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Switching Costs in Medicare Advantage

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Abstract:

This paper estimates the magnitude of switching costs in the Medicare Advantage program. Consumers are generally assumed to pick plans that provide the combination of benefits and premiums that maximize their individual utility. However, the plan choice literature has generally omitted prior choices from choice models. The analysis is based on five years of the Medicare Current Beneficiary Survey, a nationally representative longitudinal dataset. The MCBS data were combined with data on Medicare Advantage Part C plan benefits and premiums. Individual choices are modeled as a function of individual characteristics, plan characteristics and prior year plan choices using a mixed logit model. We found relatively high rates of switching between plans within insurer (20%), although less switching between insurers. Prior year plan choices were highly significant at both the contract and plan level. Premium was negative and significant. Loyalty (contract and plan), premium and plan structure were found to be heterogeneous in preferences. We found a statistically significant willingness to pay for a lower prescription drug deductible and lower copays. Switching costs were higher for sicker individuals. Switching costs between plans offered by the same insurer are far lower than switching costs between insurers; beneficiaries will switch plans if an alternative is perceived as \$233 a month better than the current choice and switch insurers if the alternative is perceived as \$944 better than the current plan/contract, on average. Premium elasticities would be 34% greater in magnitude if prior choices were irrelevant. We provide evidence that the state dependence is structural rather than spurious.

Keywords: health insurance, health plan choice, health plan switching, medicare advantage, mixed logit

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1 Introduction

The US Medicare program offers beneficiaries the choice of receiving health insurance either through the traditional fee-for-service (FFS) option or through the Medicare Advantage (MA) program. MA was introduced in 1985 to give Medicare beneficiaries more choices, similar to those available to workers with employment-based health insurance. MA plans can offer enhanced benefits, including reduced cost sharing, and may charge an additional premium. MA enrollment has waxed and waned over the years, but currently, more than 20 million Medicare beneficiaries (34%) are enrolled in an MA plan (Jacobson, Damico, and Neuman 2017). The MA program has provided considerable consumer surpluses to enrollees, although the gains are geographically uneven (Town and Liu 2003).

The choice structure of MA is intended to improve beneficiary welfare by providing varying options to consumers with varying preferences, while at the same time encouraging competition among health plans. However, policy analysts are concerned about the ability of beneficiaries to make efficient health plan choices based on premiums, benefits, and quality of care. A central question is whether beneficiaries are willing and able to choose the health plan with premiums and benefits that best match their preferences, and then to switch plans if a better option becomes available.

Although there has been considerable research into the effects of premiums and benefits on MA plan choices, there are several notable gaps in the literature. First, there is a dearth of recent studies of MA plan choice. The latest study uses data from 2008, 2 years after the Part D program was enacted (Jacobs and Buntin 2015). Use of more recent data is important, because younger beneficiaries who have more experience with managed care may be more comfortable choosing among MA plans.

Second, there are no analyses of the economic implications of low rates of plan switching among Medicare beneficiaries. Switching can be costly and risky for consumers and can have important implications for the prices and coverage set by competing MA plans. There are two levels of choice in the MA program. The upper level is the choice among insurers (referred to by CMS as “contracts”). Examples are Humana, Aetna, and Kaiser. The lower level is the specific set of benefits offered by the different “plans” associated with each insurer. A

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beneficiary cannot switch insurers without switching plans, although the opposite is possible. No studies have examined this switching structure in either MA or other settings.

We address these gaps in the literature by analyzing MA plan choices with more recent data at both the insurer and plan level.

2 Background: Prior Studies of Medicare Health Plan Choice

Studies of health plan choice in Medicare have found that Medicare beneficiaries are responsive to differences in premium and benefits, with an estimated premium elasticity in the range of -0.13 to -0.20 (Dowd, Feldman, and Coulam 2003; Atherly, Dowd, and Feldman 2004; Jacobs and Buntin 2015). Beneficiaries prefer plans with better benefits, particularly prescription drug coverage, and lower out of pocket spending (Dunn 2010; Ried et al. 2013). Beneficiaries appear to have heterogeneous preferences, with age and income being important predictors of choices (Atherly, Florence, and Thorpe 2005; Florence, Atherly, and Thorpe 2006; McCarthy and Tchernis 2010).

2.1 The Importance of Low Switching Rates

The economic literature has looked at the sources of switching costs (Jacobson, Damico, and Neuman 2017). Klemperer (1995: p. 517) observed that switching costs result “from a consumer’s desire for compatibility between his current purchase and a previous investment” and subdivided switching costs into those related to: (1) physical investment; (2) informational investment; (3) psychological investment; or (4) an artificially created price discontinuity. Other authors point to loyalty (a change in preferences due to past purchases) and search costs, which causes consumers not to consider products they have not recently purchased (Keane 2013).

Most studies of private health insurance find low switching rates. For example, Cunningham and Kohn (2000) found that 17% of commercially insured persons in the United States switched plans each year, but the overwhelming majority of switches were due to changing employers or plan offerings changing (Cunningham and Kohn 2000). Only 24% of the switches (about 4% of the total sample) were due to employees voluntarily choosing a different plan. Reitsma-van Rooijen, Jong, and Rijken (2011) reported switching rates between 3% and 6% in the Dutch health insurance system, a finding that is consistent with Beest, Lako, and Sent (2012), who found a switching rate of less than 4% in the same health system (Reitsma-van Rooijen, Jong, and Rijken 2011; Beest, Lako, and Sent 2012).

Morrisey et al. (2010), utilizing the 5% Medicare Beneficiary Sample from 1999 to 2008, found annual switching rates of 2.2% into the MA program and 7.6% out of MA (Morrisey et al. 2010). McWilliams et al. (2011) found switching rates into MA increased from 2.6% in 2004 to 6.5% in 2007, while switching out of MA remained relatively stable at 3.1%–4.3% (McWilliams et al. 2011). Most switches are within the MA sector; data from 2008 showed that 84% of switches by MA enrollees were from one MA plan to another (Center for Medicare and Medicaid Services 2013). This is consistent with Sinaiko, Afendulis, and Frank (2013), who found that the initial decision at age 65 to enroll in FFS or MA largely determined subsequent enrollment decisions (Sinaiko, Afendulis, and Frank 2013).

Low switching rates also have been found in Medicare Part D (prescription drug coverage). Part D is quite different from other forms of insurance because the drugs in different plans are chemically equivalent, yet switching rates remain low. Overall, studies find Part D switching rates of about 10% annually (Heiss et al. 2016; Polyakova 2016), which has been attributed to inattention or asymmetric search costs (Ho, Hogan, and Morton 2017). Other researchers have also found choice inconsistencies in Part D, e.g. individuals selecting a plan that is dominated by an alternative in the choice set (Abaluck and Gruber 2011, 2016).

Low switching rates are consistent with, but not necessarily proof of, high switching costs. Switching costs include search costs, the cost of becoming familiar with a new alternative, or risk aversion regarding the uncertain attributes of a new alternative. If high switching costs prevent beneficiaries from selecting preferred alternatives that are available, this reflects structural state dependence (Heckman 1981). However, low switching rates are also consistent with heterogeneous and stable beneficiary preferences across relative stable plan offerings in a market area. In other words, beneficiaries could search diligently across all the choices in their market area each year with no aversion to switching, and simply continue to choose the same plan because they like it better than all the alternatives. This is referred to as spurious state dependence (Heckman 1981).

Previous research has taken several approaches to distinguish between spurious and structural state dependence. Dubé, Hitsch, and Rossi (2010) controlled for spurious state dependence by using different distributions of the error term and flexible forms of the consumer’s utility function, suggesting that consistent results with different distributions indicate structural switching costs (Dubé, Hitsch, and Rossi 2010). Keane (1997) used

a similar approach, accounting for structural state dependence by allowing past purchases to affect current purchases, and modeling heterogeneity by letting certain parameters of the utility function be random (Keane 1997). He then estimated models with successively more flexible functional forms for heterogeneity, arguing that the least flexible model includes both structural and spurious state dependence, while the most flexible models include only structural state dependence. If previous choices remain significant predictors of current choices with more and more flexible forms of the other coefficients, that was evidence of structural state dependence.

If spurious state dependence can be ruled out, then low switching rates indicate high switching costs. High switching costs are of great policy relevance because in the presence of high switching costs, plans have two conflicting incentives in setting their prices: an “investing” incentive to set low prices to capture new enrollees; and a “harvesting” incentive to set high prices to exploit current members. Which of these incentives dominates depends on the size of the switching costs among other factors. The relative importance of investing versus harvesting on producers’ pricing decisions has been the focus of recent research, with some papers suggesting that the investing strategy dominates the harvesting strategy in some products (Dubé, Hitsch, and Rossi 2009).

3 Theoretical Model

We assume that individuals select MA plans that maximize their utility given their preferences, income and prices. Individual i 's indirect utility U from plan j at time t is a function of the premium charged by plan j (P_j), the benefits offered by plan j (B_j), and prior enrollment:

$$U_{ijt} = \alpha P_{jt} + \beta_i B_{jt} + \gamma_i L^I_{ij} + \delta_i L^P_{ij} + e_{ijt} \quad (1)$$

$$\gamma_i = \lambda_0 + \lambda_1 I_i + u_i \quad (2)$$

$$\delta_i = \kappa_0 + \nu_i \quad (3)$$

$$\beta_i = \zeta_0 + z_i \quad (4)$$

Prior choices measure the beneficiary’s loyalty to the insurer or plan, and thus enter equation (1) in two ways. The first is loyalty to the insurer, L^I , e.g. Aetna or Humana. The second is L^P which represents loyalty to the specific health plan characterized by its premium, coverage, and other characteristics. L^I is coded 1 if plan j is offered by the same insurer that was chosen in the previous year. L^P is coded 1 if the plan is the same plan (and thus the same insurer) chosen by the beneficiary in the previous year. There can be at most one choice in the choice set for which $L^P = 1$, but there can be multiple choices for which $L^I = 1$ if the insurer offers multiple plans in a county.

3.1 Estimation and Interpretation of the Results

We assume that the beneficiary faces a choice from among J plans, with the individual’s utility given by equations (1)–(4). Premiums, benefits and prior choices all are observed. The beneficiary knows the value of her own γ_{it} , δ_{it} , β_{it} and e_{ijt} for all J and chooses alternative j if and only if $U_{ijt} > U_{ikt}$ for all $k \neq j$.

Our estimation strategy is to control for sources of spurious state dependence, so the coefficients on the loyalty variables can be interpreted as structural switching costs. We account for heterogeneous beneficiary preferences by allowing the coefficients on plan characteristics to be randomly distributed. For example, some beneficiaries may have very strong preferences for remaining with the same insurer or plan, while others may have low or even negative switching costs. A negative coefficient on L^I or L^P would indicate dissatisfaction with the prior year’s choice. e_{ijt} is a vector of unobserved attributes of choice j at time t and is distributed IID, type 1 extreme value.

We initially assume that the error terms u_i , ν_i , and z_i are normally distributed. Greene (2012a,2012b) argues that the normal distribution is an appropriate choice because of the central limit theorem, unless a particular coefficient is restricted to the positive range (Greene 2012a,2012b). We allow for flexible functional forms

by testing the robustness of the results to other distributions, including log-normal, uniform and triangular distributions. We also allow a flexible covariance structure by allowing the error terms in 2 and 3 to follow a stationary autoregressive AR(1) process and by allowing the error terms for the coefficients to be correlated with one another. With these sources of spurious state dependence controlled, we interpret the coefficients on L^I and L^P as representing structural state dependence. We estimated the choice equations using random coefficients logit, also referred to as “mixed logit” (Train 2003). We also estimated a conditional logit model as a benchmark because it has a very restrictive structure for the error terms (results not shown).

Chamberlain (1985) suggests a test for structural switching costs: to remove the loyalty (prior-year choice) variables and include lagged prices in the choice equation (Chamberlain 1985). If the important attributes of the choices are included in the equation, then lagged prices would matter only if there were structural switching costs; that is, last period’s prices shouldn’t influence this period’s choices except via structural switching costs. Chamberlain’s test implicitly assumes that prices are uncorrelated with an individual’s intrinsic preferences for a product and that changes in individual preferences are uncorrelated with price changes. This assumption is more plausible if exogenous price shocks affect a subset of products, e.g. consumers have discount coupons for particular providers. We have not identified a price shock of this type for the MA market, where the correlation between premiums and lagged premiums is 0.91. The models with both premium and lagged premium produced implausible results, which we believe is due to the high degree of collinearity. Therefore, we did not pursue this approach.

Instead, our approach to identification is similar to that of Ho, Hogan, and Morton (2017). We track individuals over multiple years and have a small (190) number of observations who are “forced choosers” because either their prior year choice was unavailable (due to either their prior plan leaving the market or the beneficiary moving to a new country where their prior plan is not offered) or the beneficiary newly joining Medicare. The observations without prior choices choose without inertia. We also allow the loyalty coefficients to be normally distributed to capture residual unobserved variation.

The coefficients of the loyalty variables can be translated into switching costs by dividing by the negative of the premium coefficient. We can identify two different types of switching costs. First, the cost of switching to a different plan offered by the same insurer is given by:

$$\text{Switching Cost Plan}_i = \frac{\delta_i}{-\alpha} \quad (5)$$

The cost of switching to a different plan offered by a different insurer includes both the cost of switching plans and the cost of switching insurers, and is given by:

$$\text{Switching Cost Insurer}_i = \frac{\delta_i + \gamma_i}{-\alpha} \quad (6)$$

Because premiums are measured in dollars per month, switching costs are also monthly. They can be converted to annual switching costs by multiplying by 12. We evaluate the switching costs at the mean of the loyalty coefficients, but we can also examine the distribution of switching costs.

3.2 Data

Our main data source is the Medicare Current Beneficiary Survey (MCBS), a rolling cohort survey of Medicare beneficiaries that represents all age groups in 50 states, the District of Columbia, and Puerto Rico. We used MCBS surveys from 2007 to 2011. We selected this period because it follows a major structural change in Medicare in 2006, when prescription drug coverage offered by private plans became available. MCBS contains approximately 10,000 observations per year; the precise sample size varies depends on factors like supplemental samples.

The key to our analysis is the fact that MCBS is a panel survey that observes a rolling cohort for up to 4 years. Among individuals sampled in a typical year, 34% were surveyed in only 1 year, 19% for 2 years, and 47% for 3 years. This feature of the MCBS allows us to code prior-year insurer and plan choices except in the first year the individual was surveyed.

We selected individuals who were enrolled in Medicare Parts A and B for all months of Medicare eligibility. Following the literature on Medicare health plan choice (Atherly, Dowd, and Feldman 2004; Pizer, Frakt, and Feldman 2008), we made several additional restrictions on the sample. We excluded individuals under age 65 and those not living in the community. Currently-employed individuals and those who have a supplemental Medicare policy through their former employer were excluded because their choice set is constrained to the

plans offered by the employer. Likewise, individuals who are eligible for Medicaid were excluded because Medicaid pays their Medicare premiums and cost-sharing and limits their plan choices. We limited our analysis to individuals enrolled in MA plans. However, there is relatively little switching between the FFS and MA sectors.

The restrictions mentioned above reduced the final sample size to 1960, or approximately 500 per year. As an example of the sample reduction, the initial sample size in 2011 was 9971. This was reduced to 3634 after removing persons under age 65, Medicaid enrollees, non-community dwellers, persons with supplemental insurance and active workers. It was further reduced to 1299 when the observations enrolled in FFS were removed. Only half of these (612) could be matched to prior-year plans, largely because prior-year choices were missing for observations in their first year. Finally, a small number of observations were not matched because either the prior or current year plan could not be identified.

We augment the MCBS with Medicare Compare data from the Centers for Medicare and Medicaid Services (CMS). CMS developed Medicare Compare to help beneficiaries choose MA plans. It provides information on the out-of-pocket premiums and benefit packages, plan structure (PPO, HMO), and county of operation.

Much of the previous work on MA plan choice has the unit of analysis at the insurer level, with decision rules for determining premiums and benefits for insurers with multiple plans. We improve on previous work by matching beneficiaries to specific plans offered by an insurer. The data identify the CMS contract number plus the plan number within the contract. Contract is not precisely synonymous with insurer because insurers can offer multiple contracts in the same county, but we found that 99.4% of insurers offered a single contract within a county in 2011.

After recording the insurer and plan selected by the beneficiary in their first year in the data, we analyzed their choices for the remaining years they appeared in the sample. In each year, the beneficiary has (at most) a single health plan selected in the prior year ($L^P = 1$). In contrast, a beneficiary may have multiple options in their insurer from the prior year ($L^I = 1$). If switching costs are lower within insurers than between insurers, switching between plans within insurers will be more frequent than switching between insurers.

Plan design variables are indicators for nonprofit plans, non-traditional HMOs (local and regional PPO models and private FFS plans), and whether the plan covered prescription drugs. Cost-sharing amounts (in dollars) are included for primary care, specialty care, laboratory services, X-rays, ambulance services, emergency departments, inpatient services, and the annual deductible (in dollars) for prescription drugs.

4 Results

4.1 Descriptive Statistics

Descriptive statistics are presented in Table 1. The total sample size for our panel data set (2008–2011), after all exclusions, is 1960 person-year observations. The average age is 78 years, reflecting an older population enrolled in Medicare. The sample is predominately female (58%) and white (88%). Self-rated health averages 3.1, which roughly corresponds to midway between “good” and “fair” on a scale of 1 = Excellent to 5 = Poor, while the change in health from last year is 3.09 on a scale of 1 = much better to 5 = much worse, which is essentially no change.

Table 1: Descriptive Statistics.

Variable	Overall		Same prior year insurer		Switched prior year insurer		Same prior year plan		Switched prior year plan	
	Mean (Pct)	Std Dev	Mean (Pct)	Std Dev	Mean (Pct)	Std Dev	Mean (Pct)	Std Dev	Mean (Pct)	Std Dev
Age	78.09	7.17	78.24	7.13	77.15	7.36	78.19	7.09	77.78	7.42
Income	30,409	24,861	30,636	25,779	28,929	17,686	30,755	26,365	29,298	19,227
Female	58.0%	49.4%	57.5%	49.4%	60.8%	48.9%	57.4%	49.5%	59.8%	49.1%
White	88.0%	32.5%	87.8%	32.7%	89.2%	31.1%	87.7%	32.9%	89.0%	31.3%
College Graduate	12.2%	32.8%	12.2%	32.7%	12.7%	33.4%	12.1%	32.6%	12.7%	33.3%
Married	55.1%	49.8%	54.6%	49.8%	57.7%	49.5%	54.8%	49.8%	55.9%	49.7%
Health Compared to Year Prior	3.09	0.87	3.08	0.89	3.12	0.77	3.09	0.83	3.08	1.00
Self-Rated Health	2.57	1.23	2.55	1.26	2.73	1.03	2.57	1.22	2.59	1.29
N	1960		1700		260		1495		465	

Of the 1960 person-years observations, 260 (13.2%) switched insurers. Switching rates between plans were higher, with 465 observations (23.7%) identified as switching plans. The demographics of observations which switched insurers or plans are similar to those who did not switch on observed variables, with approximately the same income (\$30,636 vs \$28,929), college completion rate (12.2% versus 12.7%), white (87.8% versus 89.2%), married (54.6% versus 57.7%), female (57.5% versus 60.8%), and age (78.2 years versus 77.2). There was little difference between insurer non-switchers and switchers in terms of self-rated health (2.55 versus 2.73) or health compared to the year prior (3.08 versus 3.12). Only the comparisons of age ($p = 0.02$) and self-rated health ($p = 0.03$) approached statistical significance. Similarly, observations which switched plans were demographically similar to observations which did not switch plans, and none of the differences was statistically significant.

4.2 Multivariate Results

The basic multivariate mixed logit analysis is presented in Table 2. The coefficient of Premium ($\beta = -0.007$, $p < 0.001$) was negative and statistically significant. Plans offering the traditional HMO model were preferred. Plans with prescription drug coverage were strongly preferred ($\beta = 2.27$, $p < 0.001$), as were plans with lower drug deductibles ($\beta = -0.005$, $p < 0.001$). Copayments for primary care, specialists, X-ray, ambulance and laboratory services were insignificant, while the copayment for inpatient services was borderline significant with the expected negative sign ($\beta = -0.0007$, $p = 0.06$). Both insurer loyalty ($\beta = 3.94$, $p < 0.001$) and Plan loyalty ($\beta = 3.16$, $p < 0.001$) had positive and statistically significant effects on the probability of choosing an MA plan in the current year.

Table 2: Mixed Logit Model Estimating the Effect of Prior Plan Choices on the Probability of Plan Selection.

Variable	Coef.	Std. Err.	z	p > z
Insurer Loyalty	3.949	0.376	10.51	0.000
Plan Loyalty	3.158	0.235	13.47	0.000
Premium	-0.007	0.001	-6.74	0.000
Nonprofit	0.166	0.221	0.75	0.452
Non-traditional plan design	-0.703	0.183	-3.85	0.000
Drug Plan	2.265	0.319	7.09	0.000
Lab Services	-0.004	0.002	-1.57	0.117
Copayment				
X-ray Services	-0.001	0.002	-0.50	0.616
Copayment				
Specialist Physician	-0.011	0.008	-1.29	0.198
Copayment				
Primary Care	-0.011	0.008	-1.46	0.145
Physician				
Copayment				
Emergency Room	0.002	0.007	0.37	0.711
Copayment				
Ambulance	0.001	0.002	0.33	0.739
Copayment				
Inpatient Stay	-0.0007	0.0004	-1.86	0.063
Copayment				
Annual Drug Deductible	-0.005	0.001	-4.24	0.000
New Plan	-0.287	0.283	-1.02	0.310
SD				
Insurer Loyalty	1.835	0.360	5.09	0.000
Plan Loyalty	0.660	0.513	1.29	0.198
Nonprofit	0.007	0.266	-0.03	0.980
Non-traditional plan design	0.379	0.684	-0.55	0.580
Drug Plan	1.055	0.432	-2.44	0.015
Lab Services	0.002	0.005	-0.48	0.630
Copayment				
X-ray Services	0.003	0.004	-0.85	0.394
Copayment				

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Specialist Physician Copayment	0.001	0.010	0.06	0.949
Primary Care Physician Copayment	0.014	0.020	-0.73	0.464
Emergency Room Copayment	0.002	0.014	-0.11	0.913
Ambulance Copayment	0.001	0.003	-0.26	0.793
Inpatient Stay Copayment	0.0004	0.001	-0.37	0.715
Annual Drug Deductible	0.005	0.001	-3.53	0.000
New Plan	0.587	0.522	1.12	0.261

N = 1960.

Likelihood ratio $\chi^2(14) = 27.24; p = 0.018$.

Only three coefficients displayed significant heterogeneity: insurer loyalty, drug plan, and the drug deductible. The magnitude and standard deviation of the estimated coefficient for insurer loyalty suggests that virtually no one had negative utility associated with choosing the same insurer as the previous year. Given the drug plan coefficient ($\beta = 2.23, p < 0.001$) and the standard deviation on the same ($SD = 1.06, p = 0.02$), the drug benefit also has positive utility for almost the entire population. In contrast, although a lower deductible is associated with higher average utility ($\beta = -0.005, p < 0.001$), there is significant heterogeneity within the population ($SD = 0.005, p < 0.001$) for this benefit.

Table 3 presents a more flexible form of the model, which allowed the random coefficients to be correlated with each other. The main results were similar to the less flexible specification in Table 2. Insurer Loyalty and Plan Loyalty were positive and highly significant. Premium was negative and significant. Because of challenges with estimation, only three coefficients were allowed to be correlated: Premium, Insurer Loyalty, and Plan Loyalty. The covariance of Premium and Insurer Loyalty is positive and statistically significant. This suggests that individuals who are more likely to re-enroll in their prior-year insurer are less premium-sensitive. The covariance of Premium and Plan Loyalty is also positive, but statistically insignificant. Finally, the covariance of Insurer Loyalty and Plan Loyalty is positive and borderline statistically significant.

Table 3: Mixed Logit Model allowing Correlated Random Coefficients.

Variable	Coef.	Std. Err.	z	p > z
Insurer Loyalty	3.878	0.3083	12.58	0.00
Plan Loyalty	2.911	0.1477	19.72	0.00
Premium	-0.006	0.0011	-5.79	0.00
Nonprofit	0.176	0.2136	0.82	0.41
Non-traditional plan design	-0.652	0.1730	-3.77	0.00
Drug Plan	1.959	0.1871	10.47	0.00
Lab Services	-0.003	0.0022	-1.50	0.13
Copayment				
Xray Services	-0.001	0.0020	-0.26	0.80
Copayment				
Specialist Physician	-0.010	0.0079	-1.32	0.19
Copayment				
Primary Care Physician	-0.011	0.0071	-1.52	0.13
Copayment				
Emergency Room	0.003	0.0065	0.46	0.65
Copayment				
Ambulance	0.0004	0.0015	0.29	0.77
Copayment				
Inpatient Stay	-0.001	0.0004	-1.78	0.08
Copayment				
Annual Drug	-0.003	0.0007	-4.51	0.00
Deductible				
New Plan	-0.104	0.2020	-0.51	0.61

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Correlations: Premium, Loyal: Insurer, Loyal: Plan

SD: Premium	0.000009	0.000006	1.43	0.15
SD: Loyalty	2.040	0.9948	2.05	0.04
Insurer				
SD: Loyalty Plan	0.218	0.2901	0.75	0.45
Correlation (Premium, Loyalty Insurer)	0.0043	0.00192	2.24	0.03
Correlation (Premium, Loyalty Plan)	0.0013	0.00101	1.32	0.19
Correlation (Loyalty Insurer, Loyalty Plan)	0.633	0.3473	1.82	0.07

N = 1960.

Likelihood ratio χ^2 (6) = 23.57; p = 0.0006.

The model in Table 4 provides another structure for the error term: preferences for insurer and plan loyalty are heterogeneous and the error terms for both follow an AR(1) structure. The point estimates for insurer loyalty and the premium coefficient are similar to previous models, but the point estimate for plan loyalty is markedly smaller than in previous models. However, the coefficients for the AR(1) errors are not significantly different from zero.

Table 4: Mixed Logit Model Including AR(1).

Variable	Coef.	Std. Err.	z	p > z
Insurer Loyalty	4.371	0.465	9.41	0.000
Plan Loyalty	1.165	0.088	13.28	0.000
Premium	-0.005	0.001	-7.52	0.000
Nonprofit	0.080	0.278	0.29	0.772
Non-traditional plan design	-0.563	0.162	-3.47	0.001
Lab Services Copayment	-0.003	0.002	-1.71	0.088
X-ray Services Copayment	0.001	0.001	0.53	0.595
Specialist Physician Copayment	-0.016	0.007	-2.28	0.023
Primary Care Physician Copayment	-0.014	0.007	-2.13	0.033
Emergency Room Copayment	0.002	0.005	0.47	0.638
Ambulance Copayment	0.002	0.001	1.37	0.171
Inpatient Stay Copayment	-0.0002	0.0003	-0.62	0.538
Annual Drug Deductible	-0.002	0.001	-2.61	0.009
Drug Plan SD	0.645	0.121	5.33	0.000
Insurer Loyalty	1.193	0.610	1.96	0.050
Plan Loyalty	0.007	0.626	0.01	0.991
AR(1)				
Insurer Loyalty	-0.039	0.174	-0.23	0.822
Plan Loyalty	-0.0002	0.866	0.00	-1.000

N = 1960.

We extended the model with individual characteristics that might explain heterogeneity in preferences for the Prior Year Insurer (Table 5). We did not do this for Prior Year Plan because that coefficient did not exhibit significant heterogeneity. All coefficients except premium are random. Individual characteristics used to explain heterogeneous preferences were age, female, white, self-rated health, change in self-rated health, income

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and education (dichotomized to college, Yes/No). Of these, only Self-Rated Health significantly explained heterogeneity in preferences: people with excellent or very good health tended to have stronger loyalty to their prior-year insurers ($\beta = 0.54$, $p < 0.09$). This result was robust to different specifications of the self-rated health variable. Older persons have stronger loyalty, but the effect is statistically insignificant ($\beta = 0.03$, $p < 0.21$). The other estimated interactions had the expected signs – lower loyalty and therefore switching costs – for persons with better ability to evaluate options either through co-production (Married) or more education (College), but were insignificant. Other coefficients had similar signs and magnitudes to the prior model.

Table 5: Mixed Logit Model Including Interactions.

Variable	Coef.	Std. Err.	z	p > z
Insurer Loyalty	1.416	1.965	0.72	0.471
Plan Loyalty	3.215	0.244	13.18	0.000
Premium	-0.007	0.001	-6.76	0.000
Nonprofit	0.155	0.226	0.69	0.491
Non-traditional plan design	-0.683	0.186	-3.68	0.000
Drug Plan	2.330	0.331	7.04	0.000
Lab Services	-0.004	0.002	-1.54	0.124
Copayment				
Xray Services	-0.001	0.002	-0.53	0.599
Copayment				
Specialist Physician	-0.011	0.008	-1.28	0.201
Copayment				
Primary Care	-0.012	0.008	-1.50	0.133
Physician				
Copayment				
Emergency Room	0.003	0.007	0.48	0.632
Copayment				
Ambulance	0.0004	0.002	0.25	0.802
Copayment				
Inpatient Stay	-0.001	0.000	-1.83	0.067
Copayment				
Annual Drug	-0.005	0.001	-4.23	0.000
Deductible				
New Plan	-0.312	0.290	-1.08	0.282
Interactions				
Excellent/Very	0.545	0.322	1.69	0.090
Good Health				
Age	0.030	0.024	1.25	0.210
Female	0.048	0.328	0.15	0.885
College	-0.510	0.488	-1.04	0.296
Married	-0.463	0.363	-1.28	0.202
Change in Health	0.083	0.153	0.54	0.586
Income	0.000005	0.000008	0.67	0.505
SD				
Insurer Loyalty	1.963	0.385	5.09	0.000
Plan Loyalty	0.757	0.467	1.62	0.105
Nonprofit	-0.007	0.273	-0.03	0.978
Non-traditional	-0.448	0.633	-0.71	0.479
plan design				
Drug Plan	-1.123	0.422	-2.66	0.008
Lab Services	-0.002	0.005	-0.55	0.584
Copayment				
X-ray Services	-0.003	0.004	-0.84	0.398
Copayment				
Specialist	0.001	0.010	0.09	0.929
Physician				
Copayment				
Primary Care	-0.014	0.021	-0.67	0.503
Physician				
Copayment				
Emergency Room	-0.002	0.013	-0.17	0.866
Copayment				

Ambulance	-0.001	0.003	-0.25	0.801
Copayment				
Inpatient Stay	0.000	0.001	-0.44	0.659
Copayment				
Annual Drug	-0.005	0.001	-3.56	0.000
Deductible				
New Plan	0.624	0.520	1.20	0.230

N = 1960.

Likelihood ratio χ^2 (14) = 32.44; p = 0.0035.

We calculated premium elasticity estimates from a number of different perspectives using the results from Table 2. The first is the elasticity based on the mean values in the data. This suggests relatively inelastic demand ($\eta = -0.08$), which is in line with previously cited literature. The second elasticity is computed with the coefficient on insurer loyalty set to zero. This represents the price responsiveness of beneficiaries if prior plan choices mattered, but prior insurer choices did not. The price elasticity ($\eta = -0.11$) indicates that beneficiaries would be roughly 25% more responsive to premium differences if prior insurer choices were unimportant. The third elasticity is computed with the coefficients on both loyalty variables set to zero. This represents the price responsiveness of beneficiaries if prior plan and insurer choices had no impact on current choices. The price elasticity ($\eta = -0.13$) indicates that beneficiaries would be roughly 34% more responsive to premium differences if prior plan and insurer choices were unimportant.

Medicare beneficiaries are willing to pay a substantial amount to stay in their existing insurer and plan. The point estimates using the formula given in equation (5) and the results in Table 4 suggest the mean beneficiary in the sample would need to be compensated \$233 per month to switch to a different plan with the same insurer, while the point estimates using the formula given in equation (6) suggest the mean beneficiary would need to be compensated \$1107 per month to switch to a different plan with a different insurer.

The monthly switching costs for a different plan in the same insurer vary depending on the assumed error structure in the model. In the restrictive conditional logit model (not shown), the monthly switching cost is \$484, while the switching cost is \$451 for the mixed logit (Table 2), \$481 for the mixed logit with correlated errors (Table 3), and \$233 for the model with correlated errors. The sensitivity of the plan switching costs to various specifications of the error terms suggests that much of the state dependence for switching to a different plan in the same insurer is spurious rather than structural.

In contrast, the monthly switching cost for switching to a different plan in a different insurer is relatively stable across all the models. It is \$1018 for the conditional logit, \$1015 in the mixed logit model allowing heterogeneous preferences for loyalty and benefits, \$1035 in the model with heterogeneous preferences with correlated errors, and \$944 in the model with heterogeneous preferences for loyalty and autocorrelation error terms. The robustness of monthly switching cost estimates to various specifications of the error terms suggests that switching to a different plan in a different insurer has high structural switching costs.

The switching costs can be compared to the willingness to pay for other plan benefits. We took the variables with statistically significant coefficients in the model and calculated the willingness to pay for the group at the means of the variables. The most significant was having a drug benefit, with a mean WTP of \$324. The other combined benefits (including the non-profit and plan design variables) had a mean WTP of \$569, for a combined WTP of \$893 per month or \$10,716 per year. This exceeds the switching cost of \$2800 within insurers and is roughly equal to the switching cost of \$11,300 between insurers.

5 Discussion

This paper updates the literature on choice of MA plans, with emphasis on beneficiary loyalty to both the insurer and the specific health plan. We found that beneficiaries have strong preferences for remaining with the same insurer and plan over time. The mean switching costs for switching to a different plan in the same insurer is \$233 per month, or about approximately \$2800 per year. The mean switching costs for switching to a different plan in a different insurer is \$944 per month, or approximately \$11,300 per year.

The estimated switching cost can be compared with Handel (2013), who found switching costs of about \$2000 per year in the commercial health insurance market (Handel 2013). Interestingly, Handel estimated switching costs for plans that were similar to one another in terms of covered medical services, third-party administrator and physician networks. This is analogous to our switching costs for switching to a different plan in the same insurer – which is slightly higher (\$2800) than his estimate.

For Part D plans, Polyakova (2016) finds switching costs of \$576 for Part D alone, and Heiss et al. (2016) \$338. Because Part D plans are embedded in Medicare Advantage plans, this is a lower bound for switching costs in Medicare, and covers the cost for the most easily comparable element of the plan benefit.

It is possible that the structure of the Medicare program creates high switching costs through the high number of choices. In Handel (2013), consumers had three choices of similar PPO products, in contrast to more than 27 choices per person in our sample. The “choice overload” hypothesis suggests that this high number of choices could substantially increase switching costs (Lamiraud 2013).

Medicare beneficiaries have many plan choices – some suggest too many (McWilliams et al. 2011) – in a market with relatively few competitors (Biles, Casillas, and Guterman 2015). Although we find a relatively high switching rate – on average 24% of observations in our sample switch plans – nearly half (44%) of the switches were to other plans in the same insurer despite most beneficiaries having far more choices outside the insurer (25.2) than inside the insurer (2.1). This is consistent with higher switching costs for plans in different insurers than for plans in the same insurer.

Another possibility is that the high switching costs are due to some degree of omitted variables bias. Some characteristics of plans that could be related to individual utility, such as network size and composition, are omitted from the analysis. This omission would create a positive bias in the estimated loyalty coefficients. More broadly, any residual unobserved plan variation in plan benefits could appear as a switching cost. We did re-estimate the models using plan-specific intercepts and the results were robust to that specification. The possibility of unobserved omitted plan characteristics cannot be ruled out, however.

We find that the majority of switching costs are for switching to a different plan in a different insurer. To our knowledge, no other study has estimated this type of cross-insurer switching cost. The reasons for high cross-insurer switching cost are unclear. It could be that knowledge of provider networks and other benefits is specific to an insurer and transferable to other plans within the insurer, but not to plans offered by other insurers. Examples might be the location of plan information or experience using help lines. However, more research is needed into the reasons for high switching costs associated with switching to a different plan in a different insurer, particularly because our results suggest these costs are structural rather than spurious.

We also find considerable heterogeneity in loyalty to the insurer, but not to the plan.

Although it is difficult on average to convince beneficiaries to switch to a different plan in a different insurer, some beneficiaries are more moveable than others. This heterogeneity explains why we observe both extremely switching costs on average and more than 10 percent of our sample switching insurers annually.

Surprisingly, beneficiary age, marital status, income and education did not explain heterogeneity in switching costs. One explanation for this finding is that beneficiaries do not have data to reduce switching costs, regardless of their education. For example, Medicare does not offer provider participation data to beneficiaries (). Other possibilities include inattention (Abaluck and Gruber 2011, 2016; Ho, Hogan, and Morton 2017) or cognitive difficulties sorting through choice options (McWilliams et al. 2011). Indeed, inattention has been identified as a major factor behind lack of switching in Part D, although there are considerable switching costs even after controlling for inattention (Heiss et al. 2016; Ho, Hogan, and Morton 2017). Further research is needed into factors that Medicare beneficiaries consider and challenges they face when switching health plans.

What does the high level of Loyalty in MA plan choice imply for the viability of competitive markets? The large switching costs in the MA marketplace suggest that policies to lower costs and improve care through increased competition via plan choices, such as premium support or vouchers for elderly beneficiaries, may not work as well as intended. The preponderance of our evidence suggests that switching costs to different plans in different insurers are due to structural state dependence. Structural switching costs are potentially problematic. They imply that beneficiaries can't or won't select different options they would prefer if switching costs were small.

The ultimate impact of switching costs on prices is unclear and will depend on the relative strength of the investing versus harvesting strategies discussed earlier. Previous literature has shown that small switching costs may be associated with lower prices, compared with prices in markets with no switching costs (Coscelli 2000; Dubé, Hitsch, and Rossi 2009). But this finding applies to markets where switching costs are a small fraction of the product price. Large switching costs are associated with higher prices. We found the cost of switching to a different plan with a different insurer is approximately equal to the entire premium paid by government and the enrollee. This suggests switching costs may be problematic for prices. Additional research is needed to quantify the effect of switching costs on MA prices.

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