Adverse and Advantageous Selection in the Medicare Supplemental Market: A Bayesian Analysis of Prescription Drug Expenditure

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Abstract

This paper develops an extended specification of the two-part model which controls for unobservable self-selection and heterogeneity of health insurance, and analyzes the impact of Medicare supplemental plans on the prescription drug expenditure of the elderly, using a linked data set based on the Medicare Current Beneficiary Survey data for 2003-2004. The econometric analysis is conducted using a Bayesian econometric framework. We estimate the treatment effects for different counterfactuals and find significant evidence of endogeneity in plan choice and presence of both adverse and advantageous selection in the supplemental insurance market. The average incentive effect is estimated to be $757 (2004 value) or 41% increase per person per year for the elderly enrolled in supplemental plans with drug coverage against the Medicare FFS counterfactual, and is $350 or 21% against the supplemental plans without drug coverage counterfactual. The incentive effect varies by different sources of drug coverage: highest for ESI plans, followed by Medigap and MMC plans.

Keywords: advantageous selection; supplemental insurance; endogenous treatment effect; Markov-chain Monte Carlo.

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1 Introduction

Prescription drug expenditure is an important component of spending among the elderly in the United States (US). In 2005, the total prescription drug expenditure of the elderly was about $120.6 billion or $2,864 per person (Kaiser Family Foundation, 2005 [a]). Prescription drug coverage can help to ease this financial burden. But the Medicare program did not offer outpatient prescription drug coverage to the elderly until an optional Part D plan for stand-alone drug coverage was implemented since 2006. In the preceding period, the elderly seeking such coverage privately obtained access through various sources, including employer-sponsored plans (ESI), Medigap plans, and Medicare managed care plans (MMC). In this paper, we provide a Bayesian econometric analysis of the incentive effects of drug insurance coverage (aka ex post moral hazard) on the total prescription drug expenditure of the elderly, controlling for observable differences in plan attributes and unobservable self-selection to health plans.

The incentive effects of health insurance are of essential interest in many empirical studies. Unbiased estimation of these effects requires controlling for self-selection into plans, but doing so is econometrically challenging given the coexistence of multiplicity of sources and plan types which leads to heterogeneity in the responses. Most previous studies used data which is aggregated across plan types and thus cannot adequately accommodate such heterogeneous outcomes and suffer from loss of information. In this paper, by allowing for greater disaggregation in plan types, we are able to estimate incentive effects based on alternative counterfactuals. Moreover, we show that self-selection is a significant factor affecting expenditure outcomes. We also find evidence of both adverse and advantageous selection, something that cannot be established without a disaggregated analysis of the kind we undertake in this paper.

The enrollment in prescription drug coverage has increased substantially since the availability of Medicare Part D drug plan. Around 90% of Medicare beneficiaries had some drug benefit in 2009 (Centers for Medicare & Medicaid Services 2009), compared to 50% in 2002 (Kaiser Family Foundation 2005 [b]). However, there are still around 4 million Medicare beneficiaries lacked drug coverage, including those with potential high drug expenditures. Future expansion of the drug coverage continues to motivate empirical investigations. Significant positive incentive effects of Medicare Part D have been identified in several studies (e.g. Yin et al., 2008; Zhang...
et al., 2009; Kaestner and Khan, 2012). But most of these studies are based on a specific group of Medicare beneficiaries and they potentially confound the pure incentive and selection effects. Further, heterogeneity in the medical and pharmacy coverage of the Medicare beneficiaries before and after the Part D enrollment has not been specifically considered in these studies. Our study is based on older 2003–2004 Medicare Current Beneficiary Survey (MCBS) data. But this sample is nationally representative and our statistical framework which distinguishes between incentive and selection effects from different plan sources can support causal inferences about how total drug expenditure of the elderly responds to the changes in drug coverage in the complicated insurance setting in the Medicare market.

The remainder of this paper is organized as follows. In Section 2 we critique previous studies and explain the relationship of this paper with earlier analyses. The general econometric model specification is considered in Section 3. Sections 4 covers the assumptions and estimation based on the Bayesian approach. Section 5 describes the main features of the data. Section 6 presents and analyzes the results. Section 7 concludes.

## 2 Connections with Previous Research

Previous empirical studies, using data before implementation of Medicare Part D, consistently find a positive relationship between prescription drug expenditure and enrollment in drug coverage. The estimated value of the effect, however, has a wide range. For example, Sing et al. (2008) found that prescription drug expenditure will increase about 15% for drug coverage from Medicare HMO, about 20% for drug coverage from ESI, and no significant change for drug coverage from Medigap. But, the Medigap drug coverage was found to increase drug spending by 22% in the study of Shang and Goldman (2007). In terms of prescription drug usage, Shea et al. (2006) found that the Medicare supplemental plans with drug coverage will increase drug fills by almost 50% compared to supplemental plans without this benefit. But Khan et al. (2007) predicted the increase to be 6% - 14%. Clearly these studies leave room for additional work.

One likely reason for the discrepant findings in the literature is the prevailing diversity in supplemental insurance plans. Prescription drug coverage from different sources has different characteristics. In 2003, around 64% of the ESI plans offered drug benefits without separating deductible
or cap limitations from other covered benefits (Kaiser Family Foundation, 2004). Among MMC enrollees with drug coverage in 2003, more than 40% had an annual drug benefit cap of $750 or less (Kaiser Family Foundation, 2005 [a]). Unlike ESI plans and MMC plans that mostly cover some drug benefits, only 3 out of the 10 standardized Medigap plans offered drug coverage before 2006 and they required $250 annual deductible, 50% coinsurance and $1,250 - $3,000 annual benefit limit. In general, drug benefits are the most generous from ESI plans and are the most limited from Medigap plans (General Accounting Office, 2001).

It is also important to identify the plan source for the elderly without drug coverage. The elderly do not have the drug coverage if they are only enrolled in the basic Medicare fee-for-service (FFS) or they are enrolled in a supplemental plan that does not offer this benefit. Due to the cross-price elasticity between medical services and prescription drugs, the medical benefits of the health plans are found to have impacts on drug expenditure (e.g. Coulson et al., 1995; Goldman and Philipson, 2007). Given the great heterogeneity in medical benefits, the effect of drug coverage will be different for the elderly without drug coverage but enrolled in different plans. As indicated in Sing et al. (2008) and Khan et al. (2007), combining the drug effect for the elderly who are only enrolled in the basic Medicare and the elderly who are enrolled in a supplemental plan without drug coverage is potentially misleading.

Controlling for the heterogeneity in Medicare plans is a hard task for the studies on insurance effect. The set of available private supplemental plans in the Medicare program, both before and after 2006, is large and there are many differences in the plan attributes even within each plan source. Most of the literature defines broad plan categories for Medicare plans (e.g. Lillard et al., 1999; Curtis et al., 2004; Shea et al., 2006) or analyzes a subpopulation of the Medicare beneficiaries (e.g. Shang and Goldman, 2007). This paper analyzes a general Medicare population and defines the plan types according to plan source (ESI, Medigap and MMC) and drug coverage (with and without drug coverage). This definition generates 7 types of plans in the model (6 types of supplemental plans and the basic Medicare FFS) and is more refined than most of the studies in the literature. Thus, the paper provides better controls for the heterogeneity in plans.

The use of different approaches to handle self-selection on unobservables also contributes to the differences in the estimated effects of drug coverage in the literature. When some factors that
influence both insurance choice and health expenditures cannot be observed by researchers, the plan type is an endogenous variable in the analysis on health expenditure. Such factors may include health characteristics, life style, taste for medical care, etc. The endogeneity in drug coverage has been detected by many empirical analyses (e.g. Pauly and Zeng, 2006; Khan et al., 2007; Shang and Goldman, 2007). However, many studies of Medicare supplemental insurance ignore this issue (e.g. Sing et al., 2008; Curtis et al., 2004).

Controlling for endogeneity is necessary to identify the causal effect of the plan incentives without confounding it with the self-selection effect. It is of particular interest to control endogeneity in the two-part model (Duan et al., 1983), which is widely used to address the non-trivial proportion of zeros in health expenditure data. Atherly (2002) used the inverse Mill’s ratios estimated from plan choice equations in the two-part model of Medicare expenditure. Shang and Goldman (2007) implemented the discrete factor method in the two-part model of drug expenditure, which assumes that there are three types of people with different sets of unobservable factors affecting both plan choice and drug expenditure. The method is mostly used to control the endogeneity of binary variables on a continuous outcome.

Most previous econometric studies have used frequentist methods to correct for bias due to unobservable self-selection. Studies on controlling endogeneity using Bayesian approach are emerging, but most of them are for the linear endogenous regression model (e.g. Hoogerheide et al., 2007; Conley et al., 2008). Deb et al. (2006) proposed a Bayesian analysis for the endogenous two-part model. As in the discrete factor model by Shang and Goldman (2007), the Bayesian model allows for unobserved individual heterogeneity, and specifies the correlation across the plan choice and expenditure equations. But in the Bayesian model, unobserved heterogeneity can be any type of variable and is not necessary to be constrained to three types. Moreover, the Bayesian model handles the multinomial feature of insurance choice and can be applied to any dimension of plan options.

The new features of this paper, in addition to those mentioned above, relative to the extant literature are as follows. Our Bayesian analysis extends the endogenous two-part model of Deb et al. (2006) by explicitly incorporating the individual specific random effects. We also provide a better differentiation between plan types, and a priori more appealing set of instruments for
handling endogeneity. Given greater disaggregation between seven plan choices, we are able to implement a richer set of cross comparisons between plans to assess their impact on expenditures. Unlike the Medical Expenditure Panel Survey data used in Deb et al. (2006), our MCBS sample provides information on premium and market penetration variables that generate better instruments for handling endogeneity of plan choice.

3 Model Specification

We first discuss the specification of plan choices and then the two-part expenditure model with endogenous plan choice in the extended two-part model (ETPM).

3.1 Plan Choice Equation

It is assumed that each individual will choose a health plan from 7 types of sources in the Medicare market before availability of Medicare Part D. Although ESI plans may not be available to some elderly, since the data do not provide information on whether the ESI plans are offered to the individual, it is assumed that all the elderly face the same plan choice set. This assumption will not cause problem, since the purpose of the study is to identify impacts of plan choice on drug expenditure, not to investigate how the elderly choose plans. Throughout we use the abbreviation RX to refer to prescription drugs. As discussed in Wooldridge (2000) chapter 18, in the analysis with endogenous treatment, the treatment equation does not have to be correctly specified since it is only used to control for endogeneity. Let $d_0 = 1$ if the basic Medicare FFS is chosen, $d_1 = 1$ for ESI plan with drug coverage (ESI w/ RX), $d_2 = 1$ for ESI plan without drug coverage (ESI w/o RX), $d_3 = 1$ for Medigap plan with drug coverage (Medigap w/ RX), $d_4 = 1$ for Medigap plan without drug coverage (Medigap w/o RX), $d_5 = 1$ for MMC plan with drug coverage (MMC w/ RX) and $d_6 = 1$ for MMC plan without drug coverage (MMC w/o RX). Then, for each individual $i$ in year $t$, his choice of plan type $j$ is modeled as:

$$d_{itj} = 1 \text{ if } z_{itj} = \max(z_{it0}, ..., z_{it6})$$

(1)

where $z_{itj} = (x_{it}'z_{itj})a_j + p_{ijt}^j\alpha_p + u_{itj}$, $j = 0, 1, ..., 6$, is the latent utility of a plan. Vector $x_{it}$ contains a constant term, demographic and socioeconomic variables. Information contained in
this vector may also affect prescription drug expenditure. Variables that only have impacts on plan choice, but not on drug expenditure, are included in vector $\tilde{x}_{it}$ if they are individual specific or in vector $p_{itj}$ if they are plan specific. These variables serve as instrumental variables (IVs). $\alpha_j$ is the coefficient vector varying across plans and $\alpha_p$ is the coefficient vector fixed across plans. The error term $u_{itj}$ is independently and identically distributed across individual, year and plan type.

For identification purpose, the latent utility of Medicare FFS is set to zero so that $z_{it0} = 0 + u_{it0}$. Then the equation system of latent utilities can be written as:

$$
\begin{pmatrix}
  z_{it0} \\
  z_{it1} \\
  \vdots \\
  z_{it6}
\end{pmatrix} =
\begin{pmatrix}
  0 & \cdots & 0 & 0 \\
  \tilde{x}_{it}' & \tilde{\tilde{x}}_{it}' & \cdots & \tilde{p}_{it1}' \\
  \vdots & \vdots & \ddots & \vdots \\
  0 & \cdots & \tilde{x}_{it}' & \tilde{\tilde{x}}_{it}'
\end{pmatrix}
\begin{pmatrix}
  \alpha_0 \\
  \vdots \\
  \alpha_6 \\
  \alpha_p
\end{pmatrix} +
\begin{pmatrix}
  u_{it0} \\
  u_{it1} \\
  \vdots \\
  u_{it6}
\end{pmatrix}
$$

These are re-expressed as:

$$
\begin{pmatrix}
  z_{it0} \\
  z_{it1} \\
  \vdots \\
  z_{it6}
\end{pmatrix} =
\begin{pmatrix}
  0 \\
  w_{it}' \alpha
\end{pmatrix} +
\begin{pmatrix}
  u_{it0} \\
  u_{it1} \\
  \vdots \\
  u_{it6}
\end{pmatrix}
$$

where $z_{it} = (z_{it1}, \ldots, z_{it6})'$.  

### 3.2 Expenditure Equations

The two-part model carries on a sequence of analyses. Let $Y$ denotes the total prescription drug expenditure, then part one of the model analyzes the individual’s decision to spend on drugs: $I(Y > 0)$, where $I(.)$ is an indicator function for positive expenditure. Given positive expenditure, part two analyzes the amount spent. The logarithm of total drug expenditure $Y^*$ is considered in order to correct for the right skewness of the expenditure data.

More specifically, part one, i.e. the hurdle equation, applies a binary discrete choice model with latent variable $H^*$ for individual $i$ in year $t$:

$$
I(Y_{it} > 0) = 1 \text{ if } H_{it}^* \geq 0,
$$

where $H_{it}^* = \tilde{x}'_{it} \gamma + \tilde{d}'_{it} \tau + b_i + \epsilon_{1it}$.

Part two of the model is expressed as:

$$
Y_{it}^* = \ln(Y_{it}) \text{ if } I(Y_{it} > 0) = 1,
$$
where \( Y_{it} = x_{it}' \beta + d_{it}' \rho + c_i + \epsilon_{2it} \).

Vector \( x_{it} \) is the same as in the plan choice equation. Here \( d_{it} = (d_{i1}, ..., d_{i6})' \) is the vector of plan choice. \( b_i \) and \( c_i \) capture time-invariant unobserved individual effects. It is assumed that these unobservable effects have zero mean and homoskedastic variance. They are also assumed to be independent of other variables so that the specification corresponds to a panel data random effect model. The unobservables varying across both individual and year are captured by error terms \( \epsilon_{1it} \) and \( \epsilon_{2it} \), which are also assumed to have zero mean. For identification purposes, variance of \( \epsilon_{1it} \) is set to a constant. But it is assumed that variance of \( \epsilon_{2it} \) is different for individuals enrolled in different plan types.

Unobserved factors may affect both the plan choice and drug expenditure (i.e. error terms in plan choice equation and expenditure equations are correlated), which need to be controlled in order to analyze the pure impact of plan choice on drug expenditure. For identification purpose, endogeneity is assumed to only affect the choice of Medicare supplemental plans. The decision to only stay with Medicare FFS is not correlated with the drug expenditure, conditional on observable factors.

In the ETPM, data are observed for drug expenditure, plan choice, demographic and socioeconomic information, and instrumental variables. The observed data are connected with the parameters through latent variables \( z, H^* \) and \( Y^* \), where \( Y^* \) can be partially observed when the individual has positive drug expenditure.

## 4 Bayesian Estimation

This section considers the Bayesian approach to the ETPM estimation.

### 4.1 Assumptions and Algorithm

Distributional assumptions are imposed to the error terms in the ETPM to enable Bayesian estimation. The error term in the plan choice equation is assumed to follow standard normal distribution, i.e. \( u_{itj} \sim \text{i.i.d. } N(0, 1), \ j = 0, 1, ..6 \). The error terms in drug expenditure are correlated with the
error terms in plan choice through linear regressions:

\[ \epsilon_{1it} = \mathbf{u}_{it}' \delta + v_{it}, \quad v_{it} \sim N(0, 1) \]

\[ \epsilon_{2it} = \mathbf{u}_{it}' \pi + e_{it}, \quad e_{it} \sim N(0, \Sigma_{j=0}^{6} d_{itj} \sigma_j^2) \]

where \( \mathbf{u}_{it} = (u_{i1}, \ldots, u_{it})' \), and \( \Sigma_{j=0}^{6} d_{itj} \sigma_j^2 = \sigma_j^2 \) if individual chooses plan type \( j \). With \( \text{cov}[\mathbf{u}_{it}, v_{it}] = 0 \), \( \text{cov}[\mathbf{u}_{it}, e_{it}] = 0 \) and \( \text{cov}[v_{it}, e_{it}] = 0 \), the coefficients in above regressions capture the correlation of the error terms: \( \delta = E[\epsilon_{1it} \mathbf{u}_{it}] \) and \( \pi = E[\epsilon_{2it} \mathbf{u}_{it}] \). Positive correlation between the error terms indicates that unobserved factors which increase the probability to choose a type of plan are associated with increased drug expenditure. Thus, unobservable adverse self-selection into the plan type is reflected by positive values of \( \delta \) and \( \pi \). On the other hand, unobservable advantageous self-selection is reflected by negative values of \( \delta \) and \( \pi \). The random variables \( v_{it} \) and \( e_{it} \) define the distribution of the error terms \( \epsilon_{1it} \) and \( \epsilon_{2it} \), respectively; \( v_{it} \) is assumed to follow standard normal distribution for identification purpose and \( e_{it} \) is assumed to follow normal distribution with different variance across enrollees in different plan types. Endogeneity is specified as \( \delta = E[\epsilon_{1it} \mathbf{u}_{it}] \) and \( \pi = E[\epsilon_{2it} \mathbf{u}_{it}] \). So, the covariance between \( \epsilon_{1it} \) and \( \epsilon_{2it} \), i.e. \( \text{cov}[\epsilon_{1it}, \epsilon_{2it}] = \delta' \pi \) is generally not equal to zero when the plan choice is endogenous. Distributional assumptions imposed on the unobservables in the model may be restrictive. However, as mentioned in Yang et al. (2003), data are allowed to not support these distributional assumptions by leading to a zero likelihood value.

Given the specification of endogeneity, the expenditure equations become:

\[ I(Y_{it} > 0) = 1 \text{ if } H_{it}^* \geq 0 \]  

(5)

where \( H_{it}^* = \mathbf{x}_{it}' \gamma + \mathbf{d}_{it}' \tau + (\mathbf{z}_{it} - \mathbf{w}_{it}' \alpha)' \delta + b_i + v_{it}, v_{it} \sim N(0, 1) \) and

\[ Y_{it}^* = \ln(Y_{it}) \text{ if } I(Y_{it} > 0) = 1 \]  

(6)

where \( Y_{it}^* = \mathbf{x}_{it}' \beta + \mathbf{d}_{it}' \rho + (\mathbf{z}_{it} - \mathbf{w}_{it}' \alpha)' \pi + c_i + e_{it}, e_{it} \sim N(0, \Sigma_{j=0}^{6} d_{itj} \sigma_j^2) \). For the random effects, since the vector \( \mathbf{x}_{it} \) contains a constant term, it is assumed that:

\[ b_i \sim N(0, \sigma_b^2) \]

\[ c_i \sim N(0, \sigma_c^2) \]  

(7)
The joint density of the observed data and the latent variables for the ETPM described by (2, 5-7) have the structure:

\[
\prod_i \prod_t \{ p(d_{it} \mid z_{it}) \times p(z_{it} \mid w_{it}, \alpha) \\
\times p(I(Y_{it} > 0) \mid H^*_it) \times p(H^*_it \mid x_{it}, d_{it}, w_{it}, z_{it}, b_i, \alpha, \gamma, \tau, \delta) \\
\times p(Y_{it} \mid Y^*_it) \times p(Y^*_it \mid x_{it}, d_{it}, w_{it}, z_{it}, c_i, \alpha, \beta, \rho, \pi, \Sigma^6_{j=0} d_{itj} \sigma^2_j) \\
\times p(b_i \mid \sigma_b^2) \times p(c_i \mid \sigma_c^2) \cdot \}
\]

We apply diffuse conjugate priors to the parameters: \( \gamma, \tau, \beta, \rho, \alpha, \sigma_b^2, \sigma_c^2, \sigma_j^2 \ (j = 0, \ldots, 6) \). In order to implement the test of endogeneity, informative conjugate priors are imposed on the correlation between plan choice and drug expenditure: \( \delta, \pi \). The posterior density of these parameters is proportional to the product of the prior densities and the joint density of the observed data and the latent variables. The full conditional distribution of each parameter can be derived from the posterior density kernel and then the Gibbs sampling algorithm is used to generate random draws from the posterior density. After sufficient iteration, the random draws will converge to the posterior distribution of the parameters. The detailed estimation algorithm is presented in Appendix A and has been validated through simulation study.

4.2 Testing for Endogeneity

Testing if the plan choice is exogenous in expenditure equations is equivalent to testing the hypothesis that the parameters \( \delta = \pi = 0 \), which is done by calculating the Bayes factor. Since the two-part model with exogenous plan choice assumption is nested by the ETPM, the Savage-Dickey density ratio (Verdinelli and Wasserman, 1995) is used.

Let \( W \) denote the observed data. Then, the Bayes factor for the null hypothesis \( H_0 : \delta = \pi = 0 \) versus the alternative hypothesis \( H_1 : \delta \neq 0, \pi \neq 0 \) is defined as:

\[
B_{0,1} = \frac{p(\delta, \pi \mid W) \mid_{\delta=\pi=0_6}}{p(\delta, \pi) \mid_{\delta=\pi=0_6}}
\]

Here \( p(\delta, \pi \mid W) \mid_{\delta=\pi=0_6} \) is the joint posterior density of \( \delta \) and \( \pi \), evaluated at zero; and \( p(\delta, \pi) \mid_{\delta=\pi=0_6} \) is the joint prior density of the parameters, evaluated at zero.
The joint prior density of \( \delta \) and \( \pi \) can be evaluated directly, given the imposed prior densities. Informative priors are selected because large variance tends to favor the null hypothesis. For the posterior density, it is hard to calculate its normalization term. But the full conditional densities of \( \delta \) and \( \pi \) can be derived based on the normal posterior densities and in the estimation algorithm. Then, with the random draws from the Gibbs sampler, the posterior density of \( \delta \) and \( \pi \) can be approximated using Monte Carlo integration:

\[
p(\delta, \pi \mid W) \approx \frac{1}{S} \sum_{s=1}^{S} p(\delta \mid W, z^s, H^s, b^s, \alpha^s, \gamma^s, \tau^s) \times p(\pi \mid W, Y^s, z^s, c^s, \alpha^s, \beta^s, \rho^s, (\Sigma_{j=0}^{S}d_{itj}\sigma_{j}^{2s}))
\]

where \( p(\delta \mid .) \) and \( p(\pi \mid .) \) are the full conditional densities and the superscript \( s \) denotes the random draws from the \( s^{th} \) iteration of the Gibbs sampler. When the Bayes factor is essentially zero, logarithm of Bayes factor \( \ln(B_{0,1}) \) will be informative and examined.

### 4.3 Treatment Effects

The estimated parameters of ETPM can show the significance and the direction of health plan’s impact. To estimate the actual marginal effect of plan choice on drug expenditure, the treatment effect for the treated individuals (TET) should be calculated. The TET measures how the expected drug expenditure changes if the individuals enrolled in a plan type decide to choose another plan type. Different treated group and counterfactual plan choice can be defined from the 7 plan types considered in this study. For example, all the individuals enrolled in a Medicare supplemental plan can be considered as the treated group and then their drug expenditure associated with the choice of the basic Medicare FFS is then the counterfactual outcome. Or, within each plan sector (ESI, Medigap or MMC), enrollees in the plan with drug coverage is considered as the treated group and their counterfactual choice can be the plan without drug coverage.

It is assumed that each individual has the same unobservable response to different treatment, conditional on observed variables. Then, for individual \( i \) in year \( t \), who is enrolled in plan type \( j \), his TET against the counterfactual plan choice \( k \) is denoted as \( \text{TET}^{jk}_{it} \) and has the expression:

\[
\text{TET}^{jk}_{it} = E[Y_{it} \mid W_{it}, d_{itj} = 1] - E[Y_{it} \mid W_{it}, d_{itk} = 1]
\]
where $W_{it}$ is the corresponding observed data. With the random parameters, the treatment effects need to be conditional on the parameter values:

$$TET_{it}^{jk} | \eta_{it} = E[Y_{it} | W_{it}, d_{itj} = 1, \eta_{it}] - E[Y_{it} | W_{it}, d_{itk} = 1, \eta_{it}]$$

where $\eta_{it} = (z_{it}, \alpha, \gamma, \tau, \delta, \beta, \rho, \pi, b_i, c_i, \Sigma_{j=1}^{6} d_{itj} \sigma_j^2)$. Note that the log expenditure $Y_{it}^*$ needs to be transformed to level expenditure $Y_{it}$. Then, according to the distributional assumptions imposed in the Bayesian estimation, the conditional expected drug expenditure is:

$$E[Y_{it} | W_{it}, d_{it}, \eta_{it}^s] = p[Y_{it} > 0 | W_{it}, d_{it}, \eta_{it}^s] \times E[Y_{it} | Y_{it} > 0, W_{it}, d_{it}, \eta_{it}]$$

$$= \Phi((x_{it}' \gamma + d_{it}' \tau + (z_{it} - w_{it}' \alpha)' \delta + b_i)$$

$$\times (x_{it}' \beta + d_{it}' \rho + (z_{it} - w_{it}' \alpha)' \pi + c_i + 0.5(\Sigma_{j=0}^{6} d_{itj} \sigma_j^2)).$$

Then the unconditional moments of TET are obtained by Monte Carlo integration:

$$f(TET_{jk}^i) \approx \frac{1}{S} \sum_{s=1}^{S} f(TET_{it}^{jk} | \eta_{it}^s, \forall i \forall t)$$

where $f(.)$ denotes the moment function of treatment effect, such as average TET or median TET. The superscript $s$ denotes the random draws from the $s^{th}$ iteration of the Gibbs Sampler.

## 5 Data

Three data sources are linked to create our database. The Medicare Current Beneficiary Survey (MCBS) is the main source of information regarding demographics, plan enrollment and prescription drug expenditure. The Area Resource File (ARF) and the State County File (SCF) provide extra sources for the instrumental variables.

### 5.1 Sample from MCBS

MCBS is a continuous survey of a representative sample of the Medicare population. It contains plan attribute information, which can be used to define plan types and can serve as instrumental variables. Moreover, the regional information in MCBS can be linked to many other data sets useful in the analysis of Medicare market. The “Cost and Use” file generated from MCBS contains detailed information on the respondent’s Medicare utilization, expenditures, insurance coverage,
health status and demographic characteristics. The effect of prescription drug coverage on drug expenditure of the elderly is analyzed using year 2003-2004 “Cost and Use” files. In the 2003 file, 10,001 respondents completed the personal interview and lived through the year. There were 9,655 such observations in the 2004 file. These observations in the two years correspond to 13,550 unique respondents.

The study focuses on the elderly who are eligible for Medicare due to age and are not enrolled in Medicaid or other public plans. Furthermore, the sample is restricted to the elderly who hold only one health plan (either the original Medicare FFS or a Medicare supplemental health plan) and do not switch plan for the whole year. The resulting sample contains 7,964 observations. The observations are excluded if their plan type cannot be identified or their prescription drug expenditure is a negative number. Finally, observations living in Puerto Rico are excluded from the study since ARF and SCF data sets cannot be linked to this region. The final sample contains 7,664 observations with 5,725 unique respondents. Among the unique respondents, 1,831 are only observed in year 2003, 1,955 are only observed in year 2004, and 1,939 are observed in both years.

5.2 Variables in the Model

In ETPM, the vector \( x \) contains demographic and socioeconomic variables that may have exogenous impact on both plan choice and drug expenditure. The demographic variables include: age, gender, race, education level, family income, marital status, number of living children, and if the individual lives alone. Health status of the elderly is measured by: self-rated health status (= 1 if excellent, = 5 if poor), presence of comorbidities (including cardiovascular diseases, diabetes, cancer, bone problems, and mental problems), current and past smoking status, number of functional limitations, and number of limited activities of daily living. Functional limitations include difficulty with lifting 10 pounds, extending arms above shoulders, stooping/crouching/kneeling, walking 2–3 blocks, and writing. The limitations to activities of daily living cover bathing, getting in and out of chairs, dressing, eating, and walking. Variables measuring geographic location are also included and they are indicators for metropolitan area, north east area, north central area, and west area. Finally, an indicator for year 2004 is included.
5.3 Instruments

The instrumental variables in the plan choice equation affect plan choice, but are not directly correlated with drug expenditure. The instruments can be individual specific ($\bar{x}$) or plan specific ($p$). Plan premium is a natural plan-specific instrumental variable. Premium is an important determinant health insurance choice. But, once the insurance has been purchased, as a sunk cost, premium should not have impact on health care utilization. For several reasons, premiums only have negligible partial correlation with drug expenditure. First, only community rating is allowed for the Medicare managed care plans, and some states also regulate the Medigap premium. Second, higher premium does not necessary lead to better drug coverage. For example, in our sample, the average premium paid for plans with drug coverage is less than for plans without drug coverage in ESI and MMC (Table 2), while the average premium paid for Medigap with drug coverage exceeds that for ESI and MMC with drug coverage even though drug coverage from Medigap is limited. Thus premium only affects drug expenditure through plan attributes. In a regression on drug expenditure, controlling for type of plan and other health status and socio-demographic covariates, the premium has little additional explanatory power. That is, the residual partial correlation between premium and drug expenditure is trivial. and treating premium as an instrumental variable seems justified.

The basic Medicare FFS is the baseline insurance and its premium is normalized to zero. For the elderly who are also enrolled in Medicare supplemental plans, MCBS asks the respondents how much they pay for their plans in addition to the Medicare Part B. We can observe the premium of the plan chosen by the individual, but cannot observe the premium of the supplemental plans which are not chosen. The local average premium paid by the sample can be a good proxy for the missing data, since only community rating at the county level is allowed for MMC plans and some states also require community rating of Medigap plans. Then, for each plan type, the sample average of premium paid at the county level is used to impute the missing premium. If some plan types are not chosen by any respondent in a county, the state average premium paid is considered a proxy for what is charged to the individuals in that county. If the state average value is also unavailable, the national average premium paid is used instead. The interaction terms of individual characteristics (age, gender, race, education level, income, marital status and self-rated health status) and premium are also included in the plan choice equation to capture heterogeneous sensitivity to premium.
Additional instruments are generated using several county level variables that serve as individual specific instruments for plan choice. Since the elderly need to buy insurance in advance to cover health expenditures, the county MMC penetration rate in the previous year can measure the market power of MMC when the elderly make the plan choice decision and this lagged variable should not affect the current year’s drug expenditure. The SCF provides the number of MMC enrollees and the number of eligible Medicare beneficiaries in each county in each year, and the information is used to calculate the MMC penetration rate.

In the Medicare market, working history of the elderly plays an important role, especially in the choice between ESI plans and non-ESI plans. But it is possible that an individual with high expected health expenditures is willing to choose certain jobs, for example positions in government, in order to gain access to good retirement health plans. The county level industry variables, however, can describe the structure of the county labor force and are not expected to be correlated with individual health expenditures, conditional on observable geographic differences. The county level industry variables available in ARF include: unemployment rate in 2000, percentage of white-collar workers in 2000, percentage of blue-collar workers in 2000, percentage of government workers in 2000, and percentage of self-employed workers in 2000. Atherly (2002) argues that the proportion of one industry in the county labor force can affect how likely an individual holds a position in that industry and thus the associated typical retirement package. But unless individuals with high or low expected health expenditures systematically move in or out of the county, the county level proportions are not correlated with individual health expenditures. Also, the year 2000 county labor force structure should not affect the year 2003 or year 2004 drug expenditure of the elderly, but can still capture the industrial characteristics in the county due to the persistence in the labor market.

The validity of the instruments is also tested in the maximum-likelihood estimation framework. Since the plan choice is the only endogenous variable in the ETPM and we have plan premium and individual level variables as instruments, overidentifying restrictions can be assessed using Hansen J test statistics. The \( p \)-value of the test is greater than 0.25 for both parts of the expenditure equations, which supports the inference that the instruments are valid in the model. Also, the F-test of weak instruments has near zero \( p \)-value for each of the endogenous plan choice, which indicates
a strong correlation between the instruments and drug expenditures.

### 5.4 Summary Statistics

The summary statistics of the variables in the model are presented in Table 1. Note that the premium considered is what is additional to the Medicare Part B premium.

#### Table 1

The summary statistics for drug expenditure and premium paid in each plan type are provided in Table 2. Among the elderly enrolled in Medicare FFS only, 16% do not have any prescription drug expenditure. This proportion is much lower among the elderly enrolled in Medicare supplemental plans. Also, the elderly with only Medicare FFS have lower median and mean prescription drug expenditure than the elderly with Medicare supplemental plans, except for those with MMC w/o RX plans. Among the supplemental plans with drug coverage, the drug expenditure is the highest for enrollees in ESI w/ RX plans, followed by Medigap w/ RX and MMC w/ RX. Among the supplemental plans without drug coverage, however, the expenditure is the highest for Medigap w/o RX, followed by ESI w/o RX, and MMC w/o RX. In each sector of the Medicare supplemental plans (ESI, Medigap, and MMC), the median and mean drug expenditure are higher for the elderly with drug coverage than those without drug coverage. The difference is the highest in ESI sector and the lowest in Medigap sector. The median and mean premium paid by enrollees in Medigap plans are the highest among the enrollees in supplemental plans. In each sector of the Medicare supplemental plans, higher premium paid by the enrollees is associated with lower number of enrollees. In the ESI and MMC sectors, the premium paid by enrollees with drug coverage is lower than those without drug coverage. This reflects the fact that the plans without drug coverage are generous in other benefits, such as inpatient care coverage. But the premium paid for Medigap w/ RX is higher than the premium paid for Medigap w/o RX, since the benefits other than drug coverage are quite similar across these two types of plans. The summary statistics reflects the drug utilization pattern and heterogeneity among different types of plans.

#### Table 2
The elderly with different plan types also differ in other characteristics (results provided in this paper’s web appendix). On average, the elderly with supplemental plans have higher age, more income, more education and better self-rated health than the elderly with only Medicare FFS. But, the differences in age are insignificant for the ESI w/ RX enrollees and for the MMC w/o RX enrollees. Also, the differences in self-rated health are only significant for the MMC enrollees (w/ RX or w/o RX).

6 Results

The estimation results from the Bayesian algorithm described in Section 4 are presented in the following sections, with focus on the incentive effects of the health plans, and self-selection on unobservables into the plans.

The MCMC estimation algorithm is run for 40,000 iterations. After the 30,000th iteration, every 40th draw is collected to derive the estimates. Since the distribution of drug expenditures is highly skewed, we investigated if the normal distribution assumption on part two of the expenditure equations is valid. The error term in part two is estimated using \[ \Sigma S_{s=1}^S \ln(Y_{it}) - x_{it}^s \beta + d_{it}^s \rho + (z_{it}^s - w_{it}^s)^\gamma \pi + c_{it}^s \] for each observation, where superscript \( s \) denotes a random draw from the Gibbs sampler. For enrollees in each plan type, the estimated error terms have mean close to zero and skewness in the range from \(-0.7\) to \(-1\), and the density plots resemble the normal distribution. And a simulation study has shown that results are not affected much by skewed error terms in part two, thus inferences based on MCBS data should be reliable.

6.1 Results for Plan Choice

The posterior means of the coefficients for the instrumental variables in the plan choice equation are displayed in Table 3. The percentage of posterior draws having the same sign as the posterior mean is also reported as a proxy of the statistical significance level of the posterior mean. The autocorrelation functions die off very fast (details not reported), which indicates the Bayesian estimates of the parameters reach convergence. The results on the other exogenous variables (demographics, health characteristics, regional variables, and year dummy) are provided in the web appendix. The coefficients in the plan choice equation can tell us the odds of having one type of supplemental
insurance against having only Medicare FFS.

Table 3

All the instrumental variables affect plan choice nontrivially, after controlling for the other exogenous variables. As expected, the lagged county MMC penetration rate increases the odds for MMC plans to be chosen, but reduces the odds for Medigap w/o RX, which is the major competitor of MMC plans on the non-group market. Also, the county unemployment rate reduces the choice odds for ESI w/ RX, the majority of ESI plans. Plans with higher premium are less likely to be chosen. But the elderly who are older, female, white, with higher education, with higher income, single, or with worse self-rated health are less sensitive to the premium.

6.2 Results for Drug Expenditure

For the expenditure equations, the estimation includes coefficients, variances of individual random effects, and variances of heteroskedastic error terms in part two of the expenditure equations. The posterior means and posterior standard deviations are displayed in Table 4 for the parameters measuring the impact of exogenous variable, plan choice and self-selection. The Bayesian estimates reach reasonable convergence since most of the autocorrelations at the 20th lag are smaller than 0.1, with only a few around 0.3. The full set of estimation results, including autocorrelations, is provided in web appendix.

Table 4

Individual demographics and health status have important impacts on drug expenditure. The elderly, who are female, have higher education level or have higher income, are more likely to spend on prescription drugs and are also expected to spend larger amount given positive expenditure. Younger age and being white increase the amount spent conditional on positive expenditure, but do not affect the chance to spend. Being married and having more children increase the probability of positive expenditure, but do not affect the amount once the expenditure is positive. Most of the health variables, including self-rated health status, disease indicators and number of functional limitations, have positive impacts on both parts of the expenditure equations. The elderly who are
smokers have lower probability of positive expenditure and also lower propensity to spend if they do spend. But the elderly who have quit smoking tend to spend more given positive spending. This implies that smoking can be considered an indicator of current health status and attitude towards health risks.

Controlling for endogeneity, coefficients on the choice of supplemental plans \((d_1, \ldots, d_6)\) indicate the incentive effects induced by the plans, compared to choosing the baseline Medicare FFS only. The choice of a supplemental plan increases drug expenditure in both parts of the expenditure equations. The only exception is the choice of MMC w/o RX, which increases the chance to spend, but reduces the amount spent for the elderly who have drug expenditure. Since the Medicare FFS does not have drug coverage, choosing a supplemental plan with drug coverage is expected to increase the drug expenditure due to moral hazard. For supplemental plans without drug coverage, the positive impact of plan choice can be explained by the cross-price elasticity between medical services and prescription drugs. The elderly with supplemental plans, with or without drug coverage, tend to use the plan-covered services more often due to the lower out-of-pocket payment. Health services, such as doctor visits, may induce the usage of prescription drugs by being complementary inputs. Thus, due to incentive effects of benefits other than drug coverage and the associations among health service inputs, the choice of a supplemental plan without drug coverage may still motivate more spending on prescription drugs. Since the managed care system is designed to improve the control of moral hazard, this effect is expected to have less impact in MMC sector than in ESI and Medigap sector where the major plan type is FFS. As the result, the choice of MMC w/o RX has some negative impact on drug expenditure. Within each sector, the insurance with drug coverage increase the expenditure more than the insurance without drug coverage. But in the Medigap sector, the impact on the probability to have positive expenditure is similar for Medigap w/ RX and Medigap w/o RX. This may be due to the deductible design in Medigap drug benefit.

In the expenditure equations, the coefficients \((\delta, \pi)\) on error terms \((u_1, \ldots, u_6)\) of plan choice indicate how the drug expenditure is affected by unobserved self-selection. Recall that positive estimates are evidence of adverse selection, and negative estimates are evidence of advantageous selection. Advantageous selection into supplemental plans is detected in whether the elderly will
spend any drug expenditure. But, adverse selection into supplemental plans is detected for the elderly who have already spent on prescription drugs. The overall impacts of the unobserved factors on drug expenditure are inconclusive based on coefficient estimates. For plans with drug coverage, the mixed pattern of advantageous selection and adverse selection indicates that the elderly may have better understanding and more utilization of their drug benefits after drug expenditure occurs. The impacts of the unobserved factors are not strong for enrollees in ESI w/o RX in part two of the expenditure equations, or for enrollees in MMC w/o RX in overall expenditure.

6.3 Treatment Effects

The TETs estimated from the ETPM reflect the change in drug expenditure of the elderly if they change to a counterfactual health plan. Since the TETs from ETPM are conditional on both the observable factors and the unobservable factors that may affect the plan choice and the drug expenditure, the change in expenditure due to change in plan choice (i.e. TETs) can be attributed to the incentive effect of the insurance for the treated group. The task of identifying the TET not only relies on controlling for the unobservable self-selection as modeled in the ETPM, but also requires that the patients in the treated group have comparable characteristics as patients in the counterfactual (i.e. untreated) group. If a set of characteristics lead to treatment with certainty, then individuals with such characteristics need to be excluded from the study. The choice probability for each type of supplemental health plan is predicted based on the maximum likelihood estimation of the plan choice equation. The estimated choice probabilities are all less than one for all the individuals in the sample. Thus, the TET can be identified by the sample in the study. More advanced methods are available to investigate the comparability across treatment groups, but they are beyond the scope and the main purpose of this study.

Table 5

The average treatment effect (ATET) and median treatment effect (MTET) are reported in Table 5. MTETs have smaller magnitude than ATETs, which indicates that plan choice has extraordinarily large impact on drug expenditure for some of the elderly. When the counterfactual plan choice is Medicare FFS, the signs of ATET and MTET for enrollees in each type of supplemental plan
are consistent with the plan incentive analyzed in Section 6.2. Specifically, moral hazard is observed for the elderly enrolled in all Medicare supplemental plans, except for MMC w/o RX. The increased amount of drug expenditure is the highest for ESI w/ RX with an average of $1,014 and median of $733 per person and is the lowest for Medigap w/o RX with an average of $108 and median of $9 per person. The expenditure decreased by MMC w/o RX against Medicare FFS has an average of $132 and median of $86.

Comparing the plan incentives relative to Medicare FFS from different plan types, plans with drug coverage generally increases drug expenditure more than plans from the same insurance sector but without drug coverage. Among plans with drug coverage, ESI plans increase drug expenditure against Medicare FFS the most, followed by Medigap plans and MMC plans. The same pattern applies to supplemental plans without drug coverage. This pattern is consistent with the benefit design of each plan sector: ESI plans usually have generous benefits in both drug coverage and other benefits, Medigap plans target to cover the cost-sharing in Medicare FFS and have donut-hole design for drug coverage, and MMC plans have network restrictions. Therefore, the moral hazards on drug expenditure, induced by drug coverage directly or by other plan benefits indirectly, are expected to be the highest for ESI plans and the lowest for MMC plans. The ATETs relative to the counterfactual Medicare FFS are also demonstrated in Figure 1(a) and 1(b).

Figure 1(a), 1(b), 1(c)

The treatment effects are also considered for the situation where the elderly switch their drug coverage within each insurance sector. The amount of drug expenditure affected by drug coverage is consistent across different treated groups within each sector. For example, the elderly enrolled in Medigap w/ RX spend more on drug expenditure with mean $489 and median $368 per person than if they were enrolled in Medigap w/o RX, meanwhile the elderly enrolled in Medigap w/o RX spend less with mean $552 and median $408 per person than if they chose Medigap w/ RX. The impact of drug coverage is the highest in the Medigap sector. Recall that, in ESI sector and MMC sector, plans without drug coverage may be more generous in other benefits. Thus, in ESI sector and MMC sector, the impact of drug coverage on drug expenditure is subdued due to moral hazard induced indirectly by other plan benefits. This is not the case in Medigap sector and thus the
impact of drug coverage is larger in this sector. This pattern in plan incentive is also demonstrated in Figure 1(c).

The MTET for each plan type is further stratified according to health status of the elderly (results in web appendix). Compared to the choice of Medicare FFS only, the impact of each type of supplemental plans, except for Medigap w/o RX, is larger for the enrollees with poorer self-rated health status. For the elderly enrolled in Medigap w/o RX, the expenditure is higher if they rate their health as excellent or very good, but is not significantly different from the choice of Medicare FFS if their health is good, fair or poor. Medigap plans fill the cost-sharing gaps of Medicare FFS and most of them cover Medicare deductibles in hospital and medical services. This may motivate the elderly, who have very good health and do not necessarily need health services, to seek more health services and which in turn may induce drug expenditure. But, for the elderly who may need necessary health services, Medigap w/o RX does not trigger moral hazards on drug expenditure. If the elderly switch drug coverage within each insurance sector, the impact of drug coverage is always larger for poorer health. This reflects that there is less plan heterogeneity within one insurance sector.

6.4 Self-selection on Unobservables

As discussed in Section 6.3, adverse and advantageous selection on unobservables has been detected in the ETPM. In addition, the Bayes factor for the endogeneity test is essentially zero, which indicates these self-selection effects are statistically significant. To demonstrate the impact of the unobservable self-selection on the TETs, we compared the results from ETPM to those from the two-part model with exogenous plan choice assumption (TPM). TPM does not control for the endogeneity and thus TETs estimated from TPM reflects combined effects from the moral hazard and the unobservable self-selection of the health plan. If the TET from TPM is larger than from ETPM, it is interpreted as evidence that, in addition to the incentive effect, enrollees in the plan spend more than if they were enrolled in the counterfactual plan. And this extra spending, in addition to that induced by moral hazard, is considered as adverse selection on unobservables, relative to the counterfactual plan choice. Similarly, if the TET from TPM is smaller than from ETPM, the elderly enrolled in the plan spend less than the amount that should be induced by moral hazard.
This is the evidence of advantageous selection on unobservables.

We estimate the TPM using the same Bayesian algorithm for ETPM, without considering the correlation of the error terms between the plan choice and expenditure equations. The resulting ATETs for enrollees in each plan type are presented in Figure 1, which also demonstrates the ATETs from ETPM and the mean differences in the total drug expenditure between the treated and untreated groups. The comparison shows that adverse selection relative to Medicare FFS is detected for the plans with drug coverage, since ATETs from ETPM is smaller than from TPM. There is evidence of advantageous selection for ESI w/o RX and MMC w/o RX, relative to Medicare FFS, but the amount is very small. Overall adverse selection relative to Medicare FFS occurs within plans without drug coverage, due to the impact from Medigap w/o RX. The amount of adverse selection on Medigap w/o RX is even higher than that for Medigap w/ RX. This may due to the high availability of Medigap w/o RX. Before 2006, there were on average 20 insurers in each state selling a standardized Medigap plan without drug coverage, but only on average 6 insurers offering standardized Medigap plans with drug coverage (General Accounting Office, 2001). Also, ESI plans and MMC plans have limited availability. Thus, the Medigap w/o RX category absorbs the elderly who are potential users of medical services and prescription drugs but have difficulty in finding a supplemental plan. This feature of Medigap plans is also reflected in the self-selection within the same insurance sector: if the elderly switch drug coverage within Medigap sector, advantageous selection relative to Medigap w/o RX is observed. But if the elderly switch drug coverage within ESI sector or MMC sector, the plans with drug coverage incur adverse selection relative to the plans without drug coverage.

The comparison between the results from ETPM and TPM demonstrates the importance to control for unobservables in the assessment of plan incentives. As expected, the ATETs from the TPM is closer to the unadjusted differences in the mean drug expenditure between the treated and untreated groups than the ETPM results.

7 Conclusions and Discussion

Using an extended two-part model which controls for heterogeneity and unobservable selection of plan choices, our study demonstrates substantive empirical findings using a nationally representa-
tive sample of Medicare beneficiaries. The average incentive effect is estimated to be $757 (2004 value) or 41% increase per person per year for the elderly enrolled in supplemental plans with drug coverage against the Medicare FFS counterfactual, and is $350 or 21% against the supplemental plans without drug coverage counterfactual. The incentive effect varies by different sources of drug coverage: highest for ESI plans, followed by Medigap and MMC plans; for details see Table 5. Unobservable adverse selection relative to the Medicare FFS is found for all the plans with drug coverage, although the magnitude of self-selection varies across different play types. Advantageous selection is detected for ESI w/o RX and MMC w/o RX, though the evidence is weak. Adverse selection into drug coverage within ESI sector and MMC sector is found, while there is evidence for advantageous selection into drug coverage within Medigap sector.

To control for heterogeneity of plans available in the Medicare market, this paper has used a multiple treatment effects framework, with several reference groups, which generates a richer and more complex pattern of treatment effects and allows for the coexistence of both adverse and advantageous forms of self-selection. This empirical analysis points to important limitations of frameworks that involve significant aggregation across plan types in order to define and estimate a single treatment effect. This paper also emphasizes the direct and indirect effects of health insurance, not just prescription drug insurance, on the drug expenditures. Expenditure on drugs can vary as a consequence of expansion of non-drug coverage.

The arrival of Medicare Part D in 2006 changed the market place for prescription drug insurance in significant ways. These changes have instigated a number of empirical investigations into the causal connections between spending and insurance in the spirit of this paper. Although data used in this paper predates the implementation of Medicare Part D, its methodology as well as empirical findings can inform one’s understanding of the policy implications to Medicare drug coverage after 2006.

The heterogeneity of plan source for drug coverage continues to be relevant in the current Medicare market. After 2006, Medicare beneficiaries can obtain drug coverage from stand-alone drug plan, MMC, ESI or other sources, although Medigap plans no longer offer drug coverage. Drug coverage from different sources still varies in terms of co-pays, deductibles, and drugs covered. In general, drug coverage offered in MMC plans is more generous than in the stand-alone
Correspondingly, empirical studies show considerable diversity in the estimated impact of Part D insurance. For example, according to Zhang et al. (2009) the enrollment in Medicare Part D increased the total monthly drug expenditures by 74% for the elderly without previous drug coverage, 27% for those with a previous $150 quarterly cap, and 11% for those with a previous $350 cap. However, Khan et al. (2007) estimated a 40% increase in annual drug expenditures associated with Medicare Part D. If empirical studies do not control for heterogeneity of plan types and for self-selection, and if they also differ significantly in the subpopulations they study, then disparities of the kind mentioned above are likely to arise. The findings in this paper demonstrates that it is necessary to control for heterogeneity and unobservable selection of plan choices to assess the impact of Medicare Part D. Applying the extended two-part model proposed in this paper to a more recent data could provide better understanding of the current Medicare market.

This study is subject to several limitations. While disaggregation by plan types generates a richer analysis, potentially weak correlation with the endogenous treatment within some insurance sectors would reduce the power of the instruments to identify causal parameters. The instruments used in this study may have limited power to identify the impact of plan choice, especially for ESI w/o RX, Medigap w/ RX and MMC w/o RX. Some semiparametric Bayesian approaches, e.g. Conley et al. (2008), may be more robust in handling the problem of weak instruments. This approach, however, was developed for linear structural and reduced form equations and has not been extended to the two-part model and other nonlinear models.
8 Appendix A: Gibbs Sampler Algorithm

The joint density of the observed data and the latent variables for the extended two-part model have the structure:

\[ \Pi_i \{ \Pi_i [ p(d_{it} | z_{it}) \times p(z_{it} | w_{it}, \alpha) ] \times p(I(Y_{it} > 0) | H^*_{it}) \times p(H^*_{it} | x_{it}, d_{it}, w_{it}, z_{it}, b_i, \alpha, \gamma, \tau, \delta) \times p(Y_{it} | Y^*_{it}) \times p(Y^*_{it} | x_{it}, d_{it}, w_{it}, z_{it}, c_i, \beta, \rho, \pi, \Sigma^2_{j=0} d_{ij} \sigma_j^2) ] \times p(b_i | \sigma_b^2) \times p(c_i | \sigma_c^2) \} \].

Diffuse conjugate priors are imposed as follows:

\[ \gamma \sim N(0_k, 10I_k), \quad \tau \sim N(0_6, 10I_6), \quad \beta \sim N(0_k, 10I_k), \quad \rho \sim N(0_6, 10I_6), \quad \alpha \sim N(0_w, 10I_w) \]

\[ 1/\sigma_b^2 \sim \text{Gamma}(10, 0.1), \quad 1/\sigma_c^2 \sim \text{Gamma}(10, 0.1), \quad 1/\sigma_j^2 \sim \text{Gamma}(10, 0.1), \quad j = 0, ... 6 \]

where \( k \) is the dimension of \( x_{it} \) and \( w \) is the column dimension of \( w_{it} \). \( 0_6 \) and \( I_6 \) denote the null vector and identity matrix of dimension 6, respectively. Informative conjugate priors are imposed on the correlation between plan choice and drug expenditure:

\[ \delta \sim N(0_6, 0.5I_6), \quad \pi \sim N(0_6, 0.5I_6). \]

Then, denote \( D'_{it} = (x'_{it}, d'_{it}), \phi_1 = (\gamma', \tau'), \phi_2 = (\beta', \rho') \), the estimation algorithm has the following steps:

1. \[ \left( \begin{array}{c} z_{it0} \\ z_{it} \end{array} \right), \forall i, \forall t \sim N \left( \left( \begin{array}{c} 0 \\ z_{it} \end{array} \right), \left( \begin{array}{cc} 1 & 0 \\ 0 & H^{-1}_{it} \end{array} \right) \right) \];

where \( H_{it} = I_6 + \delta \delta' + (\Sigma^2_{j=0} d_{ij} \sigma_j^2) \pi \pi' \).

\( z_{it0}, z_{it} \) are truncated such that if \( d_{it} = 1 \), then \( z_{itk} < z_{itj}, \forall k \neq j \). Geweke’s (1991) algorithm is used to draw from above truncated normal distributions.

2. \( H^*_{it}, \forall i, \forall t \sim N [(D'_{it} \phi_1 + (z - w'_{it} \alpha) \delta + b_i), 1] \).

The normal distribution is truncated to \((-\infty, 0]\) if \( Y_{it} = 0 \), and to \([0, \infty)\) if \( Y_{it} > 0 \).

3. \( Y^*_{it}, \forall i, \forall t \sim N [(D'_{it} \phi_2 + (z - w'_{it} \alpha) \pi + c_i), \Sigma^2_{j=0} d_{ij} \sigma_j^2], \) if \( Y_{it} = 0 \). \( Y^*_{it} = \ln(Y_{it}), \) if \( Y_{it} > 0 \).
4. \( b_i, \forall i \sim N(\bar{b}_i, H_{\bar{b}i}^{-1}) \), \( \bar{H}_{bi} = T_i + \sigma_b^{-2}, \bar{b}_i = \bar{H}_{bi}^{-1}[\Sigma_{t=1}^{T_i}(H_{it}^* - D_{it}'\phi_1 - (z - w_{it}'\alpha)'\delta)] \). \( T_i \) denotes the number of years individual \( i \) is observed.

5. \( c_i, \forall i \sim N(\bar{c}_i, H_{\bar{c}i}^{-1}) \), \( \bar{H}_{ci} = \Sigma_{t=1}^{T_i}\Sigma_{j=0}^{d_{it}j}\sigma_j^{-2} + \sigma_c^{-2}, \bar{c}_i = \bar{H}_{ci}^{-1}[\Sigma_{t=1}^{T_i}(\Sigma_{j=0}^{d_{it}j}\sigma_j^{-2}(Y_{it}^* - D_{it}'\phi_2 - (z - w_{it}'\alpha)'\pi))]) \)

6. \( \alpha \sim N(\bar{\alpha}, \bar{H}_\alpha^{-1}) \), \( \bar{\alpha} = \Sigma_i[\Sigma_t(\omega_{it}(I_6 + \delta\delta' + (\Sigma_{j=0}^{d_{it}j}\sigma_j^{-2})\pi\pi')z_{it} - w_{it}\delta(H_{it}^* - D_{it}'\phi_1 - b_i) - (\Sigma_{j=0}^{d_{it}j}\sigma_j^{-2})w_{it}\pi(Y_{it}^* - D_{it}'\phi_2 - c_i)) + \bar{H}_\alpha\alpha] \)

where \( \alpha \) and \( \bar{H}_\alpha \) are the prior mean and variance of \( \alpha \).

7. \( \theta_1' = (\phi_1', \delta') \sim N(\bar{\theta}_1, \bar{H}_{\bar{\theta}1}^{-1}) \); \( \bar{H}_{\bar{\theta}1} = \Sigma_i[\Sigma_t(D_{it}, z_{it} - w_{it}'\alpha)'(D_{it}, z_{it} - w_{it}'\alpha) + \bar{H}_{\theta_1}1 \); \( \bar{\theta}_1 = \bar{H}_{\bar{\theta}1}^{-1}[\Sigma_i(\Sigma_t(D_{it}, z_{it} - w_{it}'\alpha)'(H_{it}^* - b_i) + \bar{H}_{\theta_1}\bar{\theta}_1] \). \( \theta_1 \) and \( \bar{H}_{\theta_1} \) are the prior mean and variance of \( \theta_1 \).

8. \( \theta_2' = (\phi_2', \pi') \sim N(\bar{\theta}_2, \bar{H}_{\bar{\theta}2}^{-1}) \); \( \bar{H}_{\bar{\theta}2} = (\Sigma_{j=0}^{d_{it}j}\sigma_j^{-2})[\Sigma_i(\Sigma_t(D_{it}, z_{it} - w_{it}'\alpha)'(D_{it}, z_{it} - w_{it}'\alpha)) + \bar{H}_{\theta_2}\bar{\theta}_2] \); \( \bar{\theta}_2 = \bar{H}_{\bar{\theta}2}^{-1}[\Sigma_{j=0}^{d_{it}j}\sigma_j^{-2}(\Sigma_i(\Sigma_t(D_{it}, z_{it} - w_{it}'\alpha)'(Y_{it}^* - c_i)) + \bar{H}_{\theta_2}\bar{\theta}_2] \). \( \theta_2 \) and \( \bar{H}_{\theta_2} \) are the prior mean and variance of \( \theta_2 \).

9. \( 1/\sigma_b^2 \sim \text{Gamma}[10 + N/2, 1/(\Sigma_i\theta_i^2/2 + 10)] \). \( N \) is the number of individuals in the sample.

10. \( 1/\sigma_c^2 \sim \text{Gamma}[10 + N/2, 1/(\Sigma_i\sigma_i^2/2 + 10)] \).

11. \( 1/\sigma_j^2 \sim \text{Gamma}[10 + N_j/2, 1/(\Sigma_{i\in j}(Y_{it}^* - D_{it}'\phi_2 - c_i - (z - w_{it}'\alpha')\pi)^2/2 + 10)] \), \( j = 0, ..., 6 \). \( N_j \) is the overall number of observations in plan \( j \), and \( i \in j \) denotes such observations.
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