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RESEARCH ARTICLE

How Does Drug Treatment for Diabetes Compare between Medicare Advantage Prescription Drug Plans (MAPDs) and Stand-Alone Prescription Drug Plans (PDPs)?

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Objective. To compare the use of guideline-recommended prescription medications for diabetes among Medicare beneficiaries enrolled in stand-alone prescription drug plans (PDPs) with Medicare Advantage prescription drug plans (MAPDs) in the presence of potential selection bias.

Data Sources/Study Setting. Centers for Medicare and Medicaid Services' Chronic Condition Data Warehouse (2006, 2007).

Study Design. Retrospective cross-sectional comparison of drug use and proportion of days covered (PDC) for oral-antidiabetics, ACE-inhibitors/ARBs, and antihyperlipidemics among PDP and MAPD enrollees with diabetes. We estimated "naïve" regression models assuming exogenous plan choice and two-stage residual inclusion (2SRI) models to study endogeneity in choice of Part D plan type.

Data Collection/Extraction Methods. We identified 111,290 diabetics based on ICD-9 codes in Medicare claims from a random 5 percent sample of Medicare beneficiaries in 2005 excluding dual eligibles.

Principal Findings. The naïve regression models indicated lower probability of drug use for oral-antidiabetics (−4 percent; $p < .001$) and ACE-inhibitors/ARBs (−2 percent; $p = .004$) among PDP enrollees, but their PDC was higher (3–5 percent) for all drug classes ($p < .001$). 2SRI models produced no significant differences in any-use equations, but significantly higher PDC values for PDP enrollees for oral-antidiabetics and ACE-inhibitors/ARBs.

Conclusions. We found similar overall use of recommended drugs in diabetes treatment and no consistent evidence of favorable or adverse selection into PDPs and MAPDs.

Key Words. Medicare Part D, diabetes treatment, PDP, MAPD, selection bias

Over the last three decades, health economists have tried to answer the question of whether there is favorable selection into managed care plans as opposed to traditional fee-for-service (FFS) Medicare coverage (Wilensky and Rossiter 1986; Cutler and Zeckhauser 1998; Call et al. 1999; Greenwald, Levy, and Ingber 2000; Mello, Stearns, and Norton 2002; Mello et al. 2003). The impetus for this line of research stems from the use of a risk adjusted capitation payment system that rewards Medicare Advantage (MA) plans for achieving equal or better quality of care while holding costs below those of the FFS care delivery system. While risk adjustment is based on observable characteristics, favorable risk selection into MA plans based on unobservable factors may create the appearance of better performance. One of the challenges to examining this question is that MA enrollment may persist over time; hence it is difficult to measure baseline characteristics that are not affected by preexisting MA enrollment. This problem is compounded by the lack of comparable measures of health status for the two groups as MA plans are not required to submit insurance claims to Centers for Medicare and Medicaid Services (CMS).

The implementation of the prescription drug benefit within Medicare (Part D) provides a new opportunity to address this issue. As a result of the new benefit being implemented as a stand-alone program and one integrated with MA in the form of Medicare Advantage Prescription Drug plans (MAPD), a substantial number of Medicare beneficiaries in the FFS program are newly enrolled in MA plans. This study examines Part D plan choice from the perspective of use of guideline-recommended prescription medications for diabetes.

As of 2010, 46.5 million elderly and disabled, nearly 15 percent of the total US population, were enrolled in Medicare. One of the biggest challenges for Medicare beneficiaries with high numbers of chronic conditions is increasing prescription drug costs over the years. With the enactment of the Medicare Prescription Drug, Improvement, and Modernization Act (MMA) in 2003, Part D prescription drug benefits were made available for the Medicare population beginning in 2006. Part D services are provided by private insurance

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companies and enrollment is optional with penalties for late enrollees. In 2010, 17.7 million beneficiaries enrolled in stand-alone prescription drug plans (PDPs) and 9.9 million enrolled in MAPDs (The Henry J. Kaiser Family Foundation 2010).

The literature suggests that beneficiaries enrolled in MAPDs are healthier and have lower drug costs compared to PDP enrollees (Riley, Levy, and Montgomery 2009). Cline et al. (2010) examined possible factors affecting Medicare beneficiaries' decision to enroll into PDPs compared to MAPDs, including demographic variables, health status, and other factors. Their findings suggest moderate level of adverse selection into PDPs. However, the impact of selection in terms of prescription drug utilization was not examined and their study was limited to a single Part D region. A study by Jung, McBean, and Kim (2012) comparing statin adherence between beneficiaries in MAPDs and PDPs found statistically significant, but very small differences. The study sample was chosen according to the presence of a statin prescription, and the authors did not take into account the potential for unobservable confounders.

The objective of our study was to compare the use of guideline-recommended prescription medications among Medicare beneficiaries with diabetes enrolled in PDPs compared with MAPDs. We hypothesize that beneficiaries enrolled in MAPDs will exhibit higher rates of use for recommended therapies because MAPDs have better access to clinical data needed to optimize drug regimens as well as the financial incentive to invest in medication management. MAPDs also tend to provide richer drug benefits, including gap coverage. However, direct tests of this hypothesis are challenging given the lack of Medicare Part A and B claims for MAPD enrollees and the potential for significant unobserved selection effects in Part D enrollment choices. To address this, we use a two-stage residual inclusion model (2SRI) to correct for potential estimation bias due to unobserved selection effects in Part D enrollment choices. We compare these results with "naïve" models based on the assumption that observable factors alone account for plan choice decisions.

METHODS

Data Sources

This study uses 2 years of data from the CMS Chronic Condition Data Warehouse (CCW) for a random 5 percent sample of Medicare beneficiaries. CCW uniquely permits researchers to link datasets across the continuum of care. Available data include limited demographics and monthly enrollment

information for Medicare Parts A, B, C, and D; Part A and B claims data, Part D drug events, and Part D plan characteristics. In addition, the CCW Summary File provides flags for 21 chronic diseases based on diagnoses in Part A and B claims from 1999 forward. From these files, it is possible to identify individuals with prevalent chronic disease even if they are currently enrolled in MA plans as long as they had some history in the FFS sector.

Study Sample

The study sample included Part D enrollees in 2006 and 2007 with a diagnosis of diabetes (ICD-9 codes 250.xx, 357.2, 362.01, 362.02, 366.41) from an inpatient, skilled nursing facility or home health agency, or two claims from an outpatient hospital or carrier between 1999 and 2005 from the CCW Summary File. To observe contemporaneous plan choice behavior, we restricted the sample to individuals with FFS coverage in 2005 who either elected to stay in FFS (i.e., enroll in PDP plans) or switch to MA plans in 2006. This sample restriction also assured that we had similar information on beneficiary comorbidities for the PDP and MAPD cohorts. We further restricted the sample to exclude dual eligibles (those enrolled in both Medicare and Medicaid; in the CCW population of 2,529,285, there were 980,064 PDP enrollees and 371,813 MAPD enrollees. Forty-two percent of PDP enrollees and 13 percent of MAPD enrollees had dual status). Dual eligibles are randomly enrolled in Medicare Part D drug benefits through the low-income subsidy (LIS) and thus do not make initial enrollment decisions regarding plan type. We retained nondual eligible LIS recipients in the study sample. The final sample included 111,290 beneficiaries, 105,956 PDP enrollees, and 5,334 MAPD enrollees (see Figure 1).

Measurement of Key Variables

The first objective of our study was to estimate the effect of the choice of PDP over MAPD enrollment on using guideline-recommended medications in three drug classes: oral antidiabetic drugs, ACE-inhibitors/ARBs, and antihyperlipidemics (including statins, bile acid sequestrants, fibrates, ezetimibe, and niacin). These medications were identified and grouped using the American Hospital Formulary Service (AHFS) classification system. Our second objective was to estimate the effect of choice of Part D coverage on drug adherence among users of these medications. We tallied any use and adherence among users for each drug class. Our adherence measure was the proportion of days covered (PDC) during the 2-year observation period, 2006–2007.

Figure 1: Inclusion Criteria for the Study Sample

A beneficiary was defined as a user of guideline-recommended medications for a specific drug class if he/she had any record of a prescription drug event during the study period. This variable defines a beneficiary as a user regardless of the duration of time he/she was a user; for example, a beneficiary with a single 30-day fill is considered a user as well as another one with 730 days of use.

The second outcome variable, PDC, is defined as the number of days for which the medication was available divided by the number of days in the observation period for each beneficiary. The observation period is defined as either the overall study period, from January 1, 2006 through December 31, 2007, or from the beginning of the study period until death. The measurement period can take any value from 366 to 730 (we required that all subjects survive through the end of 2006 to have at least a year for measuring drug use).

The challenge in comparing drug utilization patterns for beneficiaries in PDPs and MAPDs is the potential endogeneity of plan choice. While all study subjects were required to be enrolled in FFS in 2005, a small fraction chose managed care plans in 2006 and we observe only a relatively small number of variables that may be related to that choice. This raises the possibility of unobserved variables both correlated with the selection into MAPDs and the

use of guideline-recommended prescription drugs. To correct for this possible selection bias, we used an instrumental variable that is correlated with the plan choice, but not directly correlated with the outcome variables. In this study, we used county-level MA penetration rate in 2005 as our instrumental variable (Area Resource File 2009–2010). Penetration is defined as “the ratio of enrollees over eligibles multiplied by 100.” The MA penetration rate in a county is hypothesized to be positively correlated with the selection of MAPDs and is presumed to be not directly correlated with either the probability of use or adherence to diabetes drugs.

Covariates

Other variables that we believe would be correlated with plan choice included age, gender, race, geographic region, and selected comorbidities from the CCW files (atrial fibrillation, acute myocardial infarction, heart failure, ischemic heart disease, stroke, cataracts, breast cancer, colorectal cancer, lung cancer, prostate cancer, chronic kidney disease, chronic obstructive pulmonary disease (COPD), Alzheimer’s or related dementia, depression, hip/pelvic fracture, osteoporosis, and arthritis). Comorbid conditions were measured using the CCW mid-year 2006 comorbidity flags. These flags capture diagnoses any time between July 2004 and 2005 (depending on whether the CCW definition includes a 1- or 2-year look-back period) and June 2006. As indicated above, we included beneficiaries who died in 2007, which was recorded with a binary variable. We also used a binary variable to capture nondual eligible LIS status (LIS enrollees pay only nominal cost sharing and are hypothesized to have higher drug utilization rates as a result). To augment the limited demographic information available on the CCW files, we used 2000 census data at the five-digit zip-level to characterize income, education, and English language proficiency. We also used data from the 2009 Area Resource File (ARF) to identify county-level variables for the percentage of population living in urban areas, basic MA capitation rates (AAPCC), and the presence of federally qualified health centers (FQHCs).

Empirical Models

The “naïve” regression models assume exogenous plan choice controlling for the observed factors listed above. We estimated separate models for each of the three drug classes: oral antidiabetic drugs, ACE-inhibitors/ARBs, and antihyperlipidemics for each outcome variable (any use and PDC for users).

Our first outcome variable is any use of the prescription drug, a binary variable. The policy variable of interest—PDP enrollment—is a binary variable equal to 1 if enrolled in PDP during 2006, and 0 otherwise. We used probit regression to estimate the probability of any drug use (see Appendix). Our second outcome variable, PDC, is a fractional variable restricted in the $[0, 1]$ interval. For the estimation of naïve models we used a generalized linear model (GLM) with a binomial distribution and logit link function to address this interval restriction.

The 2SRI model is a consistent estimator in correcting for endogeneity for nonlinear models (Terza, Basu, and Rathouz 2008). We used the 2SRI model to address potential endogeneity due to unobserved selection effects in Part D enrollment choices. In the first stage of the 2SRI model, we estimated the probability of PDP enrollment using a probit regression. In the second stage, we estimated the probability of any drug use controlling for observed confounders and the estimated residual from the first stage.

We also used 2SRI for the PDC outcome model. The first stage of the two-stage model is the same as above and is estimated for the overall sample ($N = 111,290$). In the second stage estimation, we used GLM with a binomial distribution and logit link function. Both in endogeneity corrected any-use models and PDC models we are interested in the local average treatment effect of the choice of PDP over MAPD, as defined by Imbens and Angrist (1994). The local average treatment effect estimates in 2SRI are defined for a nonidentifiable group of beneficiaries.

In an instrumental variables model, we cannot directly test for endogeneity of the policy variable of interest; however, we can test if the instrumental variable used in the first stage is statistically significant, and also we can test if the coefficient on the residual from first stage ($\hat{x}_u$) is statistically significant in the second stage estimation. A significant coefficient for the instrumental variable represents evidence for strong association with the treatment choice variable. A significant coefficient for the residual from first stage represents evidence of selection bias. Furthermore, the sign of the coefficient estimate of $\hat{x}_u$ in the second stage estimation provides a relevant indication for the direction of bias.

RESULTS

Table 1 summarizes descriptive statistics for the drug utilization measures and the covariates used in the multivariate analysis. PDPs had older enrollees with

Table 1: Sample Characteristics by Part D Plan Type and Drug Class

Characteristics	Total			Oral Antidiabetics			ACE-inhibitors/ARBs			Antihypertipidemics		
	Total	PDP	MAPD	PDP	MAPD	PDP	PDP	MAPD	PDP	PDP	MAPD	PDP
N	111,290	105,956	5,334	65,723	3,673	73,296	3,814	70,028	3,573			
Drug utilization measures												
Any use (%)	—	—	—	62.00*	68.90	69.20*	71.50	66.10	67.00			
Proportion of days covered (mean)	—	—	—	0.65*	0.61	0.64*	0.58	0.59*	0.53			
Demographics												
Age (%)												
Under 65	10.17	9.90*	15.52	10.21*	15.65	9.57*	15.50	9.51*	15.51			
65–74	44.68	44.36*	51.14	47.35*	53.47	45.79*	51.81	47.68*	53.18			
75–84	34.63	34.98*	27.58	33.51*	25.81	34.80*	27.37	34.93*	27.18			
85+	10.52	10.76*	5.76	8.93*	5.06	9.84*	5.32	7.88*	4.14			
65+ and SSDI	7.93	7.90	8.62	7.73	8.47	7.96	8.65	7.97	8.73			
Female (%)	62.94	63.17*	58.49	61.71*	57.69	63.48*	58.70	62.37*	58.35			
Male (%)	37.06	36.83*	41.51	38.29*	42.31	36.52*	41.30	37.63*	41.65			
Race/ethnicity (%)												
White	88.09	88.55*	78.97	88.44*	79.44	88.24*	78.29	89.58*	80.24			
Black	8.77	8.43*	15.60	8.51*	15.08	8.93*	16.73	7.55*	14.50			
Hispanic	1.04	0.99*	2.01	1.06*	2.01	0.99*	1.84	0.93*	1.90			
Other	2.10	2.03*	3.43	2.00*	3.46	1.84*	3.15	1.94*	3.36			
Geographic region (%)												
West	12.58	12.51*	13.99	12.41*	14.29	12.38*	13.92	12.31	13.18			
Northeast	15.79	15.97*	12.28	14.54*	12.33	15.33*	12.27	16.09*	12.87			
North central	29.62	29.72*	27.48	30.22*	26.71	30.07*	26.98	29.80*	28.07			
South	42.01	41.80*	46.25	42.82*	46.66	42.23*	46.83	41.80*	45.87			

continued

Table 1. Continued

Characteristics	Total			Oral Antidiabetics			ACE-inhibitors/ARBs			Antihyperlipidemics		
	Total	PDP	MAPD	PDP	MAPD	PDP	PDP	MAPD	PDP	PDP	MAPD	MAPD
Dead in 2007 (%)	5.48	5.58*	3.51	4.73*	3.05	4.99*	4.99*	3.38	4.22*	4.22*	2.83	2.83
LIS status (%)												
Non-LIS	85.73	85.51*	90.12	84.92*	89.52	85.02*	85.02*	89.17	85.77*	85.77*	89.48	89.48
Nondual LIS	14.27	14.49*	9.88	15.08*	10.48	14.98*	14.98*	10.83	14.23*	14.23*	10.52	10.52
Chronic conditions (%)												
Atrial fibrillation	9.39	9.63*	4.69	8.63*	4.25	9.75*	9.75*	4.80	9.30*	9.30*	4.42	4.42
Acute myocardial infarction	1.24	1.27*	0.69	1.19*	0.60	1.47*	1.47*	0.81	1.58*	1.58*	0.76	0.76
Heart failure	22.78	23.16*	15.26	21.32*	13.94	24.40*	24.40*	16.62	23.20*	23.20*	15.53	15.53
Ischemic heart disease	42.97	43.38*	34.93	41.75*	33.60	45.20*	45.20*	36.21	48.23*	48.23*	38.90	38.90
Stroke	4.70	4.79*	2.94	4.32*	2.53	4.86*	4.86*	3.22	4.80*	4.80*	2.83	2.83
Cataracts	24.82	25.30*	15.24	24.12*	14.89	25.08*	25.08*	15.23	25.86*	25.86*	15.28	15.28
Breast cancer	2.41	2.47*	1.24	2.38*	1.28	2.42*	2.42*	1.23	2.33*	2.33*	1.01	1.01
Colorectal cancer	1.02	1.04*	0.43	0.96*	0.41	0.98*	0.98*	0.47	0.93*	0.93*	0.36	0.36
Lung cancer	0.56	0.58*	0.19	0.49*	0.19	0.48*	0.48*	0.16	0.53*	0.53*	0.11	0.11
Prostate cancer	2.52	2.57*	1.50	2.50*	1.52	2.42*	2.42*	1.39	2.52*	2.52*	1.32	1.32
Chronic kidney disease	13.70	13.95*	8.96	12.44*	8.00	14.62*	14.62*	9.47	14.52*	14.52*	9.07	9.07
COPD	10.45	10.63*	6.81	9.28*	6.15	10.08*	10.08*	6.27	10.16*	10.16*	6.47	6.47
Alzheimer's or related dementia	7.80	7.94*	5.12	6.80*	4.60	7.04*	7.04*	4.88	6.55*	6.55*	4.17	4.17
Depression	10.44	10.59*	7.44	9.67*	7.11	10.01*	10.01*	7.24	10.07*	10.07*	7.44	7.44
Hip/pelvic fracture	0.78	0.80*	0.30	0.63*	0.19	0.76*	0.76*	0.34	0.64*	0.64*	0.31	0.31
Osteoporosis	10.90	11.16*	5.74	8.95*	5.01	10.36*	10.36*	5.27	10.55*	10.55*	5.57	5.57

continued

Table 1. Continued

Characteristics	Total		Oral Antidiabetics		ACE-inhibitors/ARBs		Antihypertensives	
	Total	PDP	MAPD	PDP	MAPD	PDP	PDP	MAPD
Arthritis	21.94	22.31*	14.60	20.37*	13.64	21.65*	21.04*	13.69
Contextual variables (mean)								
Education								
% Population 65+ w/o HS diploma	0.36	0.36*	0.38	0.36*	0.38	0.36*	0.36*	0.37
% Population 65+ w/HS diploma	0.32	0.32*	0.32	0.33*	0.32	0.33*	0.33	0.32
% Population 65+ w/some college	0.17	0.17*	0.17	0.17	0.17	0.17	0.18*	0.17
% Population 65+ w/college & higher	0.14	0.14*	0.13	0.14*	0.13	0.14*	0.14*	0.13
Income								
% Population 65+ w/Income <15K	0.27	0.27*	0.28	0.28	0.28	0.28*	0.27*	0.28
% Population 65+ w/Income 15-30K	0.28	0.28*	0.29	0.29*	0.29	0.28*	0.28*	0.29
% Population 65+ w/Income 30-50K	0.21	0.21*	0.22	0.21	0.22	0.21*	0.22*	0.22
% Population 65+ w/Income 50-100K	0.16	0.17*	0.16	0.16*	0.16	0.16*	0.17*	0.16
% Population 65+ w/Income >100K	0.06	0.06*	0.05	0.06*	0.05	0.06*	0.06*	0.06
% population 65+ w/poor/no English	0.18	0.18*	0.18	0.17*	0.18	0.18*	0.18*	0.18

continued

Table 1. Continued

Characteristics	Total			Oral Antidiabetics			ACE-inhibitors/ARBs			Antihyperlipidemics		
	Total	PDP	MAPD	PDP	MAPD	MAPD	PDP	MAPD	MAPD	PDP	PDP	MAPD
% of population living in urban areas	0.70	0.70*	0.75	0.69*	0.74		0.70*	0.75		0.70*	0.76	
AAPCC in 2006	712.50	712.35*	715.45	706.52*	713.87		709.96*	715.50		712.62*	716.09	
FQHC in 2006 (%)	46.34	45.99*	53.13	44.44*	52.60		45.51*	53.36		46.09*	54.44	
Instrumental variable (mean)												
% MA penetration in 2005	0.09	0.09*	0.12	0.09*	0.13		0.09*	0.13		0.09*	0.13	

Note. Age 65–74, white, west, % Population 65+ w/college and higher, and % Population 65+ w/income >100K represents the reference groups. Differences in proportions and differences in means between PDP and MAPD samples are tested.
*Statistically significant with $p < .05$.

a higher percentage of females and white non-Hispanics. PDP enrollees were more likely to reside in northern sections of the United States. A much higher percentage of nondual LIS recipients were enrolled in PDPs. MAPD enrollees generally had lower rates for the comorbidities listed in the CCW files, thus indicating favorable selection into MAPDs.

Sample statistics for drug use and adherence (PDC) by Part D plan type—PDP versus MAPD—are presented in the top two rows in Table 1. In these unadjusted comparisons, point estimates of user rates were consistently higher in MAPDs than PDPs (68.9 percent vs. 62.0 percent for oral antidiabetics; 71.5 percent vs. 69.2 percent for ACE-inhibitors/ARBs; and 67.0 percent vs. 66.1 percent for antihyperlipidemics). However, only for oral antidiabetics and ACE-inhibitors/ARBs were the differences statistically significant at $p < .01$. On the other hand, PDC rates among drug users were consistently higher for PDP enrollees by between .04 (oral antidiabetic drugs) and .06 (ACE-inhibitors/ARBs and antihyperlipidemics) with $p < .001$ in each case.

Findings from the naïve models for the any-use measures are presented in Table 2 section (a). The naïve regression models indicate that the probability of drug use was 4.2 percent points lower among PDP enrollees for oral antidiabetics ($p < .001$); 1.9 percent points lower among PDP enrollees for ACE-inhibitors/ARBs ($p = .004$); and .7 percent points lower among PDP enrollees for antihyperlipidemics ($p = .31$). These results are consistent with the descriptive statistics.

Table 2 section (c) summarizes the naïve model results for PDC among users. The GLM estimates were consistent with the bivariate analysis; among PDP enrollees the PDC was 3.5 percent points higher among oral antidiabetic users, 4.6 percent points higher among ACE-inhibitors/ARBs users, and 4.7 percent points higher among antihyperlipidemic users compared with MAPD enrollees. Furthermore, the average treatment effect of PDP enrollment was statistically significant for all drug classes.

Table 2 section (b) presents the 2SRI local average treatment effect results for the any-use dependent variables for each drug class. In the first stage of the 2SRI model our instrument, MA penetration rate, was statistically significant ($p < .001$) (see Appendix Table A). Wald test result ($\chi^2 = 565.42$) also confirms statistical significance. The coefficient on MA penetration had a negative value, supporting the hypothesis that the probability of PDP plan selection in our study sample was lower in counties with higher MA penetration rate. In the second stage, the coefficient of the estimated residual from the first stage was statistically insignificant indicating that there is no concrete evidence of endogeneity in plan selection for the any-use outcome variable. The inclusion of the residual

Table 2: Naïve Model and Two-stage Residual Inclusion (2SRI) Model Results for Any Drug Use and PDC among Users

Drug Class	N	Naïve Model		2SRI Model	
		(a) ATE for PDP Enrollment	[95% CI]	(b) LATE for PDP Enrollment	[95% CI]
Any drug use					
Oral antidiabetics	111,290	−0.041	−0.0548	−0.1069	−0.2246
ACE-inhibitors/ARBs	111,290	−0.0187	−0.0314	−0.0489	−0.1676
Antihyperlipidemics	111,290	−0.0068	−0.0200	−0.0574	−0.1751
Proportion of days covered among users					
Drug class	N	(c) ATE for PDP Enrollment	[95% CI]	(d) LATE for PDP Enrollment	[95% CI]
Oral antidiabetics	69,396	0.0348	0.0264	0.1161	0.0205
ACE-inhibitors/ARBs	77,110	0.0468	0.0379	0.1314	0.0338
Antihyperlipidemics	73,601	0.0465	0.0372	−0.0144	−0.1089

Note. These results are adjusted for the variables listed in Table 1. The instrumental variable is the county-level MA penetration in year 2005. LATE and ATE are calculated using Stata “mix” command for naïve models, and Terza, Basu, and Rathouz (2008) definition for 2SRI models. The preferred estimates are the naïve model estimates for any drug use (in all three drug classes) and PDC of antihyperlipidemics, but the 2SRI estimates for the PDC of oral antidiabetics and antihyperlipidemics (see Results section for further discussion).

ATE, average treatment effect; LATE, local average treatment effect.

estimate in the second stage estimation had an insignificant effect on the local average treatment effect of enrollment with no sign change from the naïve model.

The 2SRI results for drug adherence among users are presented in Table 2 section (d). In the first stage, the instrumental variable was statistically significant for users of each drug class (see Appendix Table). As in the any-use equations, we found a negative correlation between MA penetration and selection into PDP plans. In the second stage, the coefficient of the estimated residual (from first stage) was marginally statistically significant and had a negative sign for two of the three drug classes—oral antidiabetics and ACE-inhibitors/ARBs. After correcting for selection into MAPDs, the PDC was estimated as 13 percent points higher for PDP enrollees compared with MAPD enrollees among ACE-inhibitors/ARBs users ($p = .008$) and 11 percent points higher among oral antidiabetic users ($p = .017$). These estimates are more than double of those from the naïve models. The 2SRI model found no evidence of selection bias in the estimated effect of plan choice on PDCs for antihyperlipidemic drugs.

Propensity score matching is a method widely used in observational studies when there is concern about confounding between treatment and outcomes on the basis of observable characteristics. In our diabetes cohort, we had a large sample of beneficiaries with PDP compared with MAPD. We performed propensity score matching to compare use and adherence between PDP and MAPD samples. We used Stata 12 “psmatch2” command to implement propensity score matching—one-to-one matching with .001 caliper using common support (Leuven and Sianesi 2003). The results are presented in Appendix Table B. The matched sample results, both for any use and PDC, are very close to naïve model results presented in Table 2. We found that any drug use was 3.9 percent points lower among PDP enrollees for oral antidiabetics, 1.8 percent points lower for ACE-inhibitors/ARBs, and 0.1 percent points lower for antihyperlipidemics using the propensity score matched sample. Naïve model results indicated any drug use was 4.2 percent points lower among PDP enrollees for oral antidiabetics, 1.9 percent points lower for ACE-inhibitors/ARBs, and 0.7 percent points lower for antihyperlipidemics. The results for PDC values were similar. These results suggest that our naïve models adequately control for observable confounders.

To test whether our findings extend beyond beneficiaries with diabetes, we performed a sensitivity analysis for a sample of beneficiaries with congestive heart failure (CHF) selected among 2005 beneficiaries in FFS and tracked through 2006 and 2007. We estimated both naïve models and 2SRI models

with the same covariates given in Table 1 for the any use and PDC for four drug classes: ACE-inhibitors/ARBs, beta blockers, digoxin, and calcium channel blockers. The results were very similar to those presented in Table 2 with no consistent evidence for selection bias in plan choice.

All the beneficiaries included in this study were continuously enrolled in Part D until the end of study period or death. However, there were 4,567 enrollees who switched between MAPDs and PDPs during the study period, where 335 enrollees were assigned to MAPD and 4,232 enrollees were assigned to PDP. In our analysis, we adopted an intention-to-treat approach in which the initial prescription drug plan was assigned to beneficiaries. We also conducted a sensitivity analysis where we dropped the 4,567 switcher enrollees. The results were very close to our main results presented in Table 2.

DISCUSSION

Since the early 1980s when Medicare began offering beneficiaries, the choice of private plans over traditional FFS coverage, health economists have investigated the possibility of favorable selection into managed care plans. Several studies have been motivated by a desire to make comparisons of utilization patterns between the two types of care that are not biased by selection on unobserved characteristics. The introduction of Part D in the Medicare program again raises the question of plan selection on unobservable characteristics.

Riley, Levy, and Montgomery (2009) examined selection into Part D plans using data from the Medicare Current Beneficiary Survey (MCBS) with linkages to other datasets. Although their analysis did not adjust for confounding variables, they also found that the MAPD population was healthier compared with PDP enrollees suggesting favorable selection into MAPDs. Another study examining the selection decision of Medicare beneficiaries between PDPs was conducted by Cline et al. (2010) using a combination of claims data and survey information to estimate plan choice in a multivariate framework. Their explanatory variables included demographic factors, socioeconomic variables, health status, LIS status, and some health specific survey questions (e.g., whether enrollee knows current pharmacist “extremely well,” etc.). However, they did not test for potential unobserved confounding in an instrumental variable context. The study sample was also very small ($N = 1,490$) and represented a single Part D region.

A more recent study by Jung, McBean, and Kim (2012) examined differences in statin adherence between beneficiaries in MAPDs and PDPs. They

hypothesized that since MAPD plans offer both medical and drug benefits under the same plan, adherence by MAPD beneficiaries would be higher compared with PDP beneficiaries. Their findings suggest significant yet very small differences between two types of plans. Similar to our study, they used the CCW 5 percent files; however, their inclusion criterion was defined as having a prescription drug event for statin during the study period. Furthermore, their model did not address the possible favorable selection into MAPD plans.

Our study examined whether there is favorable selection into MAPDs compared with PDPs, and if so, whether it changed the estimated effects of one plan type versus the other in terms of prescription drug use and adherence with medications used in diabetes treatment. We have attempted to address some of the limitations present in Riley, Levy, and Montgomery (2009), and Cline et al. (2010). Our sample was large (111,290) and represented all regions in the United States. Unlike Jung, McBean, and Kim (2012) our model controls for unobservable confounders. Our results indicate that MAPD enrollees are more likely to be users of evidence-based medications yet exhibit lower drug adherence thereafter compared with PDP enrollees. Four of our six 2SRI models failed to find evidence of selection bias from unobserved confounders; two of the six indicated favorable selection into MAPDs.

Our analysis is consistent with the traditional two-part model approach suggested by Duan et al. (1983, 1984). In the first part, we estimated the decision related to any use of the drugs investigated. In the second part, we estimated the amount of use among users. Maddala (1985) argued whether the decisions regarding drug use and the amount used are sequential or simultaneous and he presents a survey of the literature on this issue. Madden (2008) suggests that while there are merits to both approaches, individual behavior is very difficult to model, and researchers should decide which approach to use on a “case-by-case basis.” From the policy maker’s point of view, investigating both the decision to use medication and the decision of how much to use are important. Our findings indicate very different results in terms of the effect of enrollment in an MAPD or PDP on being a user and level of use conditional on any use.

Our study is subject to a variety of limitations, mostly related to limitations of the CCW database. In terms of cohort selection, we restricted our focus to those with FFS Medicare in 2005 because the CCW does not include Parts A and B claims for MA enrollees. Thus, any impact of MAPD enrollment on utilization for beneficiaries who are long-term MA enrollees is not captured in our estimates. We also note that the beneficiaries in the study had prevalent diabetes at the time of cohort entry. As a result, established drug

utilization pattern may lead to under- or overestimation of the effect of MAPD enrollment. The lack of Part A and B claims means there may be under-ascertainment of comorbid conditions, particularly for beneficiaries who might have been FFS enrolled only in 2005. Although we expect that the magnitude of this difference is small, the data limitations make it difficult to determine whether differences in observed rates of comorbid conditions are due to differential under-reporting, or that MAPD enrollees tend to be healthier along multiple dimensions. The CCW data provide limited information on beneficiary characteristics. In particular, factors such as income, education, and the presence of Medicare supplemental insurance, which would presumably play a major role in Part D plan choices. We were able to capture income and education from 2000 census data at the zip code level, but contextual variables are at best crude indicators of person-level characteristics. In this study, we did not focus on the benefit design differences between PDPs and MAPDs, and that deserves future study. Finally, we could not test the assumption that the instrument and the error term in the outcome equation were uncorrelated. Because our 2SRI models had only one instrumental variable, these models were exactly identified.

We conclude from these findings that there is no consistent evidence of selection bias in comparisons of drug utilization rates for Medicare beneficiaries with common chronic diseases such as diabetes enrolled in PDPs and MAPDs. While we found some evidence of selection bias in measures of drug adherence, the magnitude of the bias was 13 percent for ACE-inhibitors/ARBs and 11 percent for oral antidiabetics, and we found no evidence of selection bias in relation to take-up of evidence-based medications.

Although we found no consistent evidence for selection bias, for the research community this is a first test of selection effects in PDP versus MAPD and there should be greater body of evidence before final conclusions are drawn. Investigators should consider possible adverse selection into MAPD plans and conduct well-designed drug utilization studies using consistent endogeneity correction models such as 2SRI for estimation of unbiased treatment effects. For the policy community, our findings increase the credibility of results from such studies.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

- Appendix SA1: Author Matrix.
- Appendix SA2: Naïve Models.