Does Part D Abet Advantageous Selection in Medicare Advantage?

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Abstract

The use of risk-adjustment formulae in setting payments to Medicare Advantage (MA) plans reduces the potential for advantageous selection on factors included in the formulae, but can potentially worsen overall selection if plans are able to target beneficiaries based on excluded factors. Since MA medical risk-adjustment excludes prescription drug utilization, demand for drugs can be exploited by plans to induce advantageous selection. We show evidence that the introduction of Medicare Part D provided a mechanism for MA plans to increase selection, and that consumers responded, increasing MA market shares among beneficiaries taking drugs associated with the strongest advantageous selection incentives. For the average Medicare beneficiary in our sample, we estimate that this change in advantageous selection following the introduction of Medicare Part D increased the probability of enrolling in an MA plan by about 7.7%.

JEL Classifications: I13, I11, H42
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1 Introduction

A rising trend in health insurance reforms in the US has been the tendency to promote private provision of publicly-funded health insurance benefits. Medicare Part D is provided entirely by private insurers, nearly 80% of state Medicaid programs deliver benefits through private managed care organizations, and non-Medicaid coverage expansions in the ACA marketplaces include public subsidies for private insurance (KFF 2014). In each of these markets there is a unique form of interaction between public agencies and private insurance companies, with potentially different objectives; in the case of Medicare Advantage (MA), the private provision of publicly-funded Medicare promotes direct competition against traditional fee-for-service (FFS) Medicare, with the hope of increasing the efficiency of benefit delivery and coordination by allowing beneficiaries to choose the plan that delivers the most value.

However, one well-known consequence of this direct competition is that it creates a strong incentive for MA plans to instead "compete" by developing strategies for advantageously selecting beneficiaries.[1] Prior to 2004, this selection incentive was relatively simple: MA plans sought the healthiest beneficiaries conditional on their age and demographics. The introduction of risk-adjustment based on specific diagnosis, or more precisely hierarchical condition codes (HCCs), in 2004 was intended to reduce this incentive to compete based on selection. Instead, Brown et al. (2014) find that MA plans were successful at advantageously selecting beneficiaries with lower medical expenditures conditional on diagnoses, offsetting the improvements from across-condition risk-adjustment, and resulting in no observable net effect on MA selection. Lavetti and Simon (2016) extend this analysis using the universe of Medicare beneficiaries and show that beneficiaries that choose to switch into MA plans tend to have lower expenses conditional on HCC-adjusted payments on average, but the ability of MA plans to advantageously select beneficiaries also appears to vary substantially across HCCs.

[1] See Batata (2004), Brown et al. (2014), McWilliams et al. (2011).

Despite the broad evidence consistent with selection by MA plans, less is known about the mechanisms that lead to this selection.[2] In standard models of adverse or advantageous selection, it is not obvious that substantial selection should remain after conditioning payments on medical diagnoses,[3] suggesting that the increase in selection after HCC-based risk-adjustment found by Brown et al. (2014) may not have been caused by simple correlations between demand for MA plans and medical expenses. One the other hand, it is similarly unlikely that MA plans were able to use medical insurance plan design to attract low-cost beneficiaries within a particular HCC, since medical insurance tends to have fairly blunt features, such as fixed deductibles or copayments.

The introduction of Medicare Part D in 2006, however, replaced this blunt benefit design tool with a scalpel. Whereas MA beneficiaries' Part D benefits are integrated into a single MA insurance plan, FFS beneficiaries receive coverage through stand-alone private prescription drug plans (PDPs). In contrast to medical insurance, prescription drug insurance benefits tend to be extremely specific, with thousands of cost-sharing decisions made at the drug product level. Part D has the potential to change the severity of selection because MA plans are able to set generous cost-sharing rules for drugs taken by beneficiaries that tend to have below average medical expenses conditional on their diagnoses, creating a direct mechanism for inducing selection. Lavetti and Simon (2016) find that MA plans indeed responded to these incentives, and designed drug formularies that were significantly different than stand-alone Part D plans in ways that encouraged advantageous selection.

In this paper we study how the introduction of Medicare Part D changed the nature of advantageous selection into MA plans. Using data from the Medicare Current Beneficiary Survey (MCBS) from 2000-2010, Part D formulary files from 2009-2010, and estimates of risk-

[2] Afendulis, Chernew and Kessler (2013) and Duggan, Starc and Vabson (2014) show that some of this selection could be due to geographic differences in MA payment incentives, such as urban floor payments, although Cabral, Geruso and Mahoney (2014) find that this was not a substantial source of advantageous selection.

[3] See Einav and Finkelstein (2011).

adjusted selection incentives from Lavetti and Simon (2016), we show that Part D provided a mechanism for MA plans to significantly increase their market shares for beneficiaries with more profitable risk-adjusted conditions, while reducing market shares among those with less profitable conditions. Moreover, these changes in market share occurred immediately in 2006, without any clear pre-trend, and remained through the end of our sample.

The MA risk-adjusted selection incentive from Lavetti and Simon (2016), which they term "MA switcher surplus," is an HCC-specific measure of the difference in average medical expenditures of beneficiaries who switch into MA plans relative to those who remain in FFS. Since MA risk-adjustment formulae are based only on the spending of FFS beneficiaries, this difference between switchers and stayers represents one component of the profit of MA plans associated with advantageous selection, the magnitude of which may vary substantially by HCC. Using this measure, we show that the introduction of Medicare Part D led to an increase in MA market shares of 1.5 percentage points per $1,000 in risk-adjusted MA switcher surplus. For the average Medicare beneficiary in our sample, we estimate that this change in advantageous selection following the introduction of Medicare Part D increased the probability of enrolling in an MA plan by about 7.7%.

We show evidence that beneficiaries responded to the differences in drug formulary design identified by Lavetti and Simon (2016), connecting the drug formulary mechanism to changes in advantageous selection. We estimate that a $1000 decrease in switcher surplus, from the median switcher surplus to the bottom quartile, was associated with beneficiaries paying 6.4% more out-of-pocket if they were enrolled in the ex post optimal MA plan relative to the ex post optimal stand-alone drug plan. Moreover, a one-standard deviation decrease in this measure of relative MA Part D generosity was associated with a 1% decrease in the probability of a beneficiary switching into an MA plan, suggesting that consumers did indeed respond to these incentive differences when making plan choices. Consistent with the hypothesis that Part D was the mechanism behind the change in selection, we show that

beneficiaries with higher drug spending, for whom the benefits of comparing Part D plans are greater, were also more likely to respond to these differences in Part D plan generosity. Importantly, although a large literature has discussed geographic differences in MA market shares and plan entry incentives, all of our results hold in fixed effects specifications that control for county effects.

If advantageous selection did increase following the introduction of Part D, this could impose a negative externality on the Medicare program. Of course, our findings alone do not imply that any welfare gains associated with MA plans decreased overall after Part D was introduced. For example, Part D also created an incentive for MA plans to internalize many offsets between drugs and medical care. Lavetti and Simon (2016) find evidence that such incentives affected Part D formulary designs, and Starc and Town (2016) show that this incentive affected the utilization patterns of beneficiaries. These studies suggest that the integration of medical and drug benefits in MA plans, in contrast to the fragmentation of FFS benefits, could potentially improve efficiency by internalizing spillovers between different types of substitutable or complementary medical care. Still, there are policy options that have the potential to reduce the negative externality associated with the type of selection that we identify, while retaining these benefits of plan integration. We discuss several such policy options in Section 5.

2 Background on Medicare Advantage and Part D

We briefly explain the important institutional details of Medicare Advantage risk-adjustment and Medicare Part D in this section.

2.1 Medicare Advantage and Risk-Adjustment

Since the 1970s, Medicare beneficiaries have had the option of enrolling in private Medicare Advantage plans instead of traditional FFS Medicare. In competing with traditional Medicare, there are many regulations that constrain the behavior of MA plans. First, they are forbidden from declining or discouraging any eligible applicants, or from selectively inducing beneficiaries to disenroll, so effective selection that complies with these regulations would instead have to alter the applicant pool. Second, premiums are set at the plan-level, and cannot vary across individuals. In addition, MA plans' Part A and B benefits must be comparable to those provided under FFS.

MA plans are reimbursed directly by Medicare according to an individual-specific capitation payment that is risk-adjusted. The method used to calculate the capitation payment, however, has evolved over the time. Prior to 2004 risk-adjusted payments were calculated using a formula that included only demographic characteristics. Pope et al. (2004) show that this demographic model was only able to explain 1% of the variation in expenditures, causing the vast majority of variation in beneficiary-year medical expenditures to not be risk-adjusted. In this simple capitation payment scheme, MA plans could increase profits to the extent that they were able to select beneficiaries with relatively lower costs in a given age-demographic cell, causing advantageous selection (McWilliams et al. 2011).

Recognizing the importance of limiting the potential scope for selection into MA plans, CMS implemented a health-based risk-adjustment formula in 2000, which included information about inpatient claims. The current risk-adjustment formula is a revised version of this health-based model, which began being gradually phased-in in 2004, and uses a combination of hierarchical condition categories (HCCs) that adjust for medical conditions, along with demographic characteristics. Despite being intended to capture the breadth of medical conditions, HCCs are highly aggregated, with about 15,000 ICD-9 diagnosis codes condensed into 70 HCC codes. Using data on the Parts A and B expenditures, HCCs, and demographics of

a 5% sample of enrollees in FFS Medicare, CMS then regresses beneficiary-year Parts A and B expenditures on indicators for each HCC, which are largely assumed to have additively-separable effects, along with a vector of demographic factors.[4] The parameter estimates from this regression model define the risk-adjustment formula. Since the risk-adjustment model does not use data on the costs or utilization of MA enrollees, capitation payments may not reflect any potential differences in the conditional expenditures of MA enrollees relative to FFS beneficiaries. The transition into the HCC system was gradual, with 30, 50, 75 and 100 percent of the total capitation payments determined by the HCC model in 2004, 2005, 2006, and 2007 respectively, and the remaining share based on the demographic model. Still, despite this improvement the HCC-based model explains only about 11.2% of the variation in Parts A and B expenditures (Pope et al. 2004), leaving substantial residual variation in medical expenditures upon which selection could potentially occur.

There are several reasons why conditioning on HCCs may not eliminate advantageous selection into MA plans. First, the estimation of capitation payment models is based entirely on FFS beneficiaries. To the extent that the cost or efficiency of treating a particular condition systematically differs between MA plans and FFS Medicare, this error component will be correlated with the HCC indicators in the regression model, causing statistical endogeneity bias when the model is applied out-of-sample to the MA population. If MA plans have a mechanism for selecting beneficiaries with certain conditions, they can affect the distribution of this bias to increase profits. Second, since HCC codes are highly condensed, there is a large amount of unexplained variation in expenditures within HCCs associated with different medical diagnoses. Moreover, the magnitudes of these variances differ across HCCs, causing heterogeneity in the potential scope for advantageous selection across conditions, as shown by Brown et al. (2014). Finally, compared with FFS, MA plans are likely to have a stronger incentive to ensure that enrolled beneficiaries do not have any undiagnosed conditions that

[4]There are a small number of exceptions to this assumption, for which interactions between HCC indicators are also included in the model.

could increase their medical expenses without affecting capitation payments. Although it is outside the scope of our research question, this "upcoding" incentive has been shown by Geruso and Layton (2015) to be an important component of the selection problem that MA plans face.

2.2 Medicare Part D

Medicare Part D prescription drug insurance was introduced in 2006, and is delivered entirely by private insurers. Beneficiaries in FFS Medicare can enroll in a stand-alone prescription drug plan (PDP), while those in MA plans receive a single integrated insurance plan that covers medical and drug expenditures. In 2015, about 15 million beneficiaries received Part D coverage through an MA plan, out of a total of 38.5 million Part D beneficiaries (Hoadley et al. 2015). For beneficiaries in MA plans, the insurer receives a separate risk-adjusted capitation payment from CMS for Part D, and beneficiaries also frequently pay a monthly premium. Similar to the capitation payments to MA plans, the capitation payments to Part D insurers are diagnosis and demographic-specific, and the risk-adjustment formula uses a different set of medical condition codes (rxHCCs) that are specific to drug utilization.

There are many CMS regulations that affect the ability of Part D plans to select patients. First, plans are given a large amount of freedom with respect the design of plan benefits and formularies. Although CMS defines a standard benefit plan each year[5] less than 1% of beneficiaries were enrolled in plans with the standard benefit design in 2015 (Hoadley et al. 2015). In general, plans make many strategic decisions when designing drug formularies, including which drugs to include on the formulary, on which cost-sharing tier to place each drug, and whether to apply prior authorization, quantity limit, or step therapy restrictions. Lavetti and Simon (2016) discuss how the profit functions of MA plans differ from those of

[5] In 2015, for example, the standard benefit structure had a \$320 deductible, followed by a 25% coinsurance rate on the next \$2,640 spent (the initial coverage zone), then either a 45% or 65% copayment rate (depending on whether the drugs are brand-named or generic) for the next \$4,102, and finally a 5% coinsurance rate on all costs beyond that, in the catastrophic zone.

stand-alone Part D plans, and show that MA plans do take advantage of this flexibility to design different drug benefit formularies in ways that facilitate selection.

However, counteracting the impacts of this flexibility are a wide range of regulations that limit the potential for selection in Part D. First, Part D plans must accept all eligible beneficiaries that apply, preventing direct selection. Second, although plans may flexibly set formularies, all formularies must be actuarially equivalent to the standard benefit design. This constraint requires, for example, that any attempt to covertly discourage enrollment by setting high coinsurance rates for one drug must be offset by more generous coverage for another drug, constraining total selection. Although plans are technically forbidden from designing formularies that discriminate against high-cost beneficiaries (Hoadley 2005), it is unknown how or whether this requirement is monitored and enforced. Moreover, plans must include at least 2 drugs in each therapeutic category and substantially all drugs in 6 key therapeutic classes,[6] making it impossible to discriminate against consumers of an entire class of drugs. Third, payments to Part D insurers are also risk-adjusted.[7] However, Carey (2016) finds that this risk-adjustment process has substantial imperfections, largely caused by the use of formulae that hold payments fixed over time despite the entry of new products and changes in prices and/or competition. And fourth, CMS imposes risk-corridors in Part D that heavily subsidize losses to plans if average plan-level costs are more than 5% larger than predicted by risk-scores, and symmetrically tax plans whose costs turn out to be more than 5% below predictions. However, these 5% corridors are wide relative to the average profit margin in large group insurance markets, estimated to be about 3.8% (CMS 2013). In addition, these corridors only affect Part D profits, and do not include any profits that MA plans earn on Parts A and B insurance as a result of potential selection facilitated by Part D plans.

[6]The six key therapeutic classes are: antiretrovirals, antineoplastics, antidepressants, antipsychotics, anticonvulsants, and immune suppressants.

[7]For MA plans this risk-adjustment is completely separate from the Parts A and B risk-adjustment.

Of course, these regulations regarding plan design must also be considered along with consumer choice. If consumers do not respond to differences in plan generosity, then there is very limited scope for using plan design to advantageously selection beneficiaries. Although some evidence from the literature, including Abaluck and Gruber (2011), suggests that consumers were much less responsive to cost-sharing rules than they were to monthly premiums when making plan choices, suggesting choice inconsistencies, other studies including Ketcham et al. (2012) suggest that consumers quickly learned and became more responsive to plan generosity over time, reducing overspending by 55% in the second year of the program. This suggests that plans may have plausibly believed consumer choices to be at least somewhat responsive to plan design. Our empirical analyses also provide direct evidence that consumers appear to have responded to the differences in cost-sharing rules between MA and stand-alone PDPs.

3 Data and Risk-Adjustment Models

3.1 Medicare Current Beneficiary Survey

The main data source we rely on is the Medicare Current Beneficiary Survey (MCBS) Cost and Use files from 2000 to 2010. The MCBS links survey data for a nationally representative sample of about 11,000 beneficiaries each year to each respondents' administrative Medicare data. For respondents in FFS plans, the administrative component includes complete claims data, such as information on hospital admissions, diagnoses, and physician visits. For MA enrollees, however, there are no available medical claims data, and the MCBS includes only demographics and survey responses. For a subsample of respondents, CMS creates a longitudinal component to the MCBS that spans up to 3-4 years, providing a mixture of cross-sectional and panel data. During our sample period, the data contain $52,170$ unique

individuals and 116,626 person-year observations.[8]

There are at least two features of the MCBS that are important for our study. First, the data report whether each beneficiary is enrolled in an MA plan or FFS Medicare in each month. We use this information to identify beneficiaries who switch between FFS and MA plans. The data also report the fixed capitation payment that an MA plan received for each enrollee, which varies by demographics and/or medical diagnoses.

Second, the MCBS contains comprehensive drug usage information, including drug spending, drug names, and sources of payment. In addition, beginning in 2006, MCBS added Part D claims data for FFS as well as MA enrollees. Since there are often many different NDC codes associated with drugs that have the same active ingredient and are used to treat the same condition(s), so that they should have the same selection effect, we link each drug to its primary active ingredient by name and NDC using the FDA National Drug Code Directory. The matching rate in this linkage is above 95%.

Table 1: Summary Statistics on MCBS Sample

	Full MCBS Sample	FFS Analysis Sample	FFS Switcher Sample
Male	0.44	0.43	0.45
Age	72.3	73.2	70.9
Percent MA Enrollees	0.19	0	0
Percent Purchase Drugs	0.88	1	0.93
Annual Drug Expenditure	2,586	3,041	2,601
Annual Out-of-Pocket Drug Spending	604	689	644
Percent Part D Enrollees	0.63	0.55	0.62
Number Person-Year Observations	116,626	53,906	1,227
Number Unique Individuals	52,170	26,219	1,227

Notes: Drug expenditures and out-of-pocket spending are reported conditional on having a drug purchase. Percent Part D enrollees is calculated based on 2006-2010 data only. The FFS analysis sample includes beneficiaries who purchased drugs with the top 50 most common drug active ingredients between 2002-2009.

Table 1 presents summary statistics from our MCBS analysis sample. The first column

[8]We exclude the less than 0.1% of enrollees with end-stage-renal disease because these beneficiaries are prohibited from switching into MA plans, so there is no potential for selection.

in the table shows summary statistics on the full MCBS sample. The second and third columns present summary statistics on our two main analysis samples, which are restricted to beneficiaries who purchase any drug with an active ingredient in the top 50 most common active ingredients, and beneficiaries who switch from FFS to MA, respectively.

The table shows that the two analysis samples have similar shares of men and women, but switchers into MA plans tend to be slightly younger than the average beneficiary, at 70.9 years compared to 72.3. Since the FFS analysis sample conditions on drug use, beneficiaries in this sample spend about 18% more on drugs annually. The switcher sample, which does not condition on drug usage, has similar drug usage and expenditure patterns as the full MCBS sample.

Since many of our analyses focus on beneficiaries who switch between FFS and MA plans, Table 2 presents summary statistics on the frequencies of these transitions over time. We observe 1,434 individuals who switch from FFS to MA, and 51,011 who remain in FFS for consecutive years in the panel.

Table 2: Transition Frequencies between FFS and MA, 2000-2010

	2000-2001	2002-2003	2004-2005	2006-2007	2008-2009	All Years
FFS_t and FFS_{t+1}	11,301	11,201	10,528	9,615	8,366	51,011
FFS_t to MA_{t+1}	69	120	443	514	288	1,434
MA_t to FFS_{t+1}	360	133	88	120	355	1,056
MA_t and MA_{t+1}	2,107	1,804	1,771	2,511	2,688	10,881
Total	13,837	13,258	12,830	12,760	11,697	64,382

Notes: Individuals are classified as FFS if enrolled in FFS all 12 months of the calendar year, and classified as MA if enrolled in an MA plan for at least one month of the year and enrolled in any Medicare plan in every month of the year.

Table 2 also shows that about 12% of all MA enrollees in the MCBS sample were in FFS in the previous year. Brown et al. (2014) estimate that the majority of MA enrollees, over 75%, switched into MA from FFS Medicare at some point, as opposed to initially enrolling in MA. This is important because it suggests that by studying switching behavior it is possible

to gain insights that are generally relevant to the choices made by a large majority of the population of MA enrollees.

3.2 Risk-Adjustment and Selection in Medicare Advantage

Since capitation payments to MA plans are risk-adjusted, so that plans are paid more to insure sicker patients, the profit incentive of MA plans depends not simply on expected medical costs, but on the difference between costs and risk-adjusted payments. In order to study how this selection incentive affected consumers differently after the introduction of Part D, we must first characterize the selection incentives of MA plans.

We use estimates from Lavetti and Simon (2016), who employ claims data from the universe of FFS Medicare beneficiaries from 2008-2010. They apply the risk-adjustment formula to the administrative risk-scores included in the data to calculate the exact counterfactual capitation payment MA plans would have received if each beneficiary in the data were to enroll in MA, and compare this value to the actual observed FFS expenditures. Since beneficiaries who switch from FFS to MA are not randomly chosen, the average annual FFS spending of beneficiaries who subsequently switch to MA plans less than the spending of FFS beneficiaries who remain in FFS the following year. As a result, counterfactual capitation payments minus observed spending is $902 higher per year on average for FFS beneficiaries who subsequently switch into MA plans relative to those who remain in FFS. This form of conditional advantageous selection was documented by Brown et al. (2014).

Specifically, the estimates come from the following fixed effects regression:

$$\begin{aligned} MA\ Switcher\ Surp_{it} &= \alpha + \beta MA\ Switch_{it} + \sum_{k=1}^{70} \theta_k \mathbf{1}\left[HCC_{it-1} = k\right] \\ &+ \sum_{k=1}^{70} \gamma_k MA\ Switch_{it} * \mathbf{1}\left[HCC_{it-1} = k\right] + \pi X_{it} + \psi_{c(it)} + \varepsilon_{it} \quad (1) \end{aligned}$$

where $MA\ Switch_{it}$ equals one if person i switched from FFS into an MA plan in year t

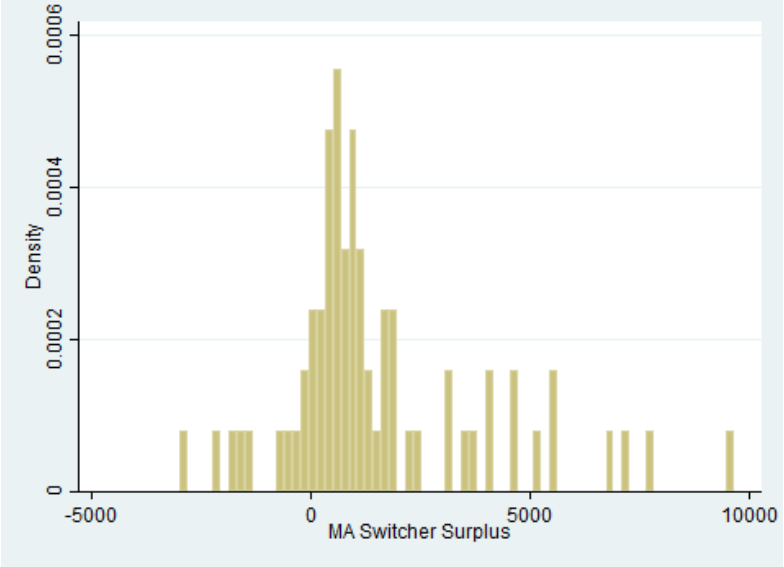
and zero otherwise; $\mathbf{1}\left[HCC_{it-1} = k\right]$ equals one if person i was diagnosed with HCC k in the prior year; X_{it} contains the same control variables used by CMS for risk-adjustment, which includes year effects, age effects, race effects, a gender effect, and interactions between race effects and a binary variable for whether the beneficiary originally enrolled in Medicare due to a disability; and $\psi_{c(it)}$ is a set of fixed effects for the county c in which beneficiary i lived in year t.

In this model, $\widehat{\gamma_k}$ primarily captures the incentive for MA plans to select a beneficiary with HCC k relative to a beneficiary with a different (reference) HCC. Since the risk-adjustment model used to calculate capitation payments includes fixed effects for each of the 70 HCCs, in theory one might expect that the average difference between the counterfactual payment and actual FFS expenses, captured by θ_k, should be zero. However, in practice this is not exactly true for two reasons. First, capitation payments are scaled such that the average payment for an MA enrollee, conditional on HCCs, may not equal 100% of the FFS expenses of an identical FFS enrollee. For example, from 2007–2009 CMS regulations led to MA plans receiving 113% to 114% of FFS payments. This statutory overpayment would cause the average difference between capitation payments and average FFS expenses to be positive. Second, the risk-adjustment model used by CMS is estimated with a 5% random sample, whereas our analyses use the full 100% population of beneficiaries. This could potentially cause a difference between capitation payments and average FFS expenses in our data due to sampling error in the risk-adjustment formula, although this error is likely to be small for common medical conditions. The combination of these two factors causes our estimate of the condition-weighted average difference between capitation payments and average FFS expenses to be \$449 per beneficiary-year. This θ_k primarily affects the levels of estimated MA switcher surplus, whereas γ_k captures the differences across HCCs. To the extent that levels matter, for example if the objective function of MA plans is to maximize enrollees with switcher surplus greater than zero, we include θ_k as part of this incentive, and estimate

MA switcher surplus as $\widehat{\gamma_k} + \widehat{\theta_k}$.

Figure 1 graphs the distribution of MA switcher surplus by HCC. For 59 of the 69 HCCs[9] the estimated MA switcher surplus is positive, consistent with advantageous selection.

Figure 1: Distribution of MA Switcher Surplus by Hierarchical Condition Code



Notes: This figure plots the estimated values of $(\widehat{\gamma_k} + \widehat{\theta_k})$ from Equation 1 for each HCC.

Since Part D drug formularies allow insurers to alter the relative coverage generosity for drugs taken by beneficiaries with different medical conditions, the mechanisms available to MA plans to induce advantageous selection became both stronger and significantly more precise when Part D was introduced in 2006. Our main analyses will test whether MA enrollment market shares increased by larger amounts for conditions that are the most profitable given risk-adjustment rules, following the introduction of Part D.

Since our analyses focus on prescription drug usage and Medicare Part D, we also calculate the expected MA switcher surplus associated with each type of drug. These estimates answer the question: if the only thing that an insurer knew about a beneficiary is that she took

[9]Beneficiaries with HCC 130, end-stage renal disease, are excluded from our analyses figure because CMS rules restrict these beneficiaries from switching into MA plans.

a particular drug, what would the insurer expect the beneficiary's switcher surplus to be? This is done by calculating the average MA switcher surplus for all FFS beneficiaries who purchase a prescription drug with a given active ingredient, using the linkage from the MCBS drug purchase data to the FDA National Drug Code Directory.

To be clear, we use the term MA switcher surplus, rather than profit, since switcher surplus may be only one component of total profits. Profits could also differ across conditions if there are systematic differences in the costs of treating beneficiaries in MA plans compared to FFS Medicare. We cannot observe any such cost differences directly since no data are available on utilization or costs once beneficiaries enroll in MA plans. In addition, Geruso and Layton (2015) show that MA plans appear to engage in upcoding, which increases the risk-scores of beneficiaries after switching into MA plans and raises capitation revenue.

4 Empirical Analyses

4.1 The Impact of Risk-Adjustment Errors on MA Market Shares

We begin by documenting suggestive patterns of enrollment changes in MA plans that are consistent with changes in advantageous selection following the introduction of Medicare Part D in 2006. Table 3 shows the percentage of beneficiaries in FFS and MA plans who took drugs in the top and bottom quartiles of the distribution of MA switcher surplus, before and after the introduction of Part D.

The patterns in Table 3 show that enrollments in MA plans grew by the largest amounts among beneficiaries who take drugs in the top quartile of the distribution of drug-level switcher surplus. The share of MA enrollees taking drugs in the top quartile grew from about 19% in the four years prior to the introduction of Medicare Part D, to over 39% in the four years following. Of course, the use of drugs generally increased following the introduction of Part D. However, this fraction of beneficiaries taking drugs in the top quartile of MA

Table 3: Percent of Beneficiaries Taking Drugs by MA Switcher Surplus and Plan Type

	Percent of Beneficiaries Taking:					
	Any Drug in Top Quartile of MA Switcher Surplus		Only Drugs in Bottom Quartile of MA Switcher Surplus		Any Drug	
	2001-2004	2006-2009	2001-2004	2006-2009	2001-2004	2006-2009
FFS_t	22.3%	38.2%	1.8%	1.3%	87.3%	94.1%
MA_t	18.5%	39.2%	2.7%	1.0%	90.0%	96.3%
FFS_t and FFS_{t+1}	22.4%	38.3%	1.8%	1.3%	87.3%	94.1%
FFS_t to MA_{t+1}	17.9%	36.3%	1.0%	1.5%	90.5%	94.9%

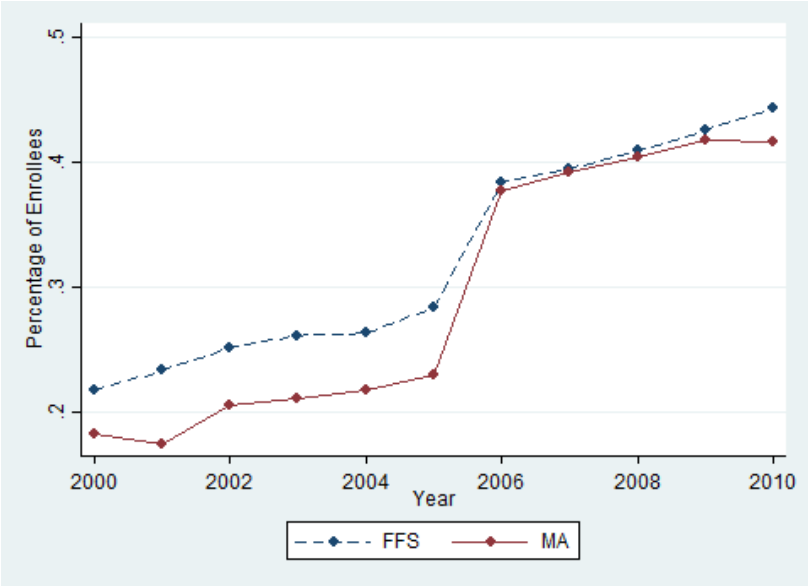
Notes: Reported values are the percentages of beneficiaries in the MCBS who take at least one drug with an MA switcher surplus in the top quartile of the drug-level MA switcher surplus distribution (columns 1-2), only drugs in the bottom quartile of the distribution (columns 3-4), or any prescription drug (columns 5-6). Row 1 includes all FFS beneficiaries, and row 2 includes all MA enrollees. Samples in rows 3 and 4 include beneficiaries who are observed in FFS for a full baseline year t, and the column headings correspond to the baseline year. Quartiles are defined using pre-period data. 2005 is omitted as a baseline year to avoid contaminating the sample with a group that spans the pre- and post-periods.

switcher surplus grew at a 41% faster rate in MA plans than it did in FFS plans. Similarly, the fraction of beneficiaries who only consume drugs on the bottom quartile decreased at more than twice the rate in MA plans as it did in FFS plans. These symmetric patterns at the top and bottom quartiles are consistent with the hypothesis that MA plans increased the intensity of advantageous selection following the introduction of Part D.

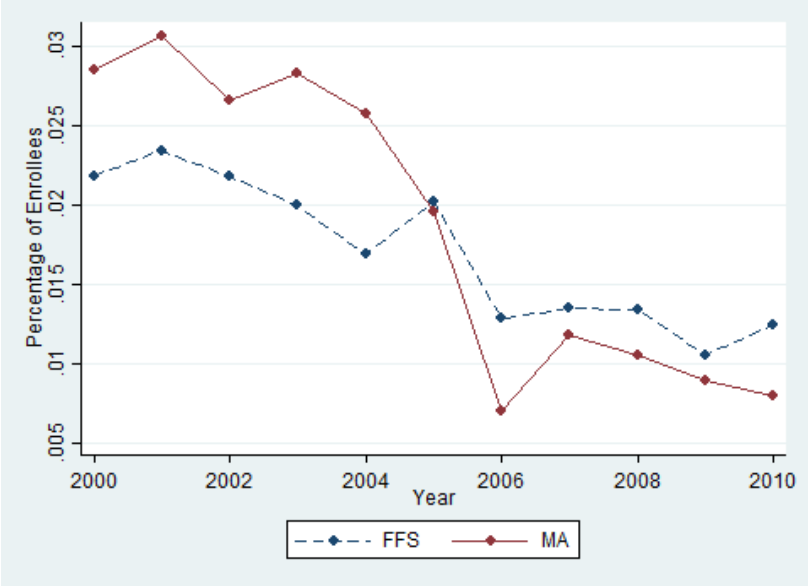
Figure 2 graphically displays these changes in enrollment patterns between 2000 and 2010. On the top, Figure 2a plots the fraction of enrollees in FFS and MA plans who take at least one drug in the top quartile of the distribution of drug-level MA switcher surplus. As the figure shows, there is a slight but steady increase in this share for both FFS and MA between 2000 to 2005. The trends appear very nearly parallel during this pre-period. 2006 is a clear outlier relative to each of the pre-period trends, as the abrupt increase in drug insurance raises the fraction of enrollees consuming these drugs in both FFS and MA plans. However, the interesting pattern is that whereas MA enrollees were 3 to 6 percentage points less likely to consume these drugs throughout the pre-period, this gap is virtually eliminated

Figure 2: Percent of Enrollees Purchasing Drugs at Top and Bottom of MA Switcher Surplus Distribution, By Year

(a) Top Quartile of MA Switcher Surplus



(b) Bottom Quartile of MA Switcher Surplus



Notes: Figure 2a plots the percentage of FFS and MA enrollees who purchased at least one drug with MA switcher surplus in the top quartile of the distribution. Figure 2b plots the percentage of FFS and MA enrollees who only purchased drugs with MA switcher surpluses in the bottom quartile of the distribution. Figures exclude beneficiary-years with zero drug purchases.

immediately in 2006. The fraction of enrollees taking drugs in the top quartile increases by 10 percentage points in FFS plans, and by 14 percentage points in MA plans.

Conversely, Figure 2b plots the fraction of beneficiaries who only take drugs in the bottom quartile of the distribution of MA switcher surplus. There is a gradual decline in this share in FFS plans throughout the period, with the exception of a small temporary increase in 2005. However, whereas the share of MA enrollees begins above the FFS share, between 2004 and 2006 there is a sharp reversal in the relative shares, resulting in the MA share being lower than the FFS share in every year after the introduction of Part D. The initial decline in 2004 could be due to the introduction of HCC-based risk-adjustment, consistent with the conclusion of Brown et al. (2014). Appendix Figure A.2 also broadens the set of drugs to show the top and bottom halves of the distribution, where there is additional evidence of diverging selection into MA plans beginning in 2004, when HCC-based risk adjustment was implemented. However, the change in MA shares relative to FFS shares was still substantially larger in 2006 than in any of the other year during which risk-adjustment was phased-in.

This evidence is suggestive that MA plans became even less attractive relative to FFS beneficiaries with the lowest MA switcher surplus after Part D was introduced, consistent a "push" based advantageous selection, as opposed to the "pull" based advantageous selection suggested by Figure 2a. Appendix Figure A.1 shows that these effects are even more pronounced when conditioning on beneficiaries with higher drug spending. We show additional evidence in Section 4.3 that Part D drug formulary differences were at least one mechanism behind these relative shifts in enrollments.

4.2 The Impact of Risk-Adjustment Errors on MA Market Shares

Our key hypothesis is that MA plans became better at precisely targeting profitable beneficiaries after the introduction of Part D. Although the evidence from unconditional summary statistics is consistent with the hypothesis, this suggestive evidence could potentially con-

found the effects of interest with geographic, intertemporal, or demographic heterogeneity.

To account for this, we first estimate a county-level fixed effects difference-in-difference model to test whether MA market shares increased disproportionately among beneficiaries taking drugs associated with the highest and lowest risk-adjusted MA switcher surpluses using data on enrollment choices in the MCBS.

$$MA\ Market\ Share_{ct} = \sum_{k=2000}^{2010} \alpha_k ShareTopQuart_{ct} * \mathbf{1}\left[Year = k\right] + \beta ShareTopQuart_{ct}$$
$$+ \sum_{k=2000}^{2010} \gamma_k ShareBotQuart_{ct} * \mathbf{1}\left[Year = k\right] + \theta ShareBotQuart_{ct} + \phi_c + \theta_t + \varepsilon_{ct} \qquad (2)$$

In this model $MA\ Market\ Share_{ct}$ is the share of Medicare beneficiaries in MA plans in county c, and year t; $ShareTopQuart_{ct}$ measures the fraction of Medicare beneficiaries who take drugs in the top quartile of the distribution of MA Switcher Surplus in county c, and year t; $ShareBotQuart_{ct}$ measures the fraction of Medicare beneficiaries who only take drugs in the bottom quartile; $\mathbf{1}\left[Year = k\right]$ is a set of indicator variables for each year from 2000 through 2010; ϕ_c is a set of county fixed effects; and θ_t are year fixed effects.

Our hypothesis is that the introduction of Part D in 2006 led to a change in the nature of selection into MA plans, resulting in larger MA market shares in counties in which more beneficiaries take drugs associated with high MA switcher surplus. Conversely, we also expect MA market shares to decline in counties in where more beneficiaries take drugs associated with lower MA switcher surplus. Since the HCC-based risk-adjustment formula began being phased in in 2004, it is possible that estimated values of α_k will begin to respond to these incentives prior to 2006. In 2005, the HCC-model was already given 50% weight in the risk-adjustment model, and this weight increased to 75% in 2006 and 100% in 2007. The purpose of this model is to look for visually suggestive evidence in the α_ks and $\gamma_k s$ on whether any change in selection appears to be gradual, consistent with the timing of the phase-in of the risk-adjustment formula, or whether there is an abrupt jump in 2006 that might suggest

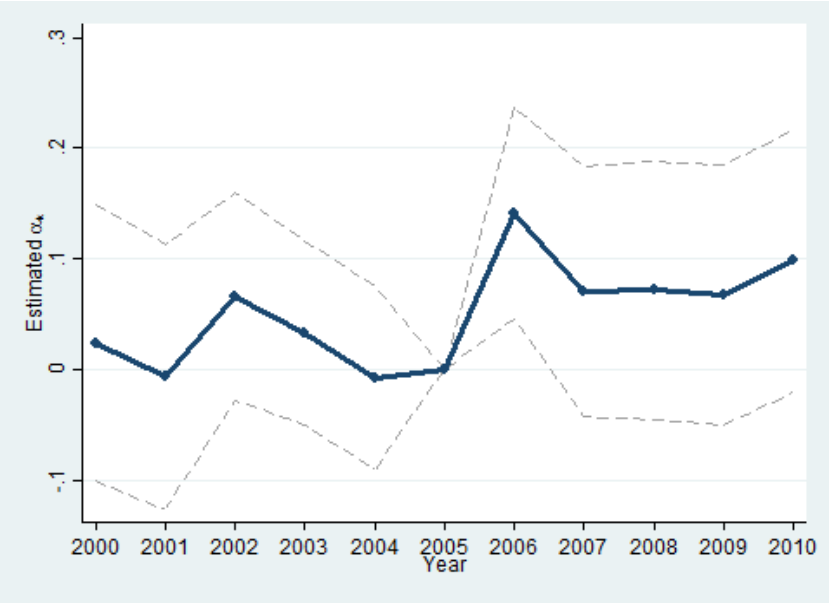
that the introduction of Part D played a distinct role in affecting selection into MA plans. This flexible model specification does not impose assumptions about when any break in MA market shares may have occurred, leaving the key parameters of interest, α_k and γ_k, unrestricted.

Figure 3 shows that prior to 2005, the share of Medicare beneficiaries taking drugs in the top quartile of the MA switcher surplus distribution had no effect on changes in MA market share over time. This suggests that to the extent there was selection into MA plans prior to 2006, any changes in selection were not strongly correlated with MA switcher surplus. Figure 3a presents estimates of α_k and their 95% confidence intervals, with 2005 set as the reference year, its coefficient normalized to zero. The figure shows that beginning in 2006, the county-level share of beneficiaries taking drugs in the top quartile becomes a significant positive predictor of MA market shares in the county, and throughout the post-period the effect remains high and above the pre-period estimates. Further contributing to this strengthening of advantageous selection in 2006, Figure 3b shows that the opposite pattern occurs in counties in which a larger share of Medicare beneficiaries take drugs in the bottom quartile. The MA market shares in these counties significantly decrease immediately in 2006, and remain lower throughout the post-period, despite remarkably stable pre-period estimates.

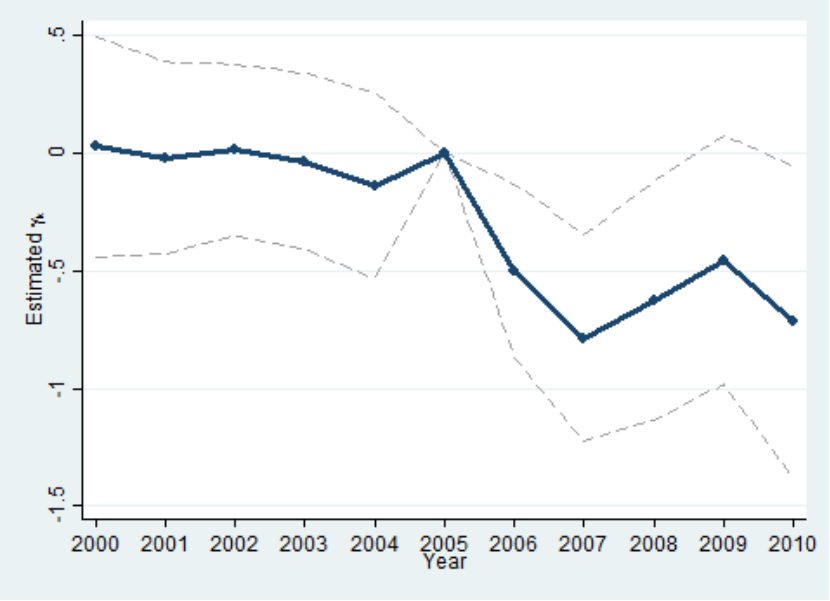
Table 4 presents difference-in-difference estimates of the average change in this relationship after the introduction of Part D. The estimates imply that after 2006, a one percentage point increase in the bottom quartile share decreased average MA market shares in the county by 0.59 percentage points more than the pre-2006 market share response. This negative coefficient on the post-2006 bottom quartile share suggests a potential enrollment deterrent effect. The point estimates suggest that on average a one percentage point increase in the top quartile share increased average MA market shares by 0.07 percentage points more than the pre-2006 market share response, although this coefficient is not statistically significant

Figure 3: Marginal Effects of Drug Use Shares at Top and Bottom of MA Switcher Surplus Distribution on MA Market Shares, By Year

(a) Top Quartile of MA Switcher Surplus



(b) Bottom Quartile of MA Switcher Surplus



Notes: Figure 3a plots the percentage of FFS and MA enrollees who purchased drugs with MA switcher surpluses in the top quartile of the distribution. Figure 3b plots the percentage of FFS and MA enrollees who only purchased drugs with MA switcher surpluses in the bottom quartile of the distribution. Figures exclude beneficiary-years with zero drug purchases.

Table 4: The Impact of Part D on the Relationship between Drug Use Shares and MA Market Shares

Dependent Variable: MA Market Share	
ShareBotQuart	0.138
	(0.077)
ShareBotQuart*Post 2006	–0.590**
	(0.141)
ShareTopQuart	–0.007
	(0.021)
ShareTopQuart*Post 2006	0.070
	(0.040)
N Observations	5,683
N Clusters	1146
Adj. R Sq.	0.804

Notes: Estimates are from a fixed effects regressions and all models include county effects and year effects. The unit of observation is a county-year, and the model is weighted by the number of MCBS respondents in each county. *ShareTopQuart* and *ShareBotQuart* measure the fractions of Medicare beneficiaries who take drugs in the top quartile, and only take drugs in the bottom quartile, of the distribution of MA switcher surplus, respectively. Standard errors are clustered by county. * indicates significance at the 0.05 level, ** indicates significance at the 0.01 level.

(p-value=0.08).

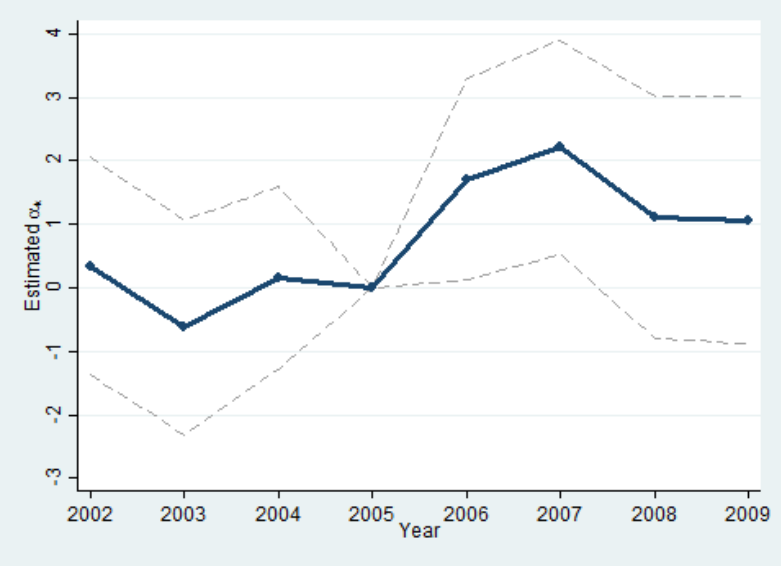
Although these difference-in-difference models are attractive for their simplicity, they may fail to capture some nuances to the extent that selection incentives vary more finely at the condition level, and there are potentially complex correlations between demand for drugs and the MA switcher surplus incentive. To incorporate these effects into the analyses, we also estimate a drug-county-year-level fixed effects model:

$$\begin{aligned} MA\ Market\ Share_{dct} &= \beta MA\ SwSurp_{dt} + \sum_{k=2002}^{2009} \alpha_k MA\ SwSurp_{dt} * \mathbf{1}\left[Year = k\right] \\ &+ r_d + \phi_c + \theta_t + \varepsilon_{dct} \end{aligned} \tag{3}$$

where $MA\ Market\ Share_{dct}$ is the Medicare Advantage market share among beneficiaries who take any prescription drug with active ingredient d, in county c, and year t;

$MA\ SwSurp_{dt}$, which we describe in Section 3.2, is the average MA switcher surplus associated with drug ingredient d in year t in the FFS analysis sample;[10] $\mathbf{1}\left[Year = k\right]$ is a set of indicator variables for each year from 2002 through 2009; r_d is a vector of fixed effects for each drug active ingredient; ϕ_c is a set of county fixed effects; and θ_t are year fixed effects. Since the model includes active ingredient effects, we limit the sample to beneficiaries who purchased at least one drug with an active ingredient among the top fifty most commonly purchased active ingredients.

Figure 4: The Impact of MA Switcher Surplus on MA Market Shares, by Year



Notes: Figure plots the estimated values of α_k from Equation 3 along with 95% confidence intervals corresponding to heteroskedasticity-robust standard errors clustered by county.

If the introduction of Medicare Part D had an effect on the ability of MA plans to more precisely target beneficiaries with profitable conditions, we expect to see a positive break in the pattern of $\widehat{\alpha_k}$ estimates at 2006. Figure 4 presents a graph of the estimated coefficients

[10] $MA\ SwSurp_{dt}$ varies over time because the distribution of HCCs associated with drug d changes over time. Since $MA\ SwSurp_{dt}$ is a generated regressor, in principle one should account for the estimation uncertainty using a two-step standard error correction method. This is not feasible since each iteration of the full model takes months to converge. Moreover, because we observe the full population of beneficiaries, the population-adjusted standard error of the generated variable is exactly zero, and our estimates are equivalent to the two-step corrected estimates.

on the interaction terms in each year, normalizing 2005 to zero. Prior to Part D there is minimal evidence of a pattern of changes in MA market shares associated with switcher surpluses. In each year the parameter estimates are statistically insignificant. However, there is a clear and abrupt increase in 2006 in MA market shares for beneficiaries taking substances with higher switcher surplus. In the first year MA market shares rose by 1.7 percentage points per $1,000 of MA switcher surplus, or 12% of the mean MA enrollment rate in 2005 (which was 14%). Relative to 2005, the coefficients remain large and positive throughout all years following the introduction of Part D, although the effect declines slightly to about 1.1 percentage points by 2009.

Table 5: The Impact of MA Switcher Surplus on MA Market Shares Post Part D

Dependent Variable:	MA Market Share	
	(1)	(2)
MA Switcher Surplus*Post 2006	1.533*	1.774**
	(0.600)	(0.627)
County Effects in Switcher Surp. Model	Yes	No
Mean Dep. Var.	18.968	18.968
N Observations	86,967	86,967
N Clusters	974	974
Adj. R Sq.	0.450	0.450

Notes: Estimates are from a fixed effects regressions and all models include county effects, year effects, drug active ingredient effects, and the base MA Switcher Surplus from Equation 1. The unit of observation is a county-year-drug active ingredient, and the model is weighted by the number of MCBS respondents in each county. Sample includes drugs with the top fifty most frequently purchased active ingredients in the MCBS and years 2002 through 2009. Standard errors are clustered by county. * indicates significance at the 0.05 level, ** indicates significance at the 0.01 level.

Table 5 also presents estimates from a model similar to Equation 3 that includes an indicator variable for the years in which Part D was available. This model imposes a break point in 2006, consistent with the patterns of evidence from the more flexible specification. The estimates suggest that on average in the four years following the introduction of Part D, MA market shares rose by 1.5 percentage points per $1,000 of MA switcher surplus, or about 11% of mean MA enrollment rate in the four years prior to Part D. Scaling this effect

by the average MA switcher surplus of the beneficiaries in the sample, we estimate that the change in advantageous selection following the introduction of Medicare Part D increased the probability of enrolling in an MA plan by about 7.7%.[11]

4.3 Was Part D the Mechanism for the Change in MA Selection?

Although these changes in MA market shares appear to systematically align with our hypothesis, in this section we provide additional evidence that the mechanism behind this change in selection was the introduction of Part D, and the differences in formulary designs between MA and PDP plans.

First, we show that in addition to Part D changing the distribution of medical conditions among enrollees in MA plans in a way that increased advantageous selection, this effect was stronger among beneficiaries with greater drug expenditures. To show this, we begin with the sample of MCBS respondents who switched from FFS to MA plans between 2003 and 2009,[12] and test the hypothesis that among the switchers into MA plans, those with the highest drug expenditures, who have the strongest relative incentive to make enrollment choices based on Part D generosity, generated a higher average switcher surplus to MA plans after 2006. Since the estimated MA switcher surplus coefficients from Equation 1 do not change over time, the only way that average switcher surplus could increase after the introduction of Part D is if the distribution of diagnoses of switchers into MA plans changes over time in a way that is systematically correlated with the error term from the risk-adjustment model applied to the MA switcher sample.

[11] This estimate is calculated as (1.533/18.968) multiplied by 938.67, the average switcher surplus in the sample, divided by 1000.

[12] As in the analyses presented in Table 5, we restrict the same to beneficiaries that were enrolled in FFS Medicare for a full year in the data prior to switching. The sample therefore spans the same years as the market share models, 2002 through 2009, with the first switches into MA plans beginning in 2003.

We estimate the model:

$$MA\ SwSurp_{i,t} = \alpha DrugExp_{i,t-1} + \sum_{k=2003}^{2009} \beta_k DrugExp_{i,k-1} * \mathbf{1}\left[Year = k\right] + \delta_t + \varepsilon_{it} \quad (4)$$

where $MA\ SwSurp_{i,t}$ is the MA switcher surplus for a beneficiary who switched into an MA plan in year t, estimated from Equation 1 for the set of HCCs that individual i was diagnosed with in year $t-1$. $DrugExp_{i,t-1}$ are the beneficiary's expenditures on prescription drugs in the same year. $\mathbf{1}\left[Year = k\right]$ is a binary variable indicating year k. δ_t is a set of year fixed effects.

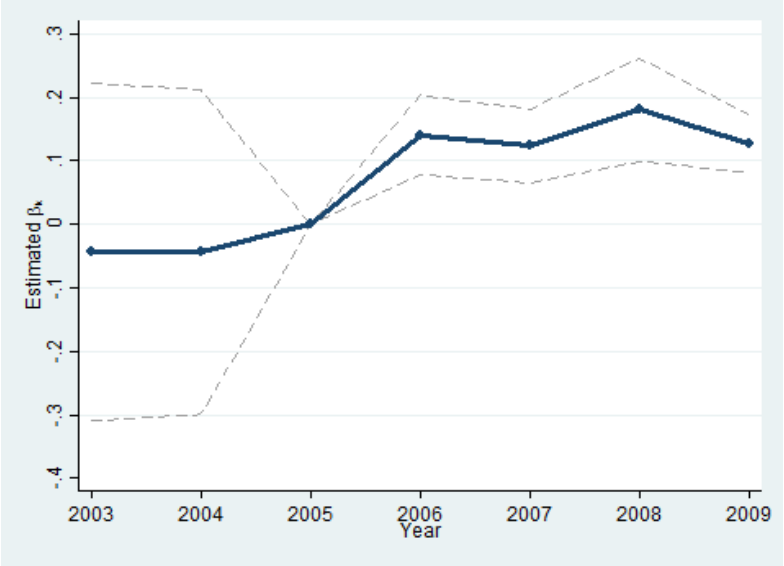
The key parameters of interest from this model are the β_ks. Our hypothesis is that β_k increased after the introduction of Part D, which would suggests that drug expenditures became a stronger predictor of the strength of advantageous selection after Part D was introduced. Although drug expenditures rose on average following the introduction of Part D, the dependent variable in this model is the average HCC-level error from the risk-adjustment model. Under the null hypothesis that Part D did not affect selection into MA plans, there is no clear reason why this *average* error term would be correlated with drug spending, since the risk-adjustment model conditions on medical diagnoses.

Figure 5 plots the estimated values $\widehat{\beta_k}$ in each year from Equation 4, along with the 95% confidence intervals, normalizing 2005 to zero. The pattern of coefficients is fairly flat throughout the pre-period, and the estimates from 2003 and 2004 are not significantly different from that in 2005.[13] Beginning immediately in 2006, however, there is a sudden and statistically significant increase in $\widehat{\beta_k}$, which then flattens and remains persistently higher and statistically significant in every year of the post-period, ranging from about 0.12 to 0.18.

Table 6 presents results from a similar model including a binary post-2006 indicator. The coefficient in the first column, 0.166, suggests that after Part D was introduced, a $1,000

[13]The confidence intervals are large in the pre-period because there are relatively fewer switchers into MA plans in these years, as shown in Table 2.

Figure 5: The Relationship between Drug Spending and MA Switcher Surplus among Switchers into MA Plans, by Year



Notes: Figure plots estimated values $\widehat{\beta_k}$ from Equation 4, along with 95% confidence intervals. The reference year, 2005, is normalized to zero. Sample includes only MCBS beneficiaries who were enrolled in FFS Medicare for a full year, and then switched into an MA plan in the subsequent year. Year shown in the figure correspond to the year in which the beneficiary switched into an MA plan.

increase in annual drug spending was associated with a $166 increase in the risk-adjusted Parts A and B surplus of switchers into MA plans. There was no significant relationship between these variables prior to 2006. This change in the nature of selection into MA plans does not appear to have been driven by geographic differences in switching patterns. Column 2 shows that when MA switcher surplus is estimated using a model that excludes county fixed effects, the relationship between drug spending and switcher surplus remains similar, with a coefficient of 0.171.

Although Lavetti and Simon (2016) present a wide range of evidence that MA Part D plans strategically design their formularies differently than stand-alone Part D plans in ways that encourage advantageous selection, their analyses focus only on plan benefit design and do not include beneficiary responses to any plan differences. We test for corroborating evidence from the beneficiary perspective that MA plans offer relatively higher Part D generosity for

Table 6: The Impact of Part D on the Relationship between Drug Spending and MA Switcher Surplus among Switchers into MA Plans

Dependent Variable	MA Switcher Surplus	
	(1)	(2)
Drug Expenditure*Post 2006	0.166*	0.171*
	(0.072)	(0.073)
Drug Expenditure	-0.018	-0.029
	(0.070)	(0.069)
County Effects in Switcher Surp. Model	Yes	No
N Observations (Individuals)	1,227	1,227
R Sq.	0.101	0.092

Notes: Sample includes only MCBS beneficiaries who were enrolled in FFS Medicare for a full year, and then switched into an MA plan in the subsequent year. All models include year fixed effects. "Drug Expenditure" is the total cost of drug purchases (the sum of all payments from any source) in the FFS year prior to the switch, "MA Switcher Surplus" is the sum of $(\widehat{\gamma_k} + \widehat{\theta_k})$ from Equation 1 over all of the HCCs associated with the diagnoses of the beneficiary while in FFS Medicare in the year prior to the switch. "Post 2006" equals one if the switch into an MA plan occurred in the year 2006 or later, and zero otherwise. Heteroskedasticity-robust standard errors are reported in parentheses. * indicates significance at the 0.05 level.

bundles of drugs taken by beneficiaries with higher MA switcher surplus. Using the sample of beneficiaries who were enrolled in FFS for a full baseline year and observed the following year, we estimate the model:

$$\begin{aligned} MA\ PctDrugSavings_{i,t+1} &= \alpha MA\ SwSurp_{i,t} + \beta MA\ SwSurp_{i,t} * TopQuartile_{i,t} \\ &+ \gamma MA\ SwSurp_{i,t} * BotQuartile_{i,t} + \phi_c + \theta_t + \varepsilon_{it} \end{aligned} \quad (5)$$

The dependent variable in the model, $MA\ PctDrugSavings_{i,t+1}$ is constructed by first calculating the counterfactual out-of-pocket costs (including premium, deductible, and cost-sharing payments) that beneficiary i would have paid in year $t+1$ given their observed drug purchases if they had enrolled in each potential plan available in their county. Using these counterfactual out-of-pocket costs we identify the lowest cost MA drug plan and the lowest cost PDP available to the beneficiary, and calculate the percent savings the beneficiary

Table 7: The Impact of MA Switcher Surplus on Beneficiary-Level Potential Part D Savings from Enrolling in MA

Dependent Variable: % Potential Savings from MA Enrollment	(1)	(2)
MA Switcher Surplus*Bottom Quartile	0.064**	0.051*
	(0.021)	(0.026)
MA Switcher Surplus*Top Quartile	0.012	0.009
	(0.012)	(0.019)
MA Switcher Surplus	–0.011	–0.011
	(0.011)	(0.018)
County Effects in Switcher Surp. Model	Yes	No
N Observations	2,926	2,926
R Sq.	0.235	0.233
P-value of t-test: $Row1 + Row3 = 0$	0.003	0.029
P-value of t-test: $Row2 + Row3 = 0$	0.791	0.505

Notes: All models include county and year fixed effects. Dependent variable is the beneficiary-level percentage reduction in out-of-pocket spending associated with enrolling the optimal (ex-post lowest-cost) MA Part D plan relative to the optimal stand-alone Part D plan in the beneficiary's county, given the their observed drug purchases in the previous year. Out-of-pocket spending includes the beneficiary's contribution to monthly premiums, the deductible payment they would have made given the plan deductible and beneficiary drug purchases, plus any cost-sharing. Sample in limited to years 2008-2010 due to available Part D formulary data. Heteroskedasticity-robust standard errors are reported in parentheses. * indicates significance at the 0.05 level, ** indicates significance at the 0.01 level.

could have achieved by selecting the ex post lowest cost MA drug plan relative to the ex post lowest cost stand-alone PDP. When this value is negative it suggests that the individual could have saved money by enrolling in a PDP. We regress this estimated potential savings on $MA\ SwSurp_{i,t}$, the individual's predicted MA switcher surplus given their diagnoses and demographic characteristics, as well as interactions between switcher surplus and binary indicators for whether the beneficiary is in the top quartile of the distribution of MA switcher surplus, $TopQuartile_{i,t}$, or only in the bottom quartile of this distribution, $BotQuartile_{i,t}$. The model also include county fixed effects and year fixed effects. Since our Part D formulary data, which are necessary to construct the dependent variable, cover the years 2009-2010, the sample in this model is limited to these years.

The estimates in Table 7 suggest that relative generosity differences between plans are

most responsive to changes in MA switcher surplus at the bottom of the distribution. For example, consider a beneficiary at the median of the MA switcher surplus distribution who receives a new diagnosis that reduces switcher surplus by $1000, moving them to the bottom quartile of the distribution, and decreasing their attractiveness to MA plans. The estimates from Table 7 suggest that the out-of-pocket costs from enrolling in the optimal MA Part D plan would increase 6.4 percentage points relative to the out-of-pocket costs from enrolling in the optimal stand-alone plan. This effect remains similar, 5.1 percentage points, when the MA switcher surplus model includes county effects, suggesting that it is not caused by differences in the geographic availability of MA or stand-alone PDP plans. The coefficient on the top quartile indicator, 0.012, also has a sign that is consistent with advantageous selection, although it is not statistically significant. This evidence on individual plan choices is consistent with the results in Table 4 showing significant declines in MA market shares in counties with more beneficiaries taking drugs in the bottom quartile of switcher surplus, but more modest and insignificant effects with respect to the top quartile.

4.4 Beneficiary Responses to Formulary Differences

Complementing the aggregate market-share analyses, we also show that these differences in Part D plan generosity affect beneficiary-level plan switching choices. Having shown that MA switcher surplus is correlated with the relative formulary generosity of MA plans, we now show that consumers respond to these formulary differences.

We begin by estimating a simple probit model in which the dependent variable equals one if a beneficiary switches into an MA plan in year $t+1$, and regress this indicator on $MA\ PctDrugSavings_{i,t+1}$ from Equation 5, year effects, and the same set of demographic variables included in the HCC-based risk-adjustment model (age effects, race effects, gender, disability status, and disability interacted with race effects). Table 8 presents the estimated marginal effects at means from this model. The estimates in column 1 suggest that a one

standard deviation increase in "MA % Drug Savings" (0.225) is associated with a 1 percentage point increase in the probability that a beneficiary will switch into an MA plan.

Table 8: Probit Models: Impact of Part D Cost-Sharing on Beneficiary Switching into MA Plans

Dependent Variable:	Switch into MA Plan		
	(1)	(2)	(3)
MA % Drug Savings	0.044**	–0.078*	–0.142*
	(0.014)	(0.037)	(0.062)
Log Out-of-Pocket Drug Costs		–0.008*	
		(0.003)	
MA % Drug Savings*Log Out-of-Pocket Drug Costs		0.023**	
		(0.007)	
Log Drug Spending			–0.007*
			(0.003)
MA % Drug Savings*Log Drug Spending			0.025**
			(0.008)
N Observations	2,441	2,301	2,441
R Sq.	0.055	0.072	0.066

Notes: Reported coefficients are Probit marginal effects at means. Dependent variable equals 1 in the year in which a beneficiary switched into an MA plan. All models also includes age effects, year effects, race effects, disability status, gender, and disability status interacted with race. Sample includes beneficiaries who were enrolled in FFS for a full baseline year prior to any potential switch. "MA % Drug Savings" equals the beneficiary-level percentage reduction in out-of-pocket spending associated with enrolling the optimal (ex-post lowest-cost) MA Part D plan relative to the optimal stand-alone Part D plan in the beneficiary's county, given the their observed drug purchases. "Log Out-of-Pocket Drug Costs" equal the log of the sum of the beneficiary's annual cost-sharing payments. Heteroskedasticity-robust standard errors are reported in parentheses. * indicates significance at the 0.05 level, ** indicates significance at the 0.01 level.

Columns 2 and 3 examine patterns of heterogeneity in this effect across beneficiaries. Since beneficiaries with higher drug expenditures have a relatively stronger incentive to consider drug formulary generosity when choosing between MA or FFS Medicare, we hypothesize that the interaction between "MA % Drug Spending" and beneficiary drug costs should have a positive coefficient. Column 2 shows that this estimate is positive, 0.023, and statistically significant when log out-of-pocket drug costs are used in the interaction term, and column 3 shows that the estimate is very similar, 0.025, when log drug spending is used instead. Appendix Table A.1 that these results are not sensitive to model assumptions, as linear

and logit models suggest very similar estimates. These findings are reinforce the conclusion that consumers are responsive to differences in Part D plan generosity, and heterogeneity in responsiveness is consistent with theory.

5 Discussion

Our goal in this paper is to show how the introduction of Medicare Part D prescription drug coverage in 2006 affected the nature of selection into MA plans. Although Medicare gradually introduced an HCC-based risk-adjustment model that adjusts capitation payments to MA plans based on beneficiaries' medical conditions between 2004 through 2007, we find broad and consistent evidence suggesting that changes in MA selection occurred abruptly in 2006 when Part D was introduced, rather than being proportional to the phase-in of risk-adjustment. This is consistent with the intuition that MA plans can use the design of their Part D benefits as a mechanism to induce selection by setting more generous cost-sharing rules for the drugs that tend to be taken by more profitable beneficiaries, conditional on risk-adjustment.

Using estimates from Lavetti and Simon (2016) that characterize the magnitudes of these selection incentives, we show that MA plans were able to increase their market shares among beneficiaries with the highest switcher surpluses, while decreasing their relative shares among beneficiaries with the lowest switcher surpluses. Our estimates imply that the change in advantageous selection following the introduction of Medicare Part D increased the probability that a beneficiary would enroll in an MA plan by about 7.7%. We also show evidence behind the mechanism, that the out-of-pocket cost of enrolling in an MA drug plan is relatively lower for beneficiaries with higher risk-adjusted switcher surplus, suggesting that MA plans reflect selection incentives in their benefit design. We then show that beneficiaries respond to these differences in benefit design when choosing plans, and that consumers with greater

drug spending respond more intensively, as expected.

The challenge faced by policymakers is to minimize the welfare loss associated with advantageous selection into MA plans, which imposes a negative externality on the Medicare program, without compromising the potential efficiency benefits of Medicare Advantage. There are several potential options that policymakers could consider that meet these criteria. The first would be to include MA enrollees in the calculation of the risk-adjustment formula, and account for any condition-specific differences in the costs associated with treating beneficiaries in MA plans relative to FFS. Although appealing in its directness and simplicity, this option may be infeasible if it is not possible to obtain comparable data on costs and utilization of MA beneficiaries. A second-best approach could be to instead condition on the average difference in FFS spending between switchers to MA plans and stayers in the risk-adjustment formula. Essentially, this approach would include the MA switcher surplus incentive directly in risk-adjustment. This approach also has a drawback, in that the population of MA switchers could differ from the population of MA enrollees in general. Although Brown et al. (2014) estimate that 75% of MA enrollees were switchers at some point, it is also possible that the cost and utilization patterns of MA enrollees diverge from those of FFS enrollees over time, in which case new MA switchers could still differ from other MA enrollees.

A third approach would be to condition on each beneficiary's prior-year medical expenses or utilization in the risk-adjustment formula. The aim of this approach would be to make use of the positive serial correlation in within-beneficiary medical spending to improve the explanatory power of the risk-adjustment model, leaving less residual variation for MA plans to select enrollees upon. While this option has similar data limitations with respect to measuring MA enrollee expenditures, including utilization measures is potentially more practical.

Finally, a method of directly reducing the specific form of selection that we discuss would

be to integrate risk-adjustment for drugs and medical care into a single risk-adjustment formula for MA plans. By conditioning on drug utilization in the medical risk-adjustment formula, this would remove demand for drugs as an excluded dimension upon which plans could induce selection. This option would likely be the easiest to implement with available data, but has the disadvantage that it is limited to addressing only the specific type of selection that we discuss, and may not be as robust to other forms of selection. In addition, using a different risk-adjustment formula for MA Part D capitation payments could alter competition between private stand-alone PDP plans and MA plans, and potentially favor one form of plan, which could itself have potential negative effects on consumer welfare.

We hope that this paper serves as a source of convincing evidence on a form of advantageous selection and its effects on Medicare beneficiaries, which have not previously been documented in the literature, and that these options for combating this form of selection are a useful starting point for policy discussions aimed at addressing this issue.

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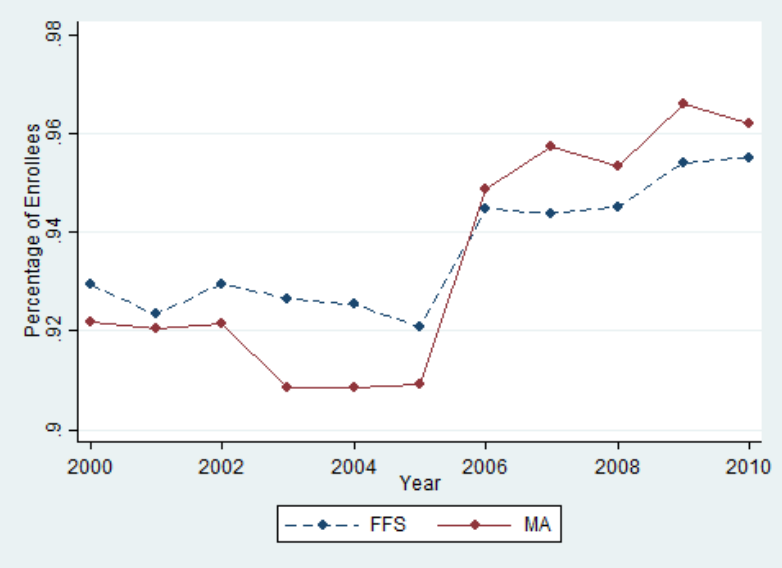
A Appendix: Supplementary Tables and Figures

Figure A.1: Percent of Enrollees Purchasing Drugs at Top and Bottom of MA Switcher Surplus Distribution, By Year, Conditional on Spending at Least $1,000 on Drugs

(a) Top Half of MA Switcher Surplus

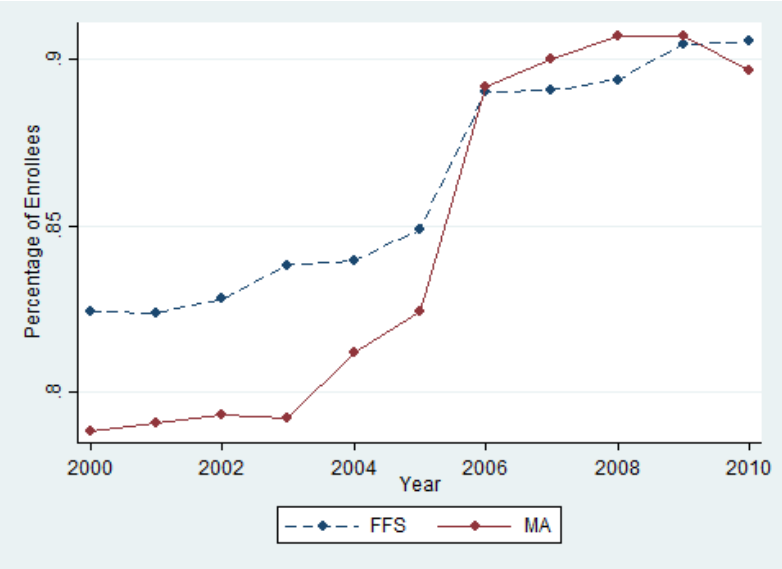


(b) Bottom Half of MA Switcher Surplus

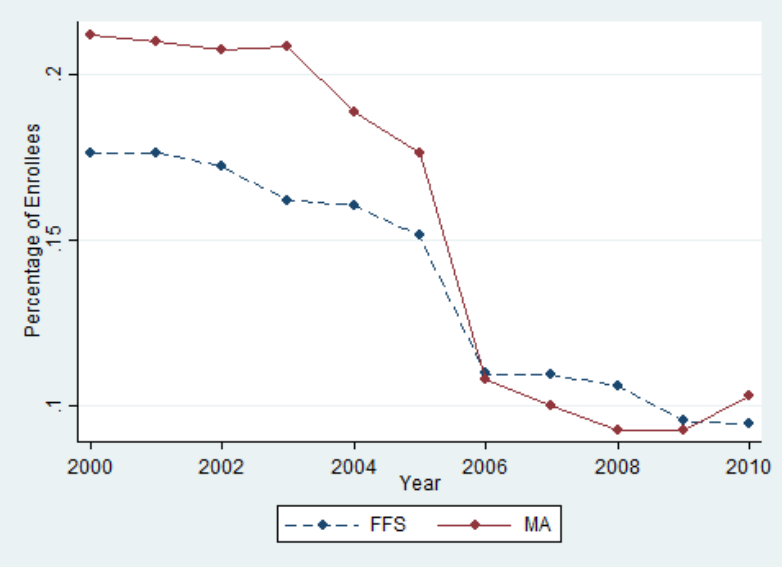
Notes: Figure A.1a plots the percentage of FFS and MA enrollees who purchased at least one drug with MA switcher surplus in the top half of the distribution. Figure A.1b plots the percentage of FFS and MA enrollees who only purchased drugs with MA switcher surpluses in the bottom half of the distribution. Figures exclude beneficiary-years with less than $1,000 in drug spending.

Figure A.2: Percent of Enrollees Purchasing Drugs at Top and Bottom of MA Switcher Surplus Distribution, By Year

(a) Top Half of MA Switcher Surplus



(b) Bottom Half of MA Switcher Surplus



Notes: Figure A.2a plots the percentage of FFS and MA enrollees who purchased at least one drug with MA switcher surplus in the top half of the distribution. Figure A.2b plots the percentage of FFS and MA enrollees who only purchased drugs with MA switcher surpluses in the bottom half of the distribution. Figures exclude beneficiary-years with zero drug purchases.

Table A.1: Comparison of Model Specifications: Impact of Part D Cost-Sharing on Beneficiary Switching into MA Plans

Dependent Variable:	Switch into MA Plan					
	Probit ME	Logit OR	Linear	Probit ME	Logit ME	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
MA % Drug Savings	0.044**	4.195**	0.041*	–0.078*	0.015*	–0.068
	(0.014)	(1.892)	(0.017)	(0.037)	(0.027)	(0.036)
Log Out-of-Pocket Drug Costs				–0.008**	0.807**	–0.006*
				(0.003)	(0.066)	(0.003)
MA % Drug Savings*Log OOP Costs				0.023**	2.137**	0.021**
				(0.007)	(0.515)	(0.008)
N Observations	2,441	2,441	2,941	2,441	2,441	2,727
R Sq.	0.055	0.055	0.021	0.066	0.066	0.026

Notes: Reported Probit coefficients are marginal effects at means. Reported Logit coefficients are odds ratios. Dependent variable equals 1 in the year in which a beneficiary switched into an MA plan. All models also includes age effects, year effects, race effects, disability status, gender, and disability status interacted with race. Sample includes beneficiaries who were enrolled in FFS for a full baseline year prior to any potential switch. "MA % Drug Savings" equals the beneficiary-level percentage reduction in out-of-pocket spending associated with enrolling the optimal (ex-post lowest-cost) MA Part D plan relative to the optimal stand-alone Part D plan in the beneficiary's county, given the their observed drug purchases. "Log Out-of-Pocket Drug Costs" equal the log of the sum of the beneficiary's annual cost-sharing payments. Heteroskedasticity-robust standard errors are reported in parentheses. * indicates significance at the 0.05 level, ** indicates significance at the 0.01 level.