rating <br> restrictions |  | Rating restrictions only |  |
| :--- | ---: | ---: | ---: | ---: |
|  | 0.004 | 0.003 | 0.003 | 0.003 |
| Part A spending, one-year lag | 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 |
|  |  | Yes |  | 0.047 |
| State fixed-effects | Yes | 0.455 | Yes |  |
| Year fixed-effects |  |  |  | Yes |
| $P$ value for joint F statistic | 0.805 |  | 0.411 | 0.776 |

*Significant at 10 per cent; ${ }^{* *}$ Significant at 5 per cent; ${ }^{* * *}$ Significant at 1 per cent.
Note: The analysis here was performed on 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.

We assume that $v_{1}, v_{2} v_{3}$ and $\eta^{\prime}$ s are independent, that $v_{1}$ and $v_{2}$ are standard normal errors and that $v_{3}$ has mean zero and variance $\sigma^{2}$. 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. ${ }^{47,49,50,51} \mathrm{Mroz}^{46}$ found that when the true model has bivariate normal disturbances, estimators using discrete factor approximations compare favourably 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 $\eta_{1}, \eta_{2}$ and $\eta_{3}$ can each take one of three values $\left(\eta_{11}, \eta_{12}, \eta_{13}\right)$, $\left(\eta_{21}, \eta_{22}, \eta_{23}\right),\left(\eta_{31}, \eta_{32}, \eta_{33}\right)$ 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 utilisation, $\left(\eta_{11}, \eta_{12}, \eta_{13}\right)$ for drug coverage,

[^12]$\left(\eta_{21}, \eta_{22}, \eta_{23}\right)$ for probability of any health care spending and $\left(\eta_{31}, \eta_{32}, \eta_{33}\right)$ 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 realisation of $\eta_{11}$ for drug coverage, $\eta_{21}$ for probability of any spending and $\eta_{31}$ 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 normalise the mean of each heterogeneity component to be zero. ${ }^{52}$ This model allows non-zero covariance across three error terms with the following variance-covariance structure:

$$
\left[\begin{array}{ccc}
1+\sum_{k=1}^{3} p_{k}\left(\eta_{1 k}\right)^{2} & \sum_{k=1}^{3} p_{k} \eta_{1 k} \eta_{2 k} & \sum_{k=1}^{3} p_{k} \eta_{1 k} \eta_{3 k} \\
& 1+\sum_{k=1}^{3} p_{k}\left(\eta_{2 k}\right)^{2} & \sum_{k=1}^{3} p_{k} \eta_{2 k} \eta_{3 k} \\
& & \sigma^{2}+\sum_{k=1}^{3} p_{k}\left(\eta_{3 k}\right)^{2}
\end{array}\right] .
$$

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

$$
\begin{aligned}
l_{i}= & \sum_{k=1}^{3} p_{k}\left\{\left(\Phi\left[\alpha_{0}+\alpha_{1} Z+\alpha_{2} X+\eta_{1 k}\right]\right)^{d}\right. \\
& \left.\left.\times\left(1-\Phi\left[\alpha_{0}+\alpha_{1} Z+\alpha_{2} X+\eta_{1 k}\right]\right]\right]^{1-d}\right) \\
& \times\left(\Phi\left[\beta_{0}+\beta_{1} X+\beta_{2} d+\beta_{3} d^{*} \text { Income }+\eta_{2 k}\right]\right)^{(Y>0)} \\
& \left.\times\left(1-\Phi\left[\beta_{0}+\beta_{1} X+\beta_{2} d+\beta_{3} d^{*} \text { Income }+\eta_{2 k}\right]\right)^{1-(Y>0)}\right) \\
& \left.\times\left[\frac{1}{\sigma} \phi\left(\frac{\ln Y-\gamma_{0}-\gamma_{1} X-\gamma_{2} d-\gamma_{3} d^{*} \text { Income }-\eta_{3 k}}{\sigma}\right)\right]^{(Y>0)}\right\}
\end{aligned}
$$

And the log likelihood function is

$$
\ln L=\sum_{i=1}^{N} w_{i} \ln \left(l_{i}\right)
$$

[^13]\[

$$
\begin{aligned}
& E\left(\eta_{1}\right)=0 \\
& \Rightarrow p_{1} \eta_{11}+p_{2} \eta_{12}+\left(1-p_{1}-p_{2}\right) \eta_{13}=0 . \\
& \Rightarrow \eta_{13}=-\left(p_{1} \eta_{11}+p_{2} \eta_{12}\right) /\left(1-p_{1}-p_{2}\right)
\end{aligned}
$$
\]

where $N$ is the sample size and $w_{i}$ is the individual weight. Robust standard errors are reported for our coefficient estimates.

## 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:

$$
\begin{aligned}
\hat{P}(Y>0) & =\int \hat{P}\left(Y>0 \mid \eta_{2}\right) \mathrm{d} F\left(\eta_{2}\right) \\
& =\int \Phi\left(\hat{\beta}_{0}+\hat{\beta}_{1} X+\hat{\beta}_{2} d+\hat{\beta}_{3} d^{*} \text { Income }+\eta_{2}\right) \mathrm{d} F\left(\eta_{2}\right) . \\
& =\sum_{j}^{3} p_{j}^{*} \Phi\left(\hat{\beta}_{0}+\hat{\beta}_{1} X+\hat{\beta}_{2} d+\hat{\beta}_{3} d^{*} \text { Income }+\hat{\eta}_{2, j}\right)
\end{aligned}
$$

We use the non-parametric smearing estimates ${ }^{53}$ to retransform the spending conditional on positive spending from log term to normal term.

$$
\begin{aligned}
\hat{E}(Y \mid Y>0)= & \int \exp \left(\hat{\gamma}_{0}+\hat{\gamma}_{1} X+\hat{\gamma}_{2} d+\hat{\gamma}_{3} d^{*} \text { Income }+\varepsilon_{3}\right) \mathrm{d} \hat{F}_{n}\left(\varepsilon_{3}\right) \\
= & \frac{1}{\sum w_{i}} \sum_{i=1}^{N} w_{i}^{*} \exp \left(\hat{\gamma}_{0}+\hat{\gamma}_{1} X+\hat{\gamma}_{2} d+\hat{\gamma}_{3} d^{*} \text { Income }+\hat{\varepsilon}_{3, i}\right) \\
= & \exp \left(\hat{\gamma}_{0}+\hat{\gamma}_{1} X+\hat{\gamma}_{2} d+\hat{\gamma}_{3} d^{*} \text { Income }\right)^{*} \\
& \frac{1}{\sum w_{i}} \sum_{i=1}^{N} w_{i}^{*} \exp \left(\hat{\varepsilon}_{3, i}\right)
\end{aligned}
$$

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

Then, the expected spending is:

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

[^14]
## 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 risk 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.
Most of the coefficient estimates make intuitive sense. For example, older beneficiaries are more likely to have positive expenditures, but incur less spending conditional on positive expenditures. This is consistent with the findings that doctors tend to treat older patients less aggressively. The results also indicate that obesity, smoking and Alzheimer's are sometimes associated with less spending after controlling for demographics and other measures of health status. There are several potential reasons. First, we have controlled for the diseases and disabilities which could be caused by obesity and smoking and the treatment options for Alzheimer's are still limited. Second, we cannot measure the severity of diseases and disabilities, and it is likely that obesity, smoking and Alzheimer's are associated with less severity of other health measures. Third, beneficiaries who smoke or are obese may not value their health as much as other beneficiaries and beneficiaries with Alzheimer's may not receive all the care they need because of limitations in their cognitive ability.
The first-stage IV estimates are shown in the drug benefit columns of Tables 6-8. Guaranteed-issue/rating restrictions, Rating restrictions only, and the interactions between age and guaranteed-issue/rating restrictions significantly predict prescription drug coverage. The first stage estimates of guaranteed-issue/rating restrictions, rating restrictions only, the interaction between age and guaranteed-issue/rating restrictions, the interaction between age and rating restrictions only, the interaction between health index and guaranteed-issue/rating restrictions, and the interaction between health index and rating restrictions only on prescription drug coverage are very similar across Tables 6-8, and the joint $\chi^{2}$ tests all have a $P$-value around 0.0001 .

Guaranteed issue and rating restrictions together and rating restrictions only, on average, reduce the likelihood of prescription drug coverage from 20.6 percentage points (no regulation) to 18.6 percentage points and to 12.3 percentage points respectively (Figure 1). The reduction in prescription drug coverage increases with age under guaranteed issue and rating restrictions together. 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. There is some evidence that the reduction in prescription drug coverage decreases with age under rate restrictions only (the coefficient on the interaction term between rating restrictions only and age is not statistically significant). 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.
Table 5 Estimates from simple two-part models

| 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 benefits | -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 per cent; **Significant at 5 per cent; *** Significant at 1 per cent.

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/rating restrictions | $1.065^{* * *}$ | 0.328 |  |  |  |  |
| Rating restrictions only | -1.504* | 0.793 |  |  |  |  |
| Age $\times$ Guaranteed-issue/rating restrictions | $-0.015^{* * *}$ | 0.004 |  |  |  |  |
| Age $\times$ Rating restrictions only | 0.013 | 0.010 |  |  |  |  |
| Health Index $\times$ Guaranteed-issue rating restrictions | 0.000 | 0.012 |  |  |  |  |
| Health Index $\times$ Rating restrictions only | 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 benefits |  |  | -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 | $0.017^{\text {a }}$ |  | $-0.971^{\text {a }}$ |  | $0.461{ }^{\text {a }}$ |  |
| Probability of first support | $0.041^{* * *}$ |  |  |  |  |  |
| Probability of second support | 0.194*** |  |  |  |  |  |
| Probability of third support | $0.765^{\text {b }}$ |  |  |  |  |  |
| Standard error |  |  |  |  | 0.712*** | 0.010 |

[^15]Table 7 Discrete factor estimates on Medicare Part A spending

| Variable | Drug benefit |  | Any spending |  | Spending/any |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Coefficient | Std. error | Coefficient | Std. error | Coefficient | Std. error |
| Age | -0.003 | 0.003 | 0.015*** | 0.003 | $-0.032^{* * *}$ | 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/rating restrictions | 1.069*** | 0.330 |  |  |  |  |
| Rating restrictions only | -1.518* | 0.799 |  |  |  |  |
| Age $\times$ Guaranteed-issue/rating restrictions | $-0.015^{* * *}$ | 0.004 |  |  |  |  |
| Age $\times$ Rating restrictions only | 0.013 | 0.011 |  |  |  |  |
| Health Index $\times$ Guaranteed-issue/ rating restrictions | 0.000 | 0.012 |  |  |  |  |
| Health Index $\times$ Rating restrictions only | 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 benefits |  |  | $-0.202^{* *}$ | 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 | $-0.180^{\text {a }}$ |  | $-2.463^{\text {a }}$ |  | $-0.406^{\text {a }}$ |  |
| Probability of first support | 0.703*** |  |  |  |  |  |
| Probability of second support | 0.046*** |  |  |  |  |  |
| Probability of third support | $0.251^{\text {b }}$ |  |  |  |  |  |
| Standard error |  |  |  |  | 0.925*** | 0.013 |

[^16]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/rating restrictions | $1.051^{* * *}$ | 0.328 |  |  |  |  |
| Rating restrictions only | -1.513* | 0.795 |  |  |  |  |
| Age $\times$ Guaranteed-issue/rating restrictions | $-0.015^{* * *}$ | 0.004 |  |  |  |  |
| Age $\times$ Rating restrictions only | 0.013 | 0.011 |  |  |  |  |
| Health Index $\times$ Guaranteed-issue/ rating restrictions | 0.000 | 0.012 |  |  |  |  |
| Health Index $\times$ Rating restrictions only | 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 benefits |  |  | -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 | $0.035^{\text {a }}$ |  | $-0.732^{\text {a }}$ |  | $0.778^{\text {a }}$ |  |
| Probability of first support | 0.332*** |  |  |  |  |  |
| Probability of second support | 0.058*** |  |  |  |  |  |
| Probability of third support | $0.610^{\text {b }}$ |  |  |  |  |  |
| Standard error |  |  |  |  | 0.910*** | 0.015 |

[^17]

Figure 1. State reforms and prescription drug coverage.


Figure 2. Increase in prescription drug spending by income.

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 US $\$ 34,000$ ), but incur more drug spending conditional on positive spending (when income is less than US $\$ 333,000$ ). 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 risk-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.


Figure 3. Cost savings in Medicare Part A by income.

Medicare beneficiaries with prescription drug benefits are less likely to have positive Medicare Part A spending (when income is less than US\$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 US $\$ 10,000$ dollar increase in income is associated with US\$47 decrease in the substitution effect between prescription drugs and Medicare Part A. The discrete factor estimates show that 70.3 per cent 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. A total of 25.1 per cent 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 US $\$ 36,000$ ) and incur less Medicare Part B spending conditional on positive spending (when income is less than US $\$ 66,000$ ). The net effects of prescription drug benefits on Medicare Part B spending decrease with income (Figure 4). The results imply that a US $\$ 10,000$ dollar increase in income is associated with US $\$ 35$ 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 riskselection 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


Figure 4. Cost savings in Medicare Part B by income.

Table 9 Simulated effects

|  | Model | With drug <br> benefits | Without drug <br> benefits | Difference |
| :--- | :--- | :---: | :---: | :---: |
| Prescription drug <br> spending | Simple two-part model | $\$ 830$ | $\$ 673$ | $\$ 157$ |
|  | Discrete factor with income <br> interaction | $\$ 821$ | $\$ 673$ | $\$ 148$ |
| Medicare Part A <br> spending | Simple two-part model | $\$ 2,602$ | $\$ 2,737$ | $-\$ 135$ |
|  | Discrete factor with income <br> interaction | $\$ 2,422$ | $\$ 2,772$ | $-\$ 350$ |
| Medicare Part <br> spending | Simple two-part model | $\$ 1,817$ | $\$ 1,786$ | $\$ 31$ |

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 US $\$ 157$, reduces Medicare Part A spending by US $\$ 135$ and increases Medicare Part B spending by US\$31.

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

## Discussion

Among beneficiaries with Medigap insurance, those in worse health-both observed and unobserved in the MCBS - are more likely to have prescription drug coverage. After controlling for this adverse 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 US\$1 increase in drug spending is associated with a steady-state US $\$ 2.06$ decrease in Medicare Part A spending and US\$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). ${ }^{54}$ This suggests that Medicare Part D could potentially remove the incentive and improve the overall efficiency of health care utilisation among the elderly. The substitution effect increases with the out-of-pocket price of prescription drugs and decreases with the out-of-pocket price of non-drug medical care. Medicare beneficiaries with Medigap supplemental coverage have very generous coverage on inpatient and outpatient care and very limited prescription drug benefits. Therefore, we expect a large substitution effect in this population. The substitution effect may differ considerably when Medicare beneficiaries face health insurance coverage with very different generosity levels.

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. Prescription drug benefits can provide low income beneficiaries the access to the essential drugs they need and increase their compliance; therefore, it has larger effects on their 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 programme 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 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 crossprice 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

[^18]Medigap supplemental coverage with or without drug coverage and adopts a discrete factor model with instrumental variables to address the selection problem. Our results are consistent with studies using quasi-experimental designs on the non-elderly population ${ }^{55,22}$ and elderly population. ${ }^{16}$ The no finding by Motheral and Fairman ${ }^{19}$ 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 per cent and the study population still has a rather generous prescription drug benefit after the change.

Gaynor et al. ${ }^{22}$ also found dynamics in the response to cost-sharing increase. Their estimates imply that a US\$1 increase in prescription drug spending would result in a US $\$ 0.23$ decrease in outpatient spending in the first year after the prices changes and a US $\$ 0.41$ 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. ${ }^{22}$ 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 utilisation.

This paper has several limitations as well. First, although Medigap plans with drug benefits and plans without drug benefits have very similar non-drug benefits, the nondrug benefits are not identical across plans. To the extent that plans with drug benefits have more generous non-drug benefits, we would underestimate the substitution effects. Second, the drug benefits in plan J are twice as generous as those in H and I, but we cannot distinguish them because most of Medigap enrollees did not provide plan letter in the MCBS. Third, we assume the under-reporting of drug use is random, and our substitution estimates are based on an assumption of 15 per cent underreporting of drug use. ${ }^{56}$

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[^19]Bundorf, K. and Simon, K. (2006) 'The effects of rate regulation on demand for supplemental health insurance', American Economic Review 96(2): 67-71.
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[^1]:    ${ }^{1}$ 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. 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.
    ${ }^{2}$ 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.
    ${ }^{3}$ Here supplemental Medicare refers to private/public policies that supplement Medicare by covering additional services or paying for part or all cost sharing under Medicare such as Medicaid and Medigap.
    ${ }^{4}$ Most Medicare-managed care plans have prescription drug benefits.
    ${ }^{5}$ Medigap is the short name for "Medicare Supplement Insurance" that is designed to fill some of the "gaps in coverage" left by Medicare.
    ${ }^{6}$ Laschober et al. (2002).

[^2]:    ${ }^{7}$ Goldman and Philipson (2007).
    ${ }^{8}$ Newhouse (1993).
    ${ }^{9}$ Goldman et al. (2007).
    ${ }^{10}$ Cole et al. (2006).
    ${ }^{11}$ Gibson et al. (2006) and Goldman et al. (2006).
    ${ }^{12}$ Mahoney (2005).
    ${ }^{13}$ Soumerai et al. (1994).
    ${ }^{14}$ Hsu et al. (2006).
    ${ }^{15}$ Lingle et al. (1987).
    ${ }^{16}$ Tamblyn et al. (2001).
    ${ }^{17}$ Soumerai et al. (1991).
    ${ }^{18}$ Fairman et al. (2003)
    ${ }^{19}$ Motheral and Fairman (2001).
    ${ }^{20}$ Johnson et al. (1997).
    ${ }^{21}$ Smith and Kirking (1992).

[^3]:    ${ }^{22}$ Gaynor et al. (2006).
    ${ }^{23}$ Lillard et al. (1999)
    ${ }^{24}$ Yang et al. (2004).
    ${ }^{25}$ Khan et al. (2007).
    ${ }^{26}$ Stuart et al. (2007).
    ${ }^{27}$ Stuart et al. (2008).

[^4]:    ${ }^{28}$ Sometimes it is also called non-group health insurance market.

[^5]:    ${ }^{29}$ Goldman et al. (2002).

[^6]:    ${ }^{\text {a }}$ Medigap plans C-J pay for skilled nursing facility coinsurance, plans B-J pay for Part A deducible and Plans C, F and J pay for Part B deductible.
    ${ }^{\mathrm{b}}$ Some providers do not accept the Medicare rate as payment in full and "balance bill" beneficiaries for additional amounts that can be no more than 15 per cent higher than the Medicare payment rate. Plan G pays 80 per cent of balance billing; plans F, I and J cover 100 per cent of these charges.
    ${ }^{\mathrm{c}}$ For Medicare Part B covered preventive care such as flu shots and mammography screening, Plan E and J pay 100 per cent of coinsurance after the Part B deductible has been paid, and pay for up to US\$120 a year for non-Medicare covered physicals, preventive tests and services.
    ${ }^{\mathrm{d}}$ The shares do not sum to 100 per cent due to rounding.
    Plans F and J also have a high-deductible option that requires the beneficiary to pay US\$1,580 before receiving Medigap coverage. This deductible is in addition to separate deductibles for prescription drugs (US\$250 per year for plan J) and foreign travel emergency (US\$250 per year for plans F and J) which are required in these plans with or without the high-deductible option.
    Plans H and I pay 50 per cent of drug charges up to US $\$ 1,250$ per year and have a US $\$ 250$ annual deductible. Plan J pays 50 per cent of drug charges up to US\$3,000 per year and has a US\$250 annual deductible.
    Source: www.gao.gov/new.items/d01941.pdf: Medigap Insurance: Plans Are Widely Available but Have Limited Benefits and May Have High Costs, July 2001.
    Basic benefits include coverage for Part A coinsurance, 365 additional hospital days during lifetime, Part B coinsurance and blood products.

[^7]:    ${ }^{30}$ Wolfe and Goddeeris (1991).
    ${ }^{31}$ Ettner (1997).
    ${ }^{32}$ Hurd and McGarry (1997).

[^8]:    ${ }^{33}$ Harris and Keane (1999); Fang et al. (2009).
    ${ }^{34}$ Pauly and Zeng (2004).
    ${ }^{35}$ The construction of the health index is similar to Dor et al. (2003). The health index is a summary of selfreported 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.

[^9]:    ${ }^{36}$ Swartz and Garnick (2000).
    ${ }^{37}$ 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.
    ${ }^{38}$ Hall (2000).
    ${ }^{39}$ Kirk (2000).
    ${ }^{40}$ Sloan and Conover (1998); Zuckerman and Rajan (1999); Percy (2000).
    ${ }^{41}$ Buchmueller and DiNardo (2002).

[^10]:    ${ }^{42}$ Lo Sasso and Lurie (2003).
    ${ }^{43}$ Bundorf and Simon (2006).
    ${ }^{44}$ 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 openenrollment 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 programme 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 preexisting conditions exclusion period may be applied.

[^11]:    ${ }^{45}$ Even with both guaranteed issue and rating restrictions together, health plans may still use other tools to select low-risk individuals such as selective advertising.
    ${ }^{46}$ Mroz (1999).
    ${ }^{47}$ Goldman et al. (1998).
    ${ }^{48}$ Goldman et al. (2001).

[^12]:    ${ }^{49}$ Cutler (1995).
    ${ }^{50}$ Goldman (1995).
    ${ }^{51}$ Bhattacharya et al. (2003).

[^13]:    ${ }^{52}$ 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:

[^14]:    ${ }^{53}$ Duan (1983).

[^15]:    *Significant at 10 per cent; ${ }^{* *}$ Significant at 5 per cent; ${ }^{* * * S i g n i f i c a n t ~ a t ~} 1$ per cent.
    ${ }^{\mathrm{a}}$ Computed as the following: $\eta_{13}=-\left(p_{1} \eta_{11}+p_{2} \eta_{12}\right) /\left(1-p_{1}-p_{2}\right)$.
    ${ }^{\mathrm{b}}$ Computed as the following: $p_{3}=1-p_{1}-p_{2}$.

[^16]:    *Significant at 10 per cent; ${ }^{* *}$ Significant at 5 per cent; ${ }^{* * *}$ Significant at 1 per cent.
    ${ }^{\text {a }}$ Computed as the following: $\eta_{13}=-\left(p_{1} \eta_{11}+p_{2} \eta_{12}\right) /\left(1-p_{1}-p_{2}\right)$.
    ${ }^{\mathrm{b}}$ Computed as the following: $p_{3}=1-p_{1}-p_{2}$.

[^17]:    *Significant at 10 per cent; ${ }^{* *}$ Significant at 5 per cent; ${ }^{* * *}$ Significant at 1 per cent.
    ${ }^{\text {a }}$ Computed as the following: $\eta_{13}=-\left(p_{1} \eta_{11}+p_{2} \eta_{12}\right) /\left(1-p_{1}-p_{2}\right)$.
    ${ }^{\mathrm{b}}$ Computed as the following: $p_{3}=1-p_{1}-p_{2}$.

[^18]:    ${ }^{54}$ All Medigap plans cover Part A and Part B coinsurance. Most Medigap plans cover Part A deductible and several of most popular plans also cover Part B deductible.

[^19]:    ${ }^{55}$ Goldman et al. (2004).
    ${ }^{56}$ Under the assumption of 10 per cent under-reporting of drug use, a $\$ 1$ increase in drug spending would be associated with a $\$ 2.15$ decrease in Medicare Part A spending and $\$ 0.45$ decrease in Medicare Part B spending; under the assumption of 20 per cent under-reporting of drug use, a $\$ 1$ increase in drug spending would be associated with a $\$ 1.97$ decrease in Medicare Part A spending and $\$ 0.42$ decrease in Medicare Part B spending.

