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 theoretically 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 7.1%.

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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 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 diagnoses, or more precisely hierarchical condition codes (HCCs), in 2004 was intended to reduce this incentive to compete based on selection. However, there is mixed evidence in the literature on the impacts of this change in risk-adjustment on selection into MA plans. 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. Newhouse et al. (2015), in contrast, find that favorable selection fell after HCC-based risk-adjustment was introduced, although some

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

selection still remained.

Despite the broad historical evidence consistent with selection by MA plans, less is known about the mechanisms that may lead to such selection (McGuire et al. 2011).[2] In standard models of selection of the form discussed by Akerlof (1970), it is not obvious that substantial selection should remain after conditioning payments on medical diagnoses, suggesting that the persistence of 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.

A different form of selection could occur if plan design is endogenous, and insurers compete in part by tailoring the set of offered plan characteristics to induce self-sorting (Rothschild and Stiglitz (1976), Glazer and McGuire (2000)). After the introduction of HCC-based risk-adjustment, it is also not obvious that MA plans were able to use this form of selection to attract low-cost beneficiaries within a particular HCC, since medical insurance tends to have fairly blunt characteristics, such as fixed deductibles or copayments. Newhouse et al. (2015) also point out that under the HCC-based risk-adjustment system, inducing selection might require MA plans to motivate physicians and hospitals within their network to assist in selecting more profitable patients within HCCs, but given the arms-length nature of contracts it is unclear how this could occur. Empirical studies testing the impacts on insurance plan design of this form of selection have been fairly limited, with recent evidence in Medicare markets by Lustig (2010), Carey (2016), and Lavetti and Simon (2016), and in ACA exchange plans by Geruso et al. (2017).

The introduction of Medicare Part D in 2006, however, transformed benefit design choice from a blunt instrument for selection into a scalpel. 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

[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.

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. Moreover, since MA beneficiaries' Part D benefits are integrated into a single MA insurance plan, while FFS beneficiaries receive coverage through stand-alone private prescription drug plans (PDPs), plans competing on formulary design in the Part D market face different expected profits for the same beneficiary if risk-adjustment is imperfect. Lavetti and Simon (2016) show that MA plans designed drug formularies that were significantly different than stand-alone Part D plans in ways that encouraged advantageous selection.

In this paper we quantify the impact of these strategic Part D formulary design choices, made possible by the introduction of Medicare Part D, on relative changes in advantageous selection in the MA market. Using data from the Medicare Current Beneficiary Survey (MCBS) from 2000-2010, Part D formulary files from 2009-2010, and estimates of risk-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 a 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 7.1%.

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 among beneficiaries in the bottom quartile of the MA switcher surplus distribution, a $1000 increase in switcher surplus reduced the total cost (premium plus out-of-pocket) of enrolling in the ex post optimal MA plan by 5.2 percentage points, relative to the cost of 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. In addition, although a large literature has discussed geographic differences in MA market shares and plan entry incentives, 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.[3] 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 potential error in the out-of-sample prediction of MA spending. If MA plans have a mechanism for selecting

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

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 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[4] less than 1% of

[4]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

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 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,[5] making it impossible to discriminate against consumers of an entire class of drugs. Third, payments to Part D insurers are also risk-adjusted.[6] 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

all costs beyond that, in the catastrophic zone.

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

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

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.

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 51,724 unique individuals and 115,622 person-year observations.[7]

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.

Table 1: Summary Statistics on MCBS Sample

	Full MCBS Sample	Top 50 Drug User Sample	FFS to MA Switcher Sample	SAPD Enrollee Sample
Male	0.44	0.42	0.45	0.44
Age	72.4	73.6	70.8	67.9
MA Enrollees	0.19	0.20	0	0
Purchase Any Drugs	0.88	1	0.93	1
Annual Drug Expenditure	2,550	2,898	2,603	4,553
Annual Out-of-Pocket Drug Spending	602	666	645	652
Percent Part D Enrollees	0.58	0.59	0.56	1
Number Person-Year Observations	115,622	66,587	1,213	2,889
Number Unique Individuals	51,724	31,444	1,213	2,298

Notes: Full MCBS sample excludes beneficiaries with end-stage renal disease (ESRD), who are not included in our population of interest because they are restricted from switching into MA plans, and beneficiaries not enrolled in Medicare Parts A and B for the full year. The 'Top 50 Drug User Sample' includes the subset of the Full MCBS beneficiary-year sample who purchased at least one drug with the top 50 most common drug active ingredients between 2002-2009. 'FFS to MA Switcher Sample' is the set of beneficiaries observed in a full baseline FFS year between 2003-2009, and observed in an MA plan the following year. 'SAPD Enrollee Sample' is the subset of the MCBS sample containing beneficiaries enrolled in a stand-alone Part D (SAPD) plans in at least one baseline year in 2008-2009, and observed the following year, with available NDC codes. 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.

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

[7]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, and exclude beneficiaries who were not enrolled in either Medicare Parts A and B or in an MA plan during each month in the year.

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 presents summary statistics from our MCBS analysis sample. The first column 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 fourth column restricts the full MCBS sample to FFS Part D enrollees in 2008-2009 who are observed for two consecutive years. We use this sample to link each beneficiary to Part D formulary data for all plans available in their county of residence, and to test the relationship between beneficiary enrollment choices and plan formulary generosity differences.

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 70.8 years compared to 73.6. Since the sample in the second column conditions on drug use, beneficiaries in this sample spend about 11% more on drugs annually. The switcher sample, which does not condition on drug usage, has similar average drug expenditures 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 1,407 individuals who switch from FFS to MA (1,213 of whom switch within 4 years of the introduction of Part D, and are included in our MA Switcher Sample above), and 50,619 who remain in FFS for consecutive years in the panel.

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

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}	11,220	11,110	10,453	9,556	8,280	50,619
FFS_t to MA_{t+1}	69	120	441	504	273	1,407
MA_t to FFS_{t+1}	359	132	86	111	349	1,037
MA_t and MA_{t+1}	2,099	1,797	1,761	2,501	2,688	10,826
Total	13,747	13,159	12,741	12,672	11,570	63,889

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. See Appendix Table A.1 for sample summary statistics.

MA. This is potentially important because it suggests that by studying switching behavior it may be possible to gain insights that are relevant to the choices made by a large majority of the population of MA enrollees. However, we are not able to directly test for differences between recent and historical switchers into MA plans since we cannot observe medical claims or other utilization data for 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 an-

nual FFS spending of beneficiaries who subsequently switch to MA plans differs from the spending of FFS beneficiaries who remain in FFS the following year. As a result, the average counterfactual capitation payment minus observed spending is $902 higher per year 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 HCC-level 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 $MA\ Switcher\ Surp_{it}$ equals the counterfactual MA capitation payment minus FFS expenditures of beneficiary i in year t, $MA\ Switch_{it}$ equals one if person i switched from FFS into an MA plan with the first month of MA enrollment in year t and zero otherwise, and $\mathbf{1}\left[HCC_{it-1} = k\right]$ equals one if person i was diagnosed with HCC k in the prior year. X_{it} 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. $\psi_{c(it)}$ is a set of fixed effects for the county c in which beneficiary i lived in year t.

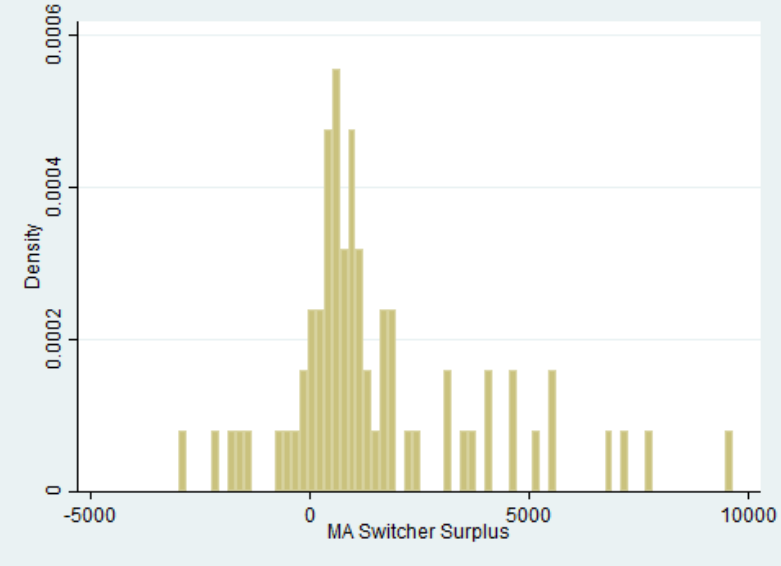
In this model, $\widehat{\gamma_k}$ primarily captures the incentive for MA plans to select a beneficiary with HCC k relative to a beneficiary with a different (reference) HCC, conditional on demographic controls and county effects. Since the risk-adjustment model used to calculate capitation payments 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. The average impact of these statutory payment rates is absorbed by year fixed effects. However, larger overpayments amplify variation in payments relative to expenditures, increasing selection incentives all else equal. 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[8] the estimated MA switcher surplus is positive, consistent with advantageous selection.

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 more precise when Part D was introduced in 2006. However, one potential concern is that other changes may also have occurred in 2006 that were correlated with MA selection incentives. Since Part D was a new source of revenue, insurers may have increased advertising that targeted consumers in particular geographic areas or demographic groups. Cai et al. (2008) study advertising patterns of MA plans and find that the majority of ads appeared to reach out to racial and ethnic minorities, for example. To address the potential concern that advertising may also

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

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.

have changed selection into MA plans in 2006, Equation 1 includes all of the demographic variables available in the data as controls, including race variables (which are not part of the CMS risk-adjustment formula.) Similarly, we include county fixed effects in the model to control, among other things, for selection among MA plans into particular geographic markets. By controlling for these factors, our measure of $\widehat{\gamma_k} + \widehat{\theta_k}$ isolates the component of selection incentives driven by medical diagnoses, conditioning on alternative selection factors that may have changed concurrently in 2006. Our main analyses will test whether MA enrollment market shares increased differentially more for the medical conditions with the strongest selection incentives following the introduction of Part D.

The majority of our analyses are estimated at the beneficiary-year level. To calculate the beneficiary-year level MA Switcher Surplus, we use the estimated coefficients from Equation 1, $\widehat{\gamma}$, $\widehat{\theta}$, and $\widehat{\pi}$, to predict the MA Switcher Surplus for each beneficiary-year in the MCBS sample. We also estimate MA market share equations at the drug active ingredient level. In these models we calculate the average beneficiary-year MA Switcher Surplus

among MCBS beneficiaries who take a drug with a given active ingredient. This average MA Switcher Surplus over all users of each drug preserves any correlations in usage across drugs and HCCs. For example, if two drugs are highly complementary and generally taken together, our estimate of the average MA Switcher Surplus by drug would be similar for both drugs, capturing the fact that either drug signals approximately the same information. Using the distribution of drug-level average beneficiary-year switcher surpluses, we also define dummy variables to indicate whether the average is in the top or bottom quartile of the distribution. To avoid potentially endogenous effects of switcher surplus on drug purchases via Part D benefit design, we define these quartiles using only data prior to Part D.

To be clear, there are some limitations associated with this approach of using MA switcher surplus to study selection. First, although it is common in the literature to study selection based on switching behavior (Morgan et al. (1997), Cao (2003), Batata (2004), Brown et al. (2014)) largely because detailed data on utilization and expenditures are not typically available once beneficiaries enroll in MA plans, as Newhouse et al. (2015) discuss there are several important limitations with this general approach. Since the average rate of switching from FFS to MA is quite low, switchers may not be representative of MA enrollees generally. Brown et al. (2014) estimate that 75% of MA enrollees were switchers from FFS at some point, whereas only 25% joined an MA plan at the point of initial eligibility. Still, it is possible that any differences in average expenditures between switchers and stayers at the time of a switch may not persist over time. In this case, interpreting estimates of switching behavior as representations of more general selection may overstate this concern. The approach of studying switchers also implicitly assumes, as do the risk-adjustment models used by CMS, that past expenditures and utilization are informative about future utilization.[9] Without data on MA enrollees, we are unable to contribute further evidence to this discussion in the literature on the general merits of studying switching behavior.

[9]Evidence from French and Jones (2004) is consistent with the presence of positive autocorrelation in medical spending. They estimate the time-series dynamics of individual health spending and find that it is well characterized by the sum of an AR(1) process with autoregressive coefficient 0.95 plus a heteroskedastic white noise component.

Second, our estimates of the beneficiary MA Switcher Surplus are calculated out-of-sample, creating potential concern about inference involving generated regressors. However, since the generated regressors we use are estimated on the 100% population of all Medicare beneficiaries, we know the exact population means; they are not sample statistics, and therefore have no sampling error. The consequence of applying finite-population standard error corrections, which we implicitly do, is that doing so restricts the interpretation of these estimates, as discussed by Abadie, Athey, Imbens and Wooldridge (2014). The estimated MA switcher surplus values can only be interpreted as data that describe what actually occurred in Medicare, but they do not reflect errors associated with alternative hypothetical populations, such as the population that could have existed if Medicare eligibility rules were different, if different drugs had been invented, or if there were different hypothetical diseases that have never been observed. As long as one interprets the estimates appropriately—as descriptive of the actual realized universe and actual Medicare program, rather than predictive of alternative hypothetical populations—then it is valid to apply finite population standard error corrections. In this case, the first-stage error associated with the generated regressor MA Switcher Surplus is zero since we observe the full population, and the standard errors we report throughout the paper are equivalent to the standard errors that would be obtained with two-step correction for generated regressors.

Third, in addition to concerns about the representativeness of switchers, our measure of the selection incentive captures only one component of total insurer 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, as documented by Curto et al. (2017). We return to this point and provide some back-of-the-envelope calculations in Section 5. The challenge to directly measuring the impact of selection on profits is that our data do not include 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, which may also

contribute to plan profits.

Our focus in this paper is not on documenting levels of selection into MA plans, but in showing that the patterns of switching appear to have changed when Part D was introduced in 2006 in ways that are consistent with plan incentives and economic theory, and describing the potential mechanism through which plans may have effectuated these changes in switching patterns. To the extent that many of the limitations associated with studying switchers remain similar before and after the introduction of Part D, there is not a clear reason to suspect that these other factors contributed to the abrupt changes in switching patterns in 2006 that we find. Nonetheless, we wish to make clear that our measure of MA Switcher Surplus is not necessarily indicative of a welfare loss associated with advantageous selection.

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 average MA switcher surplus by drug, before and after the introduction of Part D.

The patterns in Table 3 show that enrollment in MA plans grew by the largest amounts among beneficiaries who took drugs in the top quartile of the distribution of average switcher surplus by drug. The share of MA enrollees taking drugs in the top quartile grew from about 30% in the four years prior to the introduction of Medicare Part D, to over 46% in the four years following. Of course, the use of drugs generally increased following the introduction of Part D, and this causes some mechanical increase in the fraction of beneficiaries who take at least one drug in any given set of drugs. However, this fraction of beneficiaries

Table 3: Percent of Beneficiaries by Plan Type and Drug Usage

	Percent of Drug Purchasers Taking:				Percent of:	
	Any Drug in Top Quartile of MA Switcher Surplus		Only Drugs in Bottom Quartile of MA Switcher Surplus		Beneficiaries Purchasing Any Drug	
	2001-2004	2006-2009	2001-2004	2006-2009	2001-2004	2006-2009
FFS_t	33.2%	46.8%	2.2%	1.3%	83.8%	91.6%
MA_t	28.3%	46.3%	2.8%	1.0%	87.6%	93.9%
FFS_t and FFS_{t+1}	32.0%	45.3%	2.2%	1.4%	87.2%	94.1%
FFS_t to MA_{t+1}	24.7%	43.3%	1.1%	1.8%	90.5%	94.7%

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 distribution of average MA switcher surplus by drug (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-2006 data. 2005 is omitted as a baseline year to avoid contaminating the sample with a group that spans the pre- and post-periods. See Appendix Table A.1 for sample summary statistics.

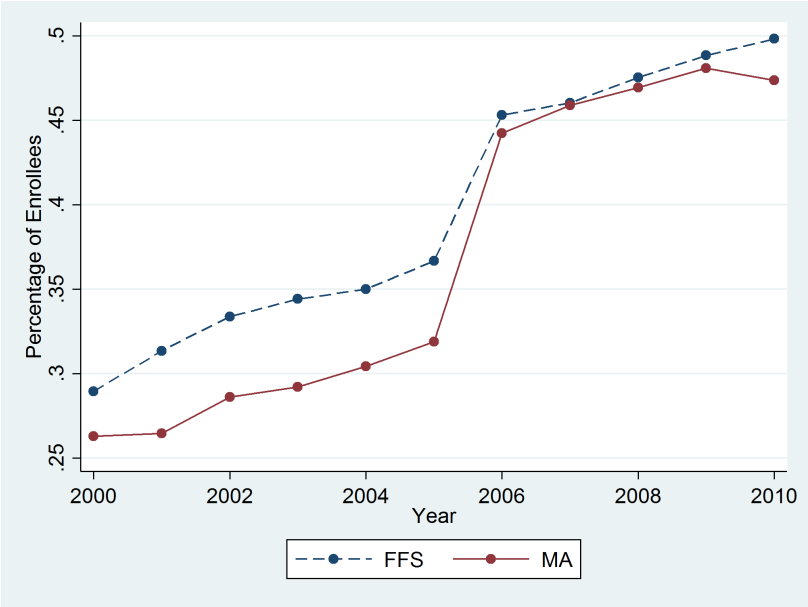
taking drugs in the top quartile of MA switcher surplus grew at a 23% faster[10] rate in MA plans than it did in FFS plans. Similarly, the fraction of beneficiaries who only purchased drugs on the bottom quartile decreased at faster rate in MA plans than it did in FFS plans. These symmetric patterns in the top and bottom quartiles are consistent with an increase in 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 took at least one drug in the top quartile of the distribution of average MA switcher surplus by drug. As the figure shows, there was 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 raised 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 5 percentage points less likely to consume these drugs throughout the pre-period, this gap was

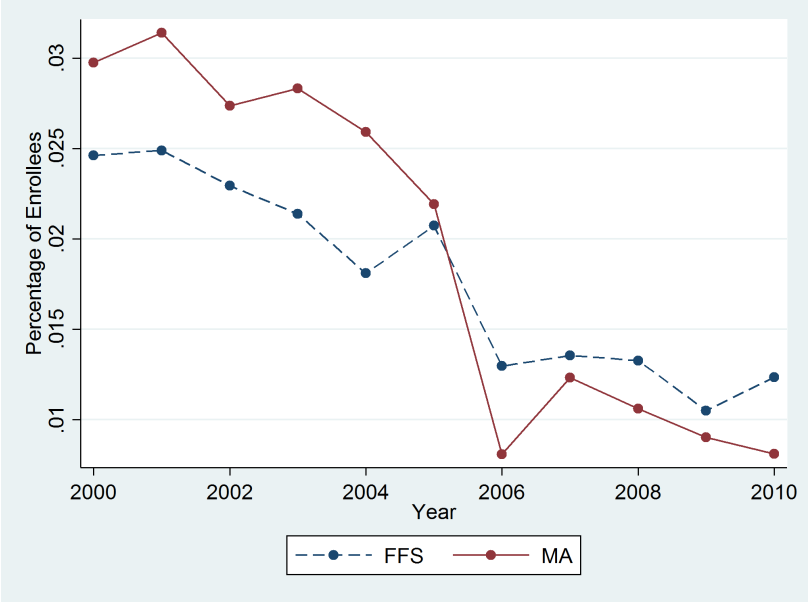
[10] 23% equals 0.463/0.283 - 0.468/0.332.

Figure 2: Annual Percentage of Enrollees Purchasing Drugs at Top and Bottom of Distribution of Average MA Switcher Surplus by Drug

(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 in the top quartile of the distribution of average MA switcher surplus by drug. Figure 2b plots the percentage of FFS and MA enrollees who only purchased drugs with MA switcher surpluses in the bottom quartile of this distribution. Figures exclude beneficiary-years with zero drug purchases. See Appendix Table A.1 for sample summary statistics.

virtually eliminated immediately in 2006. The fraction of enrollees taking drugs in the top quartile increased by 9 percentage points in FFS plans, and by 14 percentage points in MA plans between 2005-2007. This difference is statistically significant, as shown in Appendix Figure A.1.

Conversely, Figure 2b plots the fraction of beneficiaries who only took drugs in the bottom quartile of the distribution of average MA switcher surplus by drug. There was 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 began above the FFS share, between 2004 and 2006 there was 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). 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. Appendix Figure A.2 broadens the set of drugs to include the top and bottom halves of the distribution, and shows that this pattern was even more pronounced when conditioning on beneficiaries with higher drug spending, with no clear change in shares prior to 2006 but an abrupt change in 2006 that was larger for MA plans.

This summary 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. 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 confound 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.

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

In this model $MA\ Market\ Share_{ct}$ is the share of Medicare beneficiaries in MA plans in county c, and year t; $ShareBotQuart_{ct}$ measures the fraction of Medicare beneficiaries who only take drugs in the bottom quartile of the distribution of average MA switcher surplus by drug in county c, and year t; $ShareTopQuart_{ct}$ measures the fraction of Medicare beneficiaries who take drugs in the top quartile of the distribution; $\mathbf{1}\left[Year = k\right]$ 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

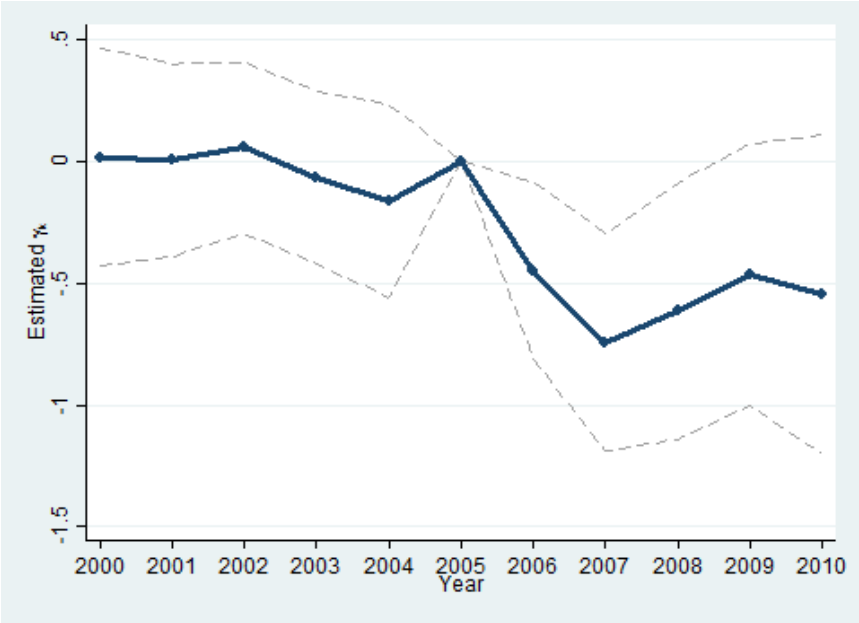
incentives prior to 2006. In 2005, the HCC-model was already given 50% weight in the risk-adjustment model, and this weight increased to 75% in 2006 and 100% in 2007. The purpose of this model is to look for visually suggestive evidence in the α_ks and $\gamma_k s$ on whether any change in selection 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. We return to a more formal evaluation of the gradual phase-in of the HCC-based risk-adjustment model, which requires further discussion on the dynamics of plans' selection incentives, in Section 4.5.

Figures 3a and 3b plot the estimated values of α_k and γ_k, respectively, in each year, along with 95% confidence intervals. Figure 3a plots the annual estimates of γ_k, and shows a sharp decline in market shares in counties in which a larger share of Medicare beneficiaries take drugs in the bottom quartile of the distribution of average MA Switcher Surplus by drug. The statistically significant decrease occurs immediately in 2006, and remains lower throughout the post-period, despite remarkably stable pre-period estimates. Table 4 presents the difference-in-difference estimate 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 0.55 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 that is consistent with a push-based form of advantageous selection.

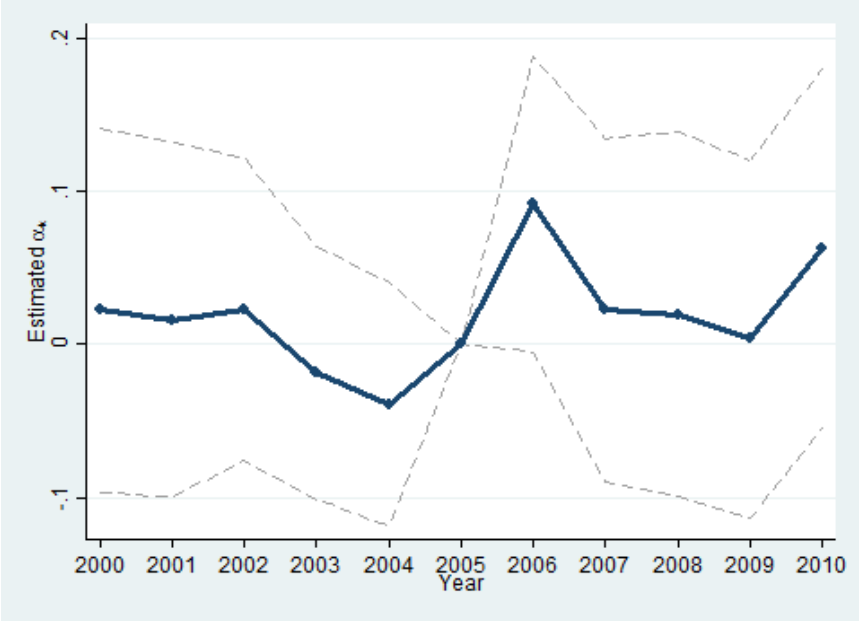
The annual estimates of α_k are fairly noisy, but there is a visible, although not significant, jump in 2006, suggesting that the county-level share of beneficiaries taking drugs in the top quartile becomes a more positive predictor of MA market shares in the county. The estimates in Table 4 suggest that the observation-weighted average value of α_k in the post-Part D

Figure 3: Annual Marginal Effects on MA Market Shares of Percentage of Beneficiaries in Bottom and Top Quartiles of Distribution of Average MA Switcher Surplus by Drug

(a) Bottom Quartile of MA Switcher Surplus



(b) Top Quartile of MA Switcher Surplus



Notes: Figure 3a plots the percentage of FFS and MA enrollees who only purchased drugs with average MA Switcher Surplus in the bottom quartile of the distribution. Figure 3b plots the percentage of FFS and MA enrollees who purchased drugs with average MA switcher surpluses in the top quartile of the distribution. Figures exclude beneficiary-years with zero drug purchases. Standard errors are clustered by county. See Appendix Table A.1 for sample summary statistics.

years is .042 percentage points higher, which can be interpreted as a one percentage point increase in the top quartile share increased average MA market shares in the county by 0.042 percentage points more in the post-Part D years, although this average difference is again not statistically significant.

Table 4: Average Effects on MA Market Shares of Percentage of Beneficiaries in Bottom and Top Quartiles of Distribution of Average MA Switcher Surplus by Drug

Dependent Variable: MA Market Share	
ShareBotQuart	0.122
	(0.077)
ShareBotQuart*Post 2006	–0.549**
	(0.149)
ShareTopQuart	0.015
	(0.021)
ShareTopQuart*Post 2006	0.042
	(0.035)
N Observations (County-Year)	5,667
N Person-Year Obs. Represented	100,887
N Clusters	1139
R Sq.	0.804

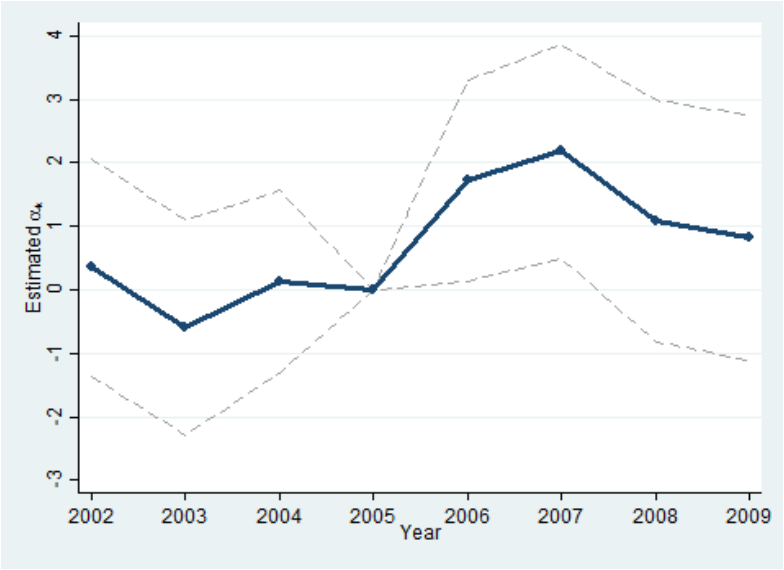
Notes: Estimates are from a fixed effects regressions and all models include county effects and year effects. The unit of observation is a county-year, and the model is weighted by the number of MCBS respondents in each county. *ShareTopQuart* and *ShareBotQuart* measure the fractions of Medicare beneficiaries who take drugs in the top quartile, and only take drugs in the bottom quartile, of the distribution of average MA switcher surplus by drug, respectively. See Appendix Table A.1 for sample summary statistics. Standard errors are clustered by county. * indicates significance at the 0.05 level, ** indicates significance at the 0.01 level.

Although these difference-in-difference models in Figure 3 and Table 4 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;[11] $\mathbf{1}\left[Year = k\right]$ is a set of indicator variables for each year within a 4-year window around the introduction of Part D; 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. We focus on beneficiaries who purchased drugs with an active ingredient among the top fifty most commonly purchased active ingredients.

Figure 4: Impact on MA Market Shares of Average MA Switcher Surplus by Drug and 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 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.

[11] $MA\ SwSurp_{dt}$ varies over time because the distribution of HCCs associated with drug d changes over time.

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 the pre-period (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 0.8 percentage points by 2009.

Table 5: Impact on MA Market Shares of Average MA Switcher Surplus by Drug and Year

Dependent Variable:	MA Market Share	
	(1)	(2)
MA Switcher Surplus*Post 2006	1.690**	1.464*
	(0.634)	(0.608)
MA Switcher Surplus	–1.557	–1.131
	(0.925)	(0.890)
County Effects in Switcher Surp. Model	No	Yes
Mean Dep. Var.	19.06	19.06
N Observations (Drug-County-Year)	86,481	86,481
N Person-Year Obs. Represented	66,587	66,587
N Clusters	969	969
R Sq.	0.45	0.45

Notes: Estimates are from a fixed effects regressions and all models include county effects, year effects, and drug active ingredient effects. 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 presents estimates from a similar model that includes a binary indicator for the years in which Part D was available:

$$MA\ Market\ Share_{dct} = \alpha MA\ SwSurp_{dt} + \beta MA\ SwSurp_{dt} * Post2006 + r_d + \phi_c + \theta_t + \varepsilon_{dct}$$

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 1.46 percentage points per $1,000 of

MA switcher surplus, or about 10% of the mean MA enrollment rate in the four years prior to Part D (14%). 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 7.1%.[12]

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 suggestive 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 is consistent with advantageous selection, this effect was stronger among beneficiaries with greater drug expenditures, who may be more likely to respond to mechanisms that operate through demand for drugs. To show this, we begin with the sample of MCBS respondents who switched from FFS to MA plans between 2003 and 2009,[13] 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.

[12] This estimate is calculated as (1.464/19.06) multiplied by 919.43, the average beneficiary-level switcher surplus in the corresponding sample, divided by 1000.

[13] As in the analyses presented in Table 5, we restrict the sample 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:

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

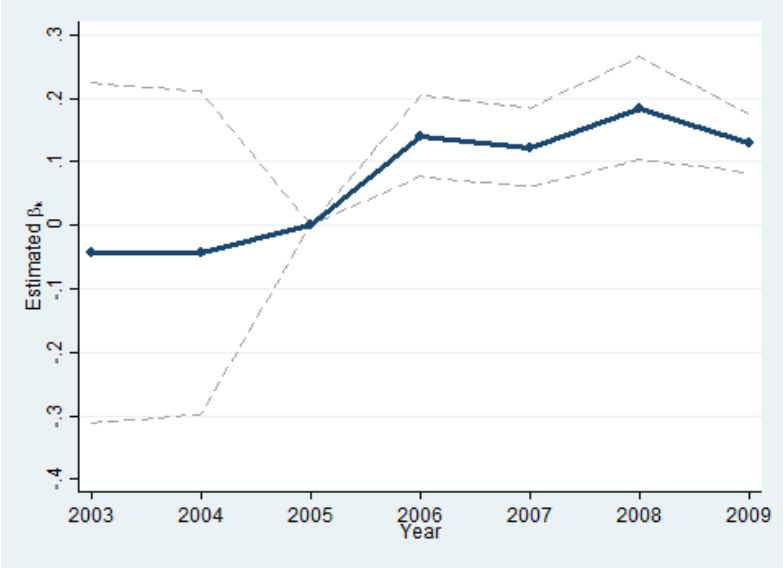
where $MA\ SwSurp_{i,t}$ is the MA switcher surplus for a beneficiary who switched into an MA plan in year t, estimated from Equation 1 for the set of HCCs that individual i was diagnosed with in year $t-1$. $DrugExp_{i,t-1}$ are the beneficiary's expenditures on prescription drugs in the same year.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

The idea behind this model is that if switchers with the highest prescription drug spending place relatively more emphasis on drug coverage when choosing plans, these beneficiaries are more likely to respond to any selection incentives induced by drug plan benefit designs under Medicare Part D. The key parameters of interest from this model are the β_ks, where a positive value of β_k suggests that higher drug spending is more strongly predictive of advantageous selection into MA plans in the corresponding year k, relative to other years. There are a few potential hypotheses that can be tested using this model. First, suppose plan incentives changed in 2004 when HCC-based risk-adjustment was introduced, and plans had an immediately available mechanism to attract lower cost beneficiaries within specific medical conditions. If the available selection mechanism was uncorrelated with drug spending, the estimated values of β_k should remain close to zero in all years. If instead the selection mechanism was related to demand for drugs and existed prior to Part D, one would expect to see the estimated β_ks increase in response to the new incentive structure immediately in 2004. Second, suppose there was no available mechanism in 2004 that plans could use to target low-cost beneficiaries within a specific HCC category. If Part D introduced such a mechanism, we expect the β_ks to remain flat in 2004-2005, to increase in 2006, and to remain high in the ensuing years.

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. Therefore a rejection of the null hypothesis would be consistent with an intertemporal change in the correlation between drug spending and the error term from the HCC-based risk-adjustment model.

Figure 5: Relationship between Drug Spending and Beneficiary 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. Standard errors are clustered by county.

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.[14] Beginning immediately in 2006, however, there is a sudden and statistically significant increase in $\widehat{\beta_k}$, which then flattens and remains persistently higher

[14]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.

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

Dependent Variable	MA Switcher Surplus	
	(1)	(2)
Drug Expenditure*Post 2006	0.172*	0.168*
	(0.073)	(0.072)
Drug Expenditure	-0.029	-0.018
	(0.069)	(0.070)
County Effects in Switcher Surp. Model	No	Yes
N Observations (Individuals)	1,213	1,213
R Sq.	0.100	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. Standard errors are clustered by county. * indicates significance at the 0.05 level.

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, 0.172, suggests that after Part D was introduced, a $1,000 increase in annual drug spending was associated with a $172 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 includes county fixed effects, the relationship between drug spending and switcher surplus remains similar, with a coefficient of 0.168.

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

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

Dependent Variable: % Potential Savings from MA Enrollment	(1)	(2)
MA Switcher Surplus*Bottom Quartile	0.064**	0.041
	(0.022)	(0.024)
MA Switcher Surplus*Top Quartile	0.013	–0.002
	(0.013)	(0.015)
MA Switcher Surplus	–0.012	0.001
	(0.013)	(0.015)
County Effects in Switcher Surp. Model	Yes	No
N Observations	2,889	2,889
R Sq.	0.236	0.233
P-value of t-test: $Row1 + Row3 = 0$	0.004	0.025
P-value of t-test: $Row2 + Row3 = 0$	0.864	0.972

Notes: All models include county and year fixed effects, and Bottom and Top Quartile indicators. 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. Standard errors are clustered by individual. * indicates significance at the 0.05 level, ** indicates significance at the 0.01 level.

from the beneficiary perspective that MA plans offer relatively higher Part D generosity for bundles of drugs taken by beneficiaries with higher MA switcher surplus. Using the sample of Part D beneficiaries who were enrolled in FFS for a full baseline year and observed the following year, we estimate the model:

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

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 Part D 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 in the beneficiary's county, and calculate the percent savings the beneficiary could have achieved by selecting the ex post lowest cost MA drug plan relative to the ex post lowest cost stand-alone PDP, and vice versa. When this value is positive 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 beneficiary-level MA switcher surplus in year t, $TopQuartile_{i,t}$, or the bottom quartile of this distribution, $BotQuartile_{i,t}$. The model also includes 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 beneficiaries who switch in these years (with corresponding FFS baseline years 2008-2009).

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. Among beneficiaries in the bottom quartile, we estimate that a $1,000 increase in MA switcher surplus reduced the cost of enrolling in the optimal MA Part D plan by 5.2 percentage points (6.4 minus 1.2). Controlling for county-level heterogeneity using fixed effects seems to be somewhat important in this model, as the estimate drops to 4.1 percentage points when county effects are excluded. The coefficient on the top quartile indicator, 0.013, 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 responded 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" (0.227) is associated with a 1 percentage point increase in the probability that a beneficiary will switch into an MA plan.

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, 0.02, 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, 0.024, when log drug spending is used instead. Appendix Table A.2 shows that these results are not sensitive to model assumptions, as linear and logit models yield very similar estimates. These findings reinforce the conclusion that consumers are at least somewhat responsive to differences in Part D plan generosity, and that heterogeneity in responsiveness is consistent with theory.

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	0.042**	–0.067*	–0.137*
	(0.012)	(0.032)	(0.054)
Log Out-of-Pocket Drug Costs		–0.007**	
		(0.002)	
MA % Drug Savings*Log Out-of-Pocket Drug Costs		0.020**	
		(0.006)	
Log Drug Spending			–0.006**
			(0.002)
MA % Drug Savings*Log Drug Spending			0.024**
			(0.007)
N Observations	2,397	2,260	2,397
R Sq.	0.056	0.074	0.069

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. See Appendix Table A.1 for sample summary statistics. Heteroskedasticity-robust standard errors are reported in parentheses. * indicates significance at the 0.05 level, ** indicates significance at the 0.01 level.

4.5 Risk-Adjustment Phase-In, Timing, and Selection Dynamics

One potentially important feature of the change in risk-adjustment, which we have not explicitly incorporated into statistical tests thus far, is the gradual phase-in of the HCC-based risk adjustment formula, which was given 30% weight in 2004, 50% in 2005, 75% in 2006, and 100% in 2007 and thereafter. From the perspective of testing whether the composition of switchers into MA plans changed over time in ways that are consistent with the change in risk-adjusted incentives, using the post phase-in measure of MA switcher surplus is informative. However, considering the timing of changes in incentives could be important for distinguishing between immediate selection responses in 2004 as opposed to delayed selection that would be consistent with Part D providing a new selection mechanism

in 2006.

This distinction is directly tied to the time-horizon over which MA plans design incentives to maximize profits. If insurers are not short-sighted, and they expect beneficiaries switching into their MA plans to remain enrolled for many years, the dynamic selection strategy consistent with profit maximization would consider the expectation of future MA switcher surplus values over the time-horizon of a typical enrollment spell in the plan. Newhouse et al. (2012) calculate that between 2004-2008 the average rate of disenrollment from MA plans ranged between 2.5% to 4.0%, suggesting that this expected time horizon is many years long. In this sense, our models using MA switcher surplus estimates calculated in the period after HCC-based risk-adjustment was fully phased-in, could be interpreted as assuming that MA plans consider long-term selection incentives, rather than ignoring the consequences of short-run selection on long-run profits. Of course, due to data limitations we cannot observe whether MA switcher surplus values change over time after enrollment in an MA plan, so what we term 'short-sighted' could also be consistent with switcher surpluses dissipating quickly towards zero after a switch.

In this section we assess the sensitivity of our key findings to incorporating the change in switcher surplus associated with the phase-in of incentives, and to alternative assumptions about the forward-looking time horizon that MA plans consider when attempting to select beneficiaries. One way to assess to the sensitivity of estimates to these factors is to consider the two extreme cases. The first is complete short-sightedness, in which MA plans only maximize current year profits without any consideration of the intertemporal consequences of selection. This short-sighted form of profit maximization implies maximizing contemporaneous MA switcher surplus in each year, suggesting that selection incentives changed during the phase-in period according to the weighting of the HCC-based risk-adjustment model. The opposite extreme would be to consider only long-run expectations of MA switcher surplus. In this model, plans would respond to the fully phased-in HCC-based selection incentives as soon as they were introduced in 2004. This model is consistent with our benchmark

estimates reported throughout the paper. In reality, of course, MA plans are most likely to behave somewhere between these two extremes. We also consider one example of such an intermediate model, in which plans consider the average selection incentives they will face in the ensuing two year time horizon.

We first re-estimate the models from Equation 3 scaling downward the MA switcher surplus values by either the contemporaneous weight associated with the phase-in timing, or the two-year forward moving average of this weight, which corresponds to the intermediate model in which plans have a two-year expected time horizon.

Table 9: MA Market Share Models using HCC Risk-Adjustment Phase-In Weights

Dependent Variable:	MA Market Share					
	Contemporaneous		2-Yr Moving Avg. Weight		Long-Run HCC Model	
	(1)	(2)	(3)	(4)	(5)	(6)
MA Switcher Surplus*Post 2006	1.900*	1.693	1.864*	1.650*	1.690**	1.464*
	(0.924)	(0.903)	(0.828)	(0.805)	(0.634)	(0.608)
MA Switcher Surplus	–0.865	–0.712	–0.936	–0.753	–1.557	–1.131
	(1.040)	(1.034)	(0.984)	(0.976)	(0.925)	(0.890)
County Effects in Switcher Surp. Model	No	Yes	No	Yes	No	Yes
N Observations (Drug-County-Year)	86,481	86,481	86,481	86,481	86,481	86,481
N Person-Year Obs. Represented	66,587	66,587	66,587	66,587	66,587	66,587
N Clusters	969	969	969	969	969	969
R Sq.	0.449	0.449	0.449	0.449	0.449	0.449

Notes: Estimates are from a fixed effects regressions and all models include county effects, year effects, and drug active ingredient effects. 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 9 presents estimates from these models, and shows that the estimated effects are not very sensitive to this assumption about timing. The coefficients increases slightly, from 1.69 to 1.90, when switching from the long-run measure of MA Switcher Surplus to the contemporaneous estimate using the phase-in formula. However, the standard errors also increase in the contemporaneous model, resulting in p-values of 0.04 and 0.06 in the models with and without county effects, respectively. Estimates from the two-year forward average model lie between the contemporaneous and long-run estimates, and both coefficients are

statistically significant.

We find similarly low sensitivity of our estimates to these timing assumptions in the models of beneficiary switching presented in Table 6. Table 10 presents estimates from each of these alternative models incorporating the phasing-in of HCC-based risk adjustment.

Since it is possible that the MA switcher surplus incentives under the demographic-based risk-adjustment model may be correlated with those under the HCC-based model, we also estimate the demographic-based version of MA switcher surplus model from Equation 1 using the MCBS sample, replacing the set of HCC effects with the demographic variables included in the risk-adjustment formula prior to the HCC-based formula. We then calculate the appropriate weighted average of the two MA switcher surplus values where the weights change during the phase-in period.[15] Although we are limited by a small MCBS sample in estimating the demographic-based MA Switcher Surplus, Appendix Tables A.3 and A.4 show that all of the estimates are not very sensitive to using this weighted average measure of MA switcher surplus.

Related to this issue of the timing, another potential caveat to our results is that we cannot pinpoint exactly what changed when Part D was introduced. To the extent that MA plans may have been offering limited forms of drug coverage in ways that promoted selection prior to Part D, our estimates could potentially understate the overall role of drug benefit design on selection into these plans. We cannot directly measure the change in the strength of the selection mechanism introduced by Part D, although there is evidence that the drug coverage offered by MA plans prior to Part D was substantially less generous than Part D plans. For example, Hsu et al. (2006) document that the vast majority of Kaiser MA plans in 2003 had drug coverage with a maximum annual plan benefit of $1,000, and estimate that this benefit maximum was responsible for a 31% reduction in drug consumption, suggesting that even within MA plans the introduction of Part D had a large intensive margin effect on

[15] Between 2000 and 2003, capitation payments were calculated as a 90/10 blend of the demographic and PIP-DCG models. We follow this formula in our calculations.

Table 10: Relationship between Drug Spending and Beneficiary MA Switcher Surplus using HCC Risk-Adjustment Phase-In Weights

Dependent Variable:	MA Switcher Surplus					
	Contemporaneous		2-Yr Moving Avg. Weight		Long-Run HCC Model	
	(1)	(2)	(3)	(4)	(5)	(6)
Drug Expenditure*Post 2006	0.131**	0.141**	0.138**	0.147**	0.172*	0.168*
	(0.036)	(0.030)	(0.043)	(0.035)	(0.078)	(0.074)
Drug Expenditure	0.005	–0.000	0.002	–0.002	–0.029	–0.018
	(0.028)	(0.023)	(0.036)	(0.030)	(0.073)	(0.072)
County Effects in Switcher Surp. Model	No	Yes	No	Yes	No	Yes
N Observations	1,213	1,213	1,213	1,213	1,213	1,213
N Clusters	273	273	273	273	273	273
R Sq.	0.219	0.144	0.182	0.136	0.100	0.109

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. "Post 2006" equals one if the switch into an MA plan occurred in the year 2006 or later, and zero otherwise. Standard errors are clustered by county. * indicates significance at the 0.05 level.

generosity.[16]

It is also plausible that the new Part D market shifted the attention of insurers towards drugs in ways that altered firm behavior. For example, we cannot distinguish our interpretation of the results from the possibility that managers at MA plans simply got better at using drug formularies to induce selection at the same time that Part D was introduced, and that this change in managerial ability or attention was primarily responsible for the observed change in selection.

[16]It is also worth noting that many beneficiaries also ended their former coverage and joined Part D plans, at which point they may have been influenced by the selection mechanisms we discuss. For example, some Medigap plans covered prescription drugs prior to 2006, but these plans all had fairly low generosity, with $250 deductibles, 50% coinsurance rates, and low annual plan benefit maxima (Antos 2005). Robst (2006) estimates that the average marginal cost of drug coverage in Medigap plans prior to Part D was $888 per year, while the actuarial benefit of the coverage was only $594, suggesting that cheaper, more generous, and subsidized Part D plans were much more attractive than Medigap drug coverage. Moreover all Medigap plans offering drug coverage became closed to new enrollees as soon as Part D was introduced.

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 7.1%. We also show evidence behind the mechanism, that the total cost to a beneficiary 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.

It is useful to put in perspective how important these effects are relative to other factors that impact MA plans' total profits. This is of course difficult to quantify precisely with available data, but our estimates suggest that between 2002 and 2009, during which time the average MA market share increased from 14% to 23%, the change in switcher surplus associated with the introduction of Part D can explain about 1.5 percentage points, or about

16%, of this total market share growth. If profits per beneficiary remained uniform, scaling by the growth in the number of enrollees,[17] our estimates would imply a 14% increase in total MA profits over this period.

To be sure, profits per beneficiary were not uniform–the Government Accounting Office concluded that total MA profits increased by 93% in a single year from 2005 to 2006, and average annual profits per MA beneficiary increased by 34%, or $154.[18] Quantifying how much of this change in MA profits due to enrollment composition was related to the changes in MA switcher surplus that we document, as opposed to the counterfactual increase in profits that would have occurred if Part D had been introduced without any change in selection, would require much more data, including utilization data from beneficiaries after enrolling in MA plans, which is not available in the MCBS. As a rough comparison, our estimates from Table 6 suggest that MA switcher surplus increased by an average of $168 per $1,000 of drug spending after 2006. If we assume that MA switcher surplus fully persists over time (which is likely to overstate the true selection effect on profits), and about 75% of new MA enrollees switch into MA plans from FFS Medicare, at the average 2006 drug spending level of $2,217,[19] the estimates predict that average profits per beneficiary would have increased by $279. This back-of-the-envelope calculation clearly requires many strong assumptions, but suggests that we cannot reject that all of the change in enrollment composition over this period may have been due to selection made possible by the introduction of Part D. Some potential explanations why our estimate may overstate the observed difference is that MA plans may have returned some of the additional profits to beneficiaries in the form of benefit enhancements that are not included in our analyses, or MA switcher surplus may dissipate somewhat over time after enrollment, which we cannot observe directly.

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

[17] There were 10.5 million MA enrollees in 2009 and 5.6 million in 2002.
[18] Source: http://www.gao.gov/products/GAO-09-132R
[19] Source: $https://meps.ahrq.gov/data_files/publications/st240/stat240.pdf$

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.

One second-best approach may be to introduce a self-correction mechanism into risk-adjustment that accounts for nonrandom selection. For example, conditioning on the average difference in FFS spending between switchers to MA plans and stayers during the prior year in the risk-adjustment formula could lead in the steady-state to a capitation payment that equals average expenditures even under nonrandom selection into MA plans, and without conditioning on utilization of MA enrollees. 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. This approach has been proposed by CMS for potential implementation beginning in 2018.[20] By conditioning on drug utilization in the medical risk-adjustment formula, the idea behind this strategy is to remove demand for drugs as an excluded dimension upon which plans could possibly induce selection. This option is attractive for its simplicity and feasibility 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 effects on consumer welfare that should be considered.

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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[20] See HHS announcement at: https://www.cms.gov/Newsroom/MediaReleaseDatabase/Fact-sheets/2016-Fact-sheets-items/2016-06-08.html

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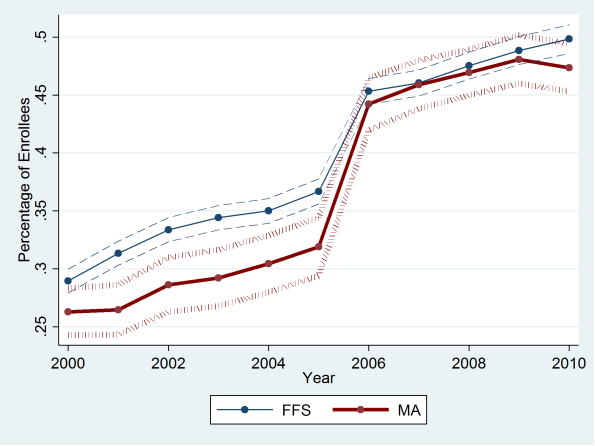
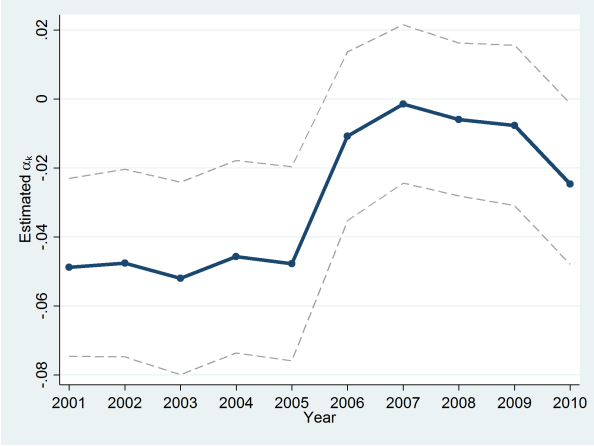
A Appendix: Supplementary Tables and Figures

Figure A.1: Annual Percentage of Enrollees Purchasing Drugs at Top and Bottom of Distribution of Average MA Switcher Surplus by Drug

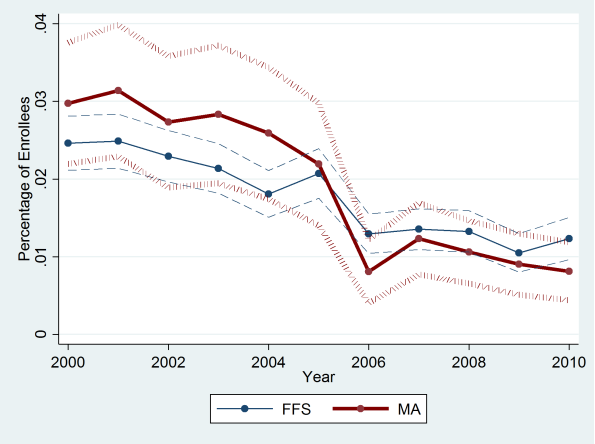
(a) Top Quartile of MA Switcher Surplus



(b) Percentage Point Difference



(c) Bottom Quartile of MA Switcher Surplus

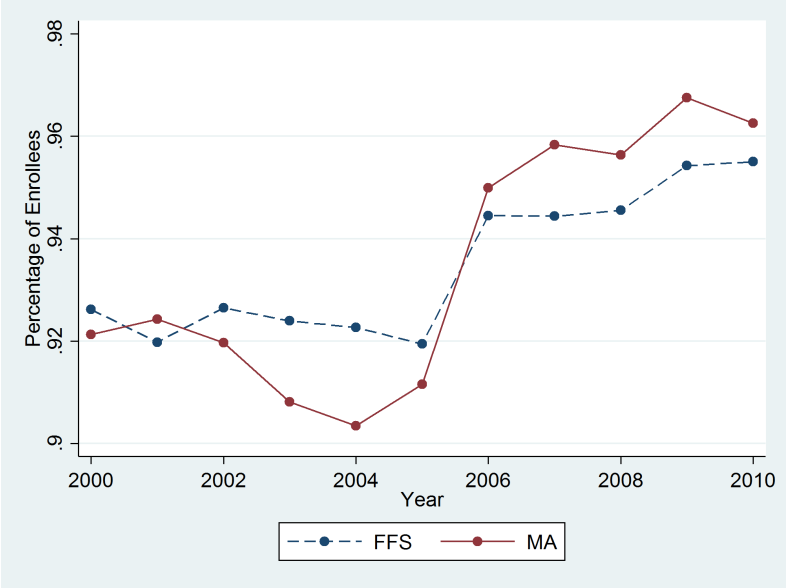


(d) Percentage Point Difference

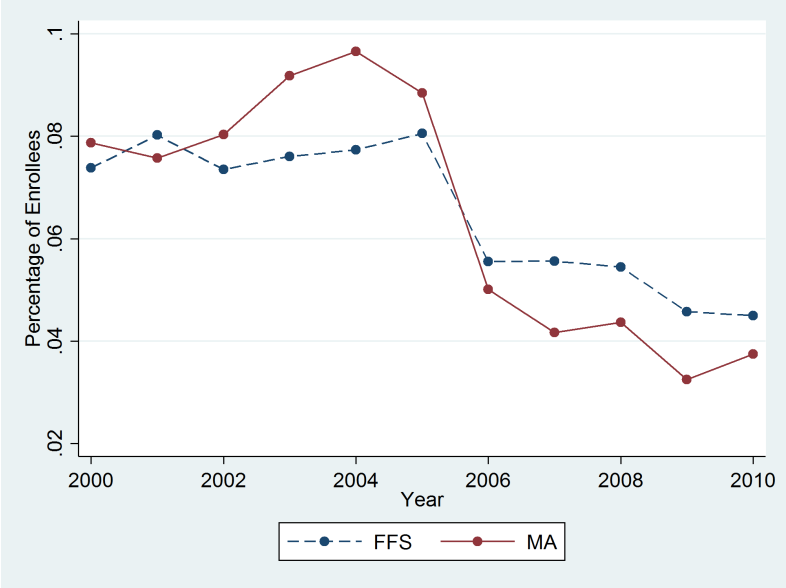
Notes: Figure A.1a plots the percentage of FFS and MA enrollees who purchased at least one drug with MA switcher surplus in the top quartile of the distribution of average MA Switcher Surplus by drug. Figure A.1b plots the difference in percentages from Figure A.1a. Figure A.1c plots the percentage of FFS and MA enrollees who only purchased drugs with MA switcher surpluses in the bottom quartile of the distribution. Figure A.1d plots the difference in percentages from Figure A.1c. All confidence intervals are 95% intervals.

Figure A.2: Annual Percentage of Enrollees Purchasing Drugs at Top and Bottom of Distribution of Average MA Switcher Surplus by Drug, Conditional on Spending at Least $1,000 on Drugs

(a) Top Half of MA Switcher Surplus



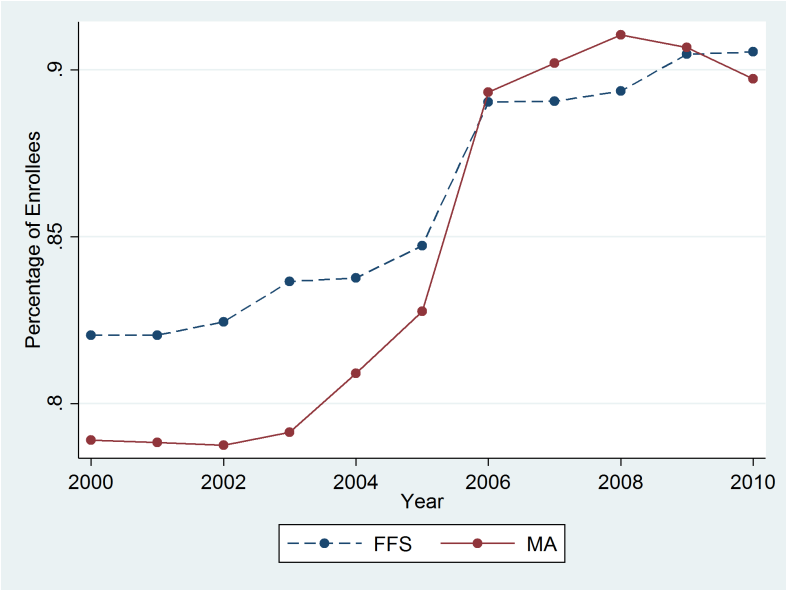
(b) Bottom Half of MA Switcher Surplus



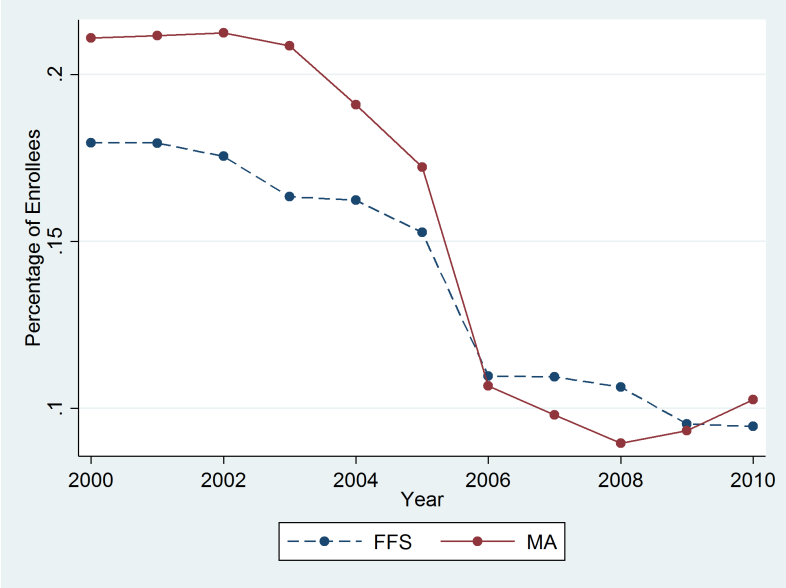
Notes: Figure A.2a plots the percentage of FFS and MA enrollees who purchased at least one drug with MA switcher surplus in the top half of the distribution of average MA Switcher Surplus by drug. Figure A.2b plots the percentage of FFS and MA enrollees who only purchased drugs with MA switcher surpluses in the bottom half of the distribution. Figures exclude beneficiary-years with less than $1,000 in drug spending.

Figure A.3: Annual Percentage of Enrollees Purchasing Drugs at Top and Bottom of Distribution of Average MA Switcher Surplus by Drug

(a) Top Half of MA Switcher Surplus



(b) Bottom Half of MA Switcher Surplus



Notes: Figure A.3a 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 of average MA Switcher Surplus by drug. Figure A.3b 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: Summary Statistics on MCBS Sample

	Full MCBS Sample	Top 50 Drug User Sample	FFS to MA Switcher Sample	Full Market Share Sample	SAPD Enrollee Full Sample	SAPD Enrollee Sample 2	SAPD Enrollee Sample 3	Transition Frequency Sample	Top Quartile Sample	Bottom Quartitle Sample	Drug User Sample
Male	0.44	0.42	0.45	0.43	0.44	0.46	0.46	0.44	0.43	0.29	0.43
Age	72.4	73.6	70.8	72.9	67.9	64.7	64.7	72.1	72.5	75.1	72.8
Percent MA Enrollees	0.19	0.20	0	0.20	0	0	0	0.19	0.19	0.19	0.20
Percent Purchase Drugs	0.88	1	0.93	1	1	1	1	0.90	1	1	1
Annual Drug Expenditure	2,550	2,898	2,603	2,565	4,553	4,705	4,594	2,465	3,851	428	2550
Annual Out-of-Pocket Drug Spending	602	666	645	605	652	636	675	607	798	199	602
Percent Part D Enrollees	0.58	0.59	0.56	0.59	1	1	1	0.58	0.64	0.37	0.59
Number Person-Year Observations	115,622	66,587	1,213	100,887	2,889	2,397	2,260	63,889	39,554	1,808	101,518
Number Unique Individuals	51,724	31,444	1,213	44,821	2,298	1,960	1,847	36,487	22,175	1,307	45,030
Sample Used in		Tables 5, 9, A.3, Figure 4	Tables 6, 10, A.4, Figures 5	Table 4 Figure 3b, 3a	Tables 7	Tables 8, A.2	Tables 8, A.2	Table 2	Figure 2a	Figure 2b	Table 3

Notes: Full MCBS sample excludes beneficiaries with end-stage renal disease (ESRD), who are not included in our population of interest because they are restricted from switching into MA plans, and beneficiaries not enrolled in Medicare Parts A and B for the full year. The 'Top 50 Drug User Sample' is the subset of the Full MCBS Sample who purchased at least one drug with the top 50 most common drug active ingredients between 2002-2009. The 'FFS to MA Switcher Sample' is the subset of the Full MCBS Sample observed in a full baseline FFS year between 2002-2009, and observed in an MA plan the following year. The 'Full Market Share Sample' is the subset of the Full MCBS Sample who purchased at least one drug with identifiable active ingredient(s) between 2000-2010. The 'SAPD Enrollee Full Sample' is the subset of the Full MCBS Sample containing beneficiaries enrolled in a stand-alone Part D plan (SAPD) in at least one baseline year in 2008-2009, and observed the following year, with available NDC codes. The 'SAPD Enrollee Sample 2' is the subset of the SAPD Enrollee Full Sample excluding cells in which demographic variables perfectly predict whether a beneficiary switches into an MA plan. The 'SAPD Enrollee Sample 3' is the subset of the SAPD Enrollee Sample 2 with out-of-pocket drug spending greater than \$0. The 'Transition Frequency Sample' is the subset of the Full MCBS Sample who were observed for at least two consecutive years. The 'Top Quartile Sample' is the subset of the Full MCBS Sample who purchased at least one drug with identifiable active ingredient(s) in the top quartile of the MA surplus distribution by ingredient. The 'Bottom Quartile Sample' is the subset of the Full MCBS Sample who only purchased drug(s) with identifiable active ingredient(s) in the bottom quartile of the MA surplus distribution by ingredient. The 'Drug User Sample' is the subset of the Full MCBS Sample whose annual total drug cost is greater than \$0. 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.

Table A.2: 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 OR	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
MA % Drug Savings	0.042**	4.553**	0.051*	–0.067*	0.110	–0.095*
	(0.012)	(1.970)	(0.020)	(0.032)	(0.130)	(0.043)
Log Out-of-Pocket Drug Costs				–0.007**	0.775**	–0.008*
				(0.002)	(0.071)	(0.003)
MA % Drug Savings*Log OOP Costs				0.020**	2.011**	0.029**
				(0.006)	(0.415)	(0.010)
N Observations	2,397	2,397	2,397	2,260	2,260	2,260
R Sq.	0.056	0.056	0.018	0.074	0.073	0.025

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.

Table A.3: MA Market Share Models using HCC Risk-Adjustment Phase-In and Demographic Phase-Out Weights

Dependent Variable:	MA Market Share					
	Contemporaneous		2-Yr Moving Avg. Weight		Long-Run HCC Model	
	(1)	(2)	(3)	(4)	(5)	(6)
MA Switcher Surplus*Post 2006	1.926*	1.731*	1.973*	1.760*	1.690**	1.464*
	(0.872)	(0.841)	(0.790)	(0.761)	(0.634)	(0.608)
MA Switcher Surplus	–1.057	–0.909	–1.272	–1.082	–1.557	–1.131
	1.166	(1.151)	(1.069)	(1.058)	(0.925)	(0.890)
County Effects in Switcher Surp. Model	No	Yes	No	Yes	No	Yes
N Observations	86,481	86,481	86,481	86,481	86,481	86,481
N Person-Year Obs. Represented	66,587	66,587	66,587	66,587	66,587	66,587
N Clusters	969	969	969	969	969	969
R Sq.	0.449	0.449	0.449	0.449	0.449	0.449

Notes: Estimates are from a fixed effects regressions and all models include county effects, year effects, and drug active ingredient effects. 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 A.4: Relationship between Drug Spending and Beneficiary MA Switcher Surplus using HCC Risk-Adjustment Phase-In and Demographic Phase-Out Weights

Dependent Variable:	MA Switcher Surplus					
	Contemporaneous		2-Yr Moving Avg. Weight		Long-Run HCC Model	
	(1)	(2)	(3)	(4)	(5)	(6)
Drug Expenditure*Post 2006	0.243*	0.248*	0.241*	0.246*	0.172*	0.168*
	(0.114)	(0.112)	(0.103)	(0.101)	(0.078)	(0.074)
Drug Expenditure	–0.110	–0.110	–0.102	–0.102	–0.029	–0.018
	(0.113)	(0.112)	(0.102)	(0.101)	(0.073)	(0.072)
County Effects in Switcher Surp. Model	No	Yes	No	Yes	No	Yes
N Observations	1,213	1,213	1,213	1,213	1,213	1,213
N Clusters	273	273	273	273	273	273
R Sq.	0.491	0.103	0.447	0.114	0.100	0.109

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. "Post 2006" equals one if the switch into an MA plan occurred in the year 2006 or later, and zero otherwise. Standard errors are clustered by county. * indicates significance at the 0.05 level.

Table A.5: Robustness: MA Market Shares Estimates
Excluding MCBS Part D Claims Data

Dependent Variable:	MA Market Share	
	(1)	(2)
MA Switcher Surplus*Post 2006	1.626*	1.315*
	(0.681)	(0.655)
MA Switcher Surplus	–2.108*	–1.408
	(0.944)	(0.914)
County Effects in Switcher Surp. Model	No	Yes
Mean Dep. Var.	18.78	18.78
N Observations (Drug-County-Year)	83,293	83,293
N Clusters	944	944
R Sq.	0.44	0.44

Notes: Estimates are from a fixed effects regressions and all models include county effects, year effects, and drug active ingredient effects. 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. Models are estimated dropping all drug purchase information that appears in the MCBS Part D claims data but is not also reported by the beneficiary, holding the MCBS drug purchase elicitation approach constant throughout the time period. 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.