Strategic Formulary Design in Medicare Part D Plans*

Kurt Lavetti
Ohio State University

Kosali Simon
Indiana University
and NBER

June 24, 2016

Abstract

The design of Medicare Part D causes most Medicare beneficiaries to receive fragmented health insurance, whereby prescription drugs and other medical care are covered by separate insurance plans. Fragmentation of insurance plans is potentially inefficient since separate insurers maximize profits over only one component of healthcare spending, despite many complementarities and substitutabilities between types of healthcare. Fragmentation of some plans but not others can also lead to market distortions due to differential adverse selection, as integrated plans may use drug formulary designs to induce enrollment by patients who are profitable under Parts A & B, while stand-alone drug plans have no such incentive. We study whether the design of insurance plans in Medicare Part D reflects these two differences in incentives using data on the universe of Part D plan formularies, drug prices, and Medicare claims data. We find evidence consistent with both hypotheses. Relative to fragmented plans, integrated plans systematically design their drug formularies to encourage enrollment by beneficiaries with medical conditions that are profitable under Parts A & B. However, integrated plans also more generously cover drugs that have the potential to causally reduce medical costs. These large differences in incentives and plan design between integrated and fragmented plans are likely the precursors of substantial differential selection of enrollees, and the basic design of Medicare Part D abets this covert selection.

JEL Classifications: I11, I13
Keywords: Insurance Integration, Insurance Selection, Public Provision of Private Insurance

*We are grateful to Vilsa Curto for creating measures of risk-adjusted cost differences for Medicare Advantage switchers; to Collen Carey for sharing data on risk-adjustment profitability in Part D plans; to Amitabh Chandra, Jason Hockenberry, Amanda Starc, Ashley Swanson, and seminar participants at the AEA 2010 Annual Meetings, ASHEcon 2014, RAND, and UC Berkeley for helpful comments; and to the NIH for funding through grant R03AG033211.

1 Introduction

A growing share of all public expenditures on health insurance in the US is paid to private companies that deliver public health insurance benefits. Medicare Parts C and D, which account for about one-third of all Medicare expenses, are delivered entirely by private companies, and 39 states have contracts with private managed care organizations to deliver Medicaid benefits (KFF, 2014). Although the intention behind privatization is generally to increase efficiency, in the case of Medicare Part D the split between public and private provision of benefits has also introduced several strategic opportunities for insurers that may have reduced efficiency and increased total costs.

First, the decision to privately deliver Part D benefits led to fragmentation of insurance benefits for enrollees in traditional Medicare, who receive public hospital and physician insurance, but private drug insurance. A minority (about 30%) of beneficiaries in Medicare Advantage (MA) plans have fully-integrated private insurance that bundles parts A, B, and D. As a result, beneficiaries in traditional Medicare receive benefits from public and private entities that care only about efficiently delivering one type of medical care, but have no incentive to consider the complementarity or substitutability between different treatment options when designing insurance plans. Empirical evidence from outside the Part D context, including Goldman and Philipson (2007); Chandra, Gruber, and McKnight (2010); and Fendrick et al. (2001), suggests that spillovers between drug and medical spending exist, and may be quite large. In fact, internalizing these spillovers was a key stated reason why Medicare Part D was created in the first place.[1]

Second, the fragmentation of some plans but not others can lead to market distortions due to differential adverse selection. Specifically, MA Part D (MAPD) plans are incentivized to design their formularies to induce enrollment by beneficiaries from whom they expect to earn profits in Medicare Parts A & B, and to discourage enrollment by beneficiaries whose expected costs exceed the risk-adjusted revenue they would bring to the plan. It would be very difficult for most medical insurance plans to target enrollees with particular conditions through plan design features, since cost-sharing rules tend to span broad categories of care. However, for prescription drugs this is not the case—plans vary cost-sharing rules at the drug level,[2] providing a mechanism to very precisely alter the attractiveness of a plan to individuals with any condition associated with a prescription drug.

[1] On the 38th Anniversary of Medicare, President George W. Bush called for action on Medicare reform saying: "Medicare today will pay for extended hospital stays for ulcer surgery. That's at a cost of about $28,000 per patient. Yet Medicare will not pay for the drugs that eliminate the cause of most ulcers, drugs that cost about $500 a year....Drug coverage under Medicare will allow seniors to replace more expensive surgeries and hospitalizations with less expensive prescription medicine." (Source: G.W.B., July 30, 2003, transcript available at https://www.ssa.gov/history/gwbushstmts3.html)

[2] This is done in part by choosing whether to include a drug on the formulary, and if so, on which cost-sharing tier to place the drug. In addition there are certain non-price components of prescription drug formularies, including quantity limits, prior authorization requirements, and step therapy restrictions. We discuss these non-price formulary features in more detail in Section 5.5.

In this paper we study how the decision to add Part D benefits into the existing Medicare benefit structure by offering beneficiaries a choice between integrated MA plans or fragmented insurance affected the efficiency of the Medicare program. We examine whether integrated plans design drug formularies differently than fragmented plans to take advantage of the relationships between drug consumption and non-drug medical spending. First, we test whether integrated plans choose more generous formulary rules for drugs taken by patients that tend to be profitable in Medicare Parts A & B. If so, this would suggest that the introduction of Medicare Part D created an additional tool for insurers to induce selection into Medicare Advantage.[3] Second, we test whether integrated plans set cost-sharing rules in ways that internalize spillovers between drug and non-drug medical spending. For example, if the use of albuterol inhalers has the potential to reduce hospitalizations among asthma patients, MA plans should have stronger financial incentives to set low copayments to ensure that their enrollees have access to inhalers, since MA plans are liable for hospital costs whereas stand-alone Part D drug plans (SAPDs) are not. This difference in incentives between plan types has implications for the efficient allocation of medical spending across major classes of medical care.

Although there have been many papers that study adverse selection in health insurance markets, including theoretical discussions such as Rothschild and Stiglitz (1976) and empirical studies such as Handel (2013) and Polyakova (2015), less attention has been paid to empirically testing how adverse selection affects the design of insurance plans. One exception is Lustig (2010), who studies how adverse selection affects the generosity of coverage in Medicare Advantage. In contrast, we study the mechanism itself that is likely to lead to beneficiary selection—the design of insurance plan formularies. Our analyses test whether MAPD formularies have features that are systematically different than stand-alone Part D formularies in ways that enhance advantageous selection and internalize the effects of spillovers between drug and medical spending.

Advantageous selection by MAPD plans is a well-known concern, and Medicare has several policies aimed at limiting selection. First, MA plans are required to be guaranteed issue, which prevents plans from overtly selecting beneficiaries by declining some applicants. However, guaranteed issue does not eliminate selection since plans can strategically design their benefits to induce non-random self-selection, or advertise to targeted audiences. In addition, Medicare uses risk-adjustment of payments to private firms to reduce the incentive for selection. Conceptually, the goal of risk-adjustment is to pay MA plans whatever amount of revenue equates expected profit for each enrollee, so that there is no expected benefit from selection. In practice, risk-adjustment also does not completely eliminate selection incentives. To the extent that the risk-adjustment equation has either systematic error or excluded dimensions that are correlated with medical expenses, firms can increase selection on these dimensions, potentially increasing the total costs to the government

[3]Einav, Finkelstein, and Polyakova (2016) find evidence that insurers in Part D markets are fairly sophisticated in setting lower cost-sharing requirements for drugs with less elastic demand to reduce deadweight loss from moral hazard. This is consistent with our hypothesis that formulary design strategies are complicated enough to consider drug-level selection incentives.

of providing public insurance. For example, Brown et al. (2014) find that when Medicare changed the risk-adjustment formula to account for differences in the average costs of treating medical conditions, MA plans simply changed their strategies from selecting the lowest cost beneficiaries to selecting based on costs conditional on medical diagnoses. As a result, they find that these efforts to improve the risk-adjustment formula had no net effect on overpayments to MA plans, and the deadweight loss from advantageous selection into MA plans increased the total cost to the government by $30 billion in 2006 alone. Carey (2016) also shows that the separate risk-adjustment formula used for Medicare Part D has systematic errors caused in part by technological change over time, so that risk-adjustment does not neutralize selection incentives.

To test whether integrated MAPD formularies are designed to advantageously select beneficiaries with conditions that are profitable on the hospital and physician insurance segment, we use data from the universe of fee-for-service (FFS) Medicare beneficiary claims from 2008-2010. We first create a measure of average potential profits to MA plans from selection for each medical condition. Following the approach developed by Brown et al. (2014), we calculate the total expenditures of all beneficiaries enrolled in FFS Medicare in each year. We then use the full population of Medicare beneficiaries who subsequently switch to MA plans, and calculate what the MA capitation payment would have been if the individual had been in an MA plan the prior year, and compare this to the actual FFS cost of that individual. Since the risk-adjustment formula is designed to set expected profits equal to zero for each medical condition, the extent to which there is a non-zero difference between capitation payments and FFS costs is due to the fact that switchers into MA plans are not randomly selected, whereas risk-adjustment formulas are calculated using the entire FFS population rather than just the subsequent switchers.

Next, we use claims data from the entire population of FFS Medicare beneficiaries, including diagnosis codes and prescription drug purchases, to estimate the relationships between each medical condition and each prescription drug active ingredient. This set of estimates can be thought of as an $n \times m$ matrix of n active ingredients and m medical conditions, where the ij^{th} element in the matrix equals the marginal effect of a diagnosis of medical condition j on the probability of filling a prescription with active ingredient i. We then use these estimated joint probability distributions to calculate the expected risk-adjusted profit by drug active ingredient.[4] Finally, we use the ingredient-level risk-adjusted expected profit to test whether active ingredients taken by individuals with more profitable conditions are covered more generously by MAPDs than by SAPDs. Throughout the paper, we use the term '*MA switcher surplus*' to refer to this expected risk-adjusted difference between counterfactual costs and revenue for each drug active ingredient. We also use estimates from Carey (2016) to control for drug-level risk-adjustment errors in Medicare Part D that could affect plan formulary design, and may otherwise confound our analyses. We call this *Part D Surplus*.

[4]We are extremely grateful to Vilsa Curto for assistance in creating these measures.

Our second primary hypothesis is that MAPDs more generously cover drugs that can causally reduce medical spending. This hypothesis is based on the body of literature documenting substantial spillovers between drug and non-drug healthcare spending, especially among the elderly and individuals with chronic conditions. Chandra, Gruber, and McKnight (2010), find that 20% of the savings from increasing copayments for prescription drugs and physician visits are offset by increases in hospital costs, and 43% of the savings are offset among patients with chronic illnesses. The implication is that Part D formulary decisions could have substantial effects on both prescription drug spending and other medical spending.

To test whether drugs with medical spending offsets are covered more generously by MAPD plans, we first isolate the set of drugs where spillovers are most likely to occur. We use several alternative definitions that have been developed previously for similar purposes, each of which is based on information from medical experts. The first set of definitions comes from Chandra, Gruber, and McKnight (2010), who assembled a team of physicians and pharmacists to create drug groups for this purpose. They define acute spillover drugs (CGM Acute Spillover) as those that "if not taken, will increase the probability of an adverse health event within a month or two,"[5] and chronic spillover drugs (CGM Chronic Spillover) as those that are designed to treat "more persistent conditions that, if not treated, will result in a potentially adverse health event within the year."[6] We also use the list from Tamblyn et al. (2001), who define classes of "essential" drugs as "medications that prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis."

Although MAPD and SAPD plans have similar generosity levels on average, we show that this masks considerable differences in generosity across classes of drugs used to treat different diseases. For example, to an MA beneficiary purchasing Ace Inhibitors, Beta Blockers, or Coronary Vasodilators the share of total costs paid by the beneficiary is 32-38% higher on average than a beneficiary in an SAPD would pay, while the same share is about 11% lower for Antipsychotic and Antimanic drugs.

These coverage differences are not random. We find that a one standard deviation change in a drug's MA switcher surplus measure ($151 annually) is associated with beneficiaries paying 8%-9% less out-of-pocket in MAPDs than they do in SAPDs during open enrollment, when the selection incentive is strongest. This suggests MA plans use Part D formularies as a mechanism to induce selection. Moreover, these differences remain about the same when comparing MAPD and SAPD plans owned by the same parent organization, suggesting that the difference in generosity is strategic, rather than due to information differences or firm-level insurance design strategies. Since MA risk-adjustment does not consider prescription drugs, the Part D market provides an excluded dimension from the risk-adjustment formula that allows MAPD plans to

[5]Examples of drugs on this list are: anticonvulsants, antimalarials, antiangials, coronary vasodilators, and thrombolytics.

[6]Examples of drugs on this list are: analgesics, antivirals, ACE inhibitors, antigout medications, beta-blockers, hypertension drugs, statins, and glaucoma medications.

increase their ability to positively select healthier patients.

Consistent with evidence of spillover effects between drugs and other medical care, we also estimate that MA plans more generously cover drugs that causally reduce medical spending. Out-of-pocket costs are about 12%-13% lower for drugs that have spillover effects within 1-2 months (CGM Acute Spillover drugs), and about 3%-6% lower for drugs with spillover effects within 12 months (CGM Chronic Spillover drugs) in MA plans relative to SA plans. In addition, Tamblyn's list of essential drugs have about 7% lower out-of-pocket costs in MA plans. All of these effects persist when we compare generosity across plans for the exact same drug NDCs. MA plans are also less likely to use non-price formulary hurdles like prior authorization requirements and step therapy restrictions on CGM Acute and Chronic spillover drugs.

A related study by Starc and Town (2016) extends our work on spillover effects using reimbursement rate discontinuities as an instrument for enrollment in MA plans, following Afendulis, Chernew, and Kessler (2013), to estimate that MA enrollment causes spending on drugs to increase, and that the effects are largest for this same set of CGM drugs. Their primary goal is to estimate a structural model to evaluate alternative policy scenarios, such as forcing SAPD plans to internalize spillover effects, which they estimate would cause drug spending to increase by 13% in SAPDs. Our paper instead focuses on the supply-side responses to spillover incentives in formulary design and also incorporates selection incentives, which we find to be correlated with spillover incentives.

Our findings suggest that the Medicare Part D regulations aimed at preventing targeted selection, including the rules that all Part D plans must cover at least two drugs in every therapeutic class, and the rule that forbids plans from discriminating against those with costly medical conditions (Hoadley 2005), have not been entirely successful at eliminating selection incentives. However, the welfare effects of fragmentation of insurance coverage under Part D are ambiguous because MA plans also internalize spillover incentives. In addition, since all MA plans have similar incentives, competition for consumers with profitable medical conditions may cause some of the potential rents from selection to be transferred back to consumers in the form of enhanced insurance benefits.[7] However, several studies have shown that similar types of cost savings are retained by insurers, and only around 20% is passed-through to consumers (see Cabral, Geruso and Mahoney (2014); Curto et al. (2015); Duggan, Starc and Vabson (2015)).

We focus in this paper on insurer behavior in responding to these Part D incentives when designing plans, and not on the resulting consumer behavior or net welfare effects.[8] The selection effect that we identity, however, clearly increases the cost to Medicare, and Part D formularies provide a mechanism for MA plans to select patients by medical condition with surgical precision.

[7]For the remaining consumers, the ability to choose SAPD plans that do not face the same risk-adjustment problem mitigates some of the potential redistribution between beneficiaries that would otherwise occur if everyone were in MA plans.

[8]See Han and Lavetti (2016) and Starc and Town (2016) for more on beneficiary responses to these plan differences.

2 Medicare Part D Background

There are several important institutional details and regulations governing plan design and reimbursement in Medicare Part D that affect how incentives could possibly manifest in plan formularies. We provide a brief description of the relevant Medicare Part D rules, but more detailed explanations can be found in MedPAC (2005, 2006a), Hoadley and Simon (2010) and in the public law itself (U.S. Congress, 2003).

2.1 Plan Design

Beginning in 2006, Medicare Part D has provided prescription drug insurance to Medicare beneficiaries, who face a choice between traditional public Medicare with a private stand-alone drug plan or integrated private coverage of all medical and drug care through a Medicare Advantage plan. MA and SA plans receive a subsidy for each beneficiary to whom they provide drug coverage, and the subsidies are risk-adjusted based on diagnosed illnesses of the beneficiary. Plans are forbidden from declining to insure anyone eligible. As of 2015 there were 15 million people receiving drug coverage through MAPD plans and 23.5 million through SAPDs (Hoadley et al. 2015).

Part D insurance is heavily subsidized, although beneficiaries pay some out-of-pocket costs in addition to monthly premiums. In the 2010 standard benefit structure, beneficiaries pay the first $310 of annual drug costs (the deductible), then pay a 25% coinsurance on the next $2,520 spent, then pay 100% of the cost for the next $3526 (the "doughnut hole"), and 5% of all costs beyond that (the "catastrophic zone").

Although there was very active debate about the design of the standard benefit structure,[9] the law allows Part D plans a great deal of freedom in designing formularies, which was done to encourage private sector competition. By 2015, zero SAPDs and only 1% of MAPDs (enrollment weighted) offered the standard drug benefit (Hoadley et al. 2015), suggesting that plans have been very active in designing formularies. Most Part D plans have four coverage tiers, with the first, second, and third tiers having sequentially higher cost-sharing requirements, and a fourth specialty tier, reserved for "very high cost and unique items" (CMS 2007).[10] Generally, plans can choose which drugs are listed on their formularies (i.e., covered at all), on which tiers drugs are listed, how out-of-pocket costs are assigned to each tier, and drug-specific non-price hurdles, such as whether prior authorization is required. Once a formulary has been offered for sale during the open-enrollment period, between Oct. 15 and Dec. 7 of each year, insurers are generally not allowed to make the formulary more restrictive thereafter without written approval from CMS (CMS 2008, section 30.3.3.1). However, plans may increase the generosity of the coverage without prior approval.

[9] See Newhouse (2004)

[10] See Hoadley et al. 2005, 2006 and 2008 for detailed reviews of formularies used by Part D plans, and Lucarelli, Prince, and Simon (2012) for more on consumer demand and welfare effects of plan competition in Part D.

Plans are allowed to deviate from the standard benefit design provided they follow certain regulations. First, the alternative cost-sharing structures must be actuarially equivalent to the standard plan, and must be "in accordance with standard industry practices" (CMS, 2007). Plan formularies must also include at least two drugs in each therapeutic category (see CMS 2007 for details of categories), and must include substantially all drugs in six key therapeutic classes, although there is no restriction on how generously each drug must be covered. Plans are also forbidden from designing formularies that discriminate against those with costly medical conditions (Hoadley, 2005), although it is not known how these requirements are audited. The rules governing formulary design apply equally to MAPDs and SAPDs, so the regulations themselves should not generate differences in formulary design. The existence of these rules simply limits the degree to which MA plans can respond to the differential economic incentives they face.

2.2 Selection Incentives

Concerns about adverse selection are present in nearly every insurance market. These concerns can be especially heightened when risks are systematically correlated, as they are in the context of prescription drugs, where demand is highly autocorrelated from one year to the next. Selection may be heightened in prescription drug insurance markets as individuals often have private information that allows them to better predict their future demand for drugs than for other types of medical care.[11] In fact, Pauly and Zeng (2004) find that adverse selection problems may be so heightened in stand-alone prescription drug insurance that this market would not exist unless plans were subsidized, as they are under Part D, or bundled with other coverage to create a more comprehensive insurance product with less persistent spending, as is the case with MAPDs. Recent data show empirical evidence that insurers feared adverse selection when designing plans in the Medicare Advantage (MA) market prior to Part D. Lustig (2010) finds that insurers responded to adverse selection by constraining plan design, leading to a 14.5% reduction in the economic surpluses created by Medicare Advantage between 2000-2003.

There are several factors that reduce the incentive to strategically select beneficiaries. Starting in 2007 all reimbursements to MA plans became fully risk-adjusted, the culmination of a multi-year phase-in of a system known as hierarchical condition category (MedPAC 2006b), whereas prior rates were only adjusted for geographic and demographic factors.[12] MedPAC (2006b) explains that part of the reason for these changes was to encourage participation by private insurers in traditionally under-served rural areas of the country. However, there is evidence that even after risk adjustment was fully introduced in 2007, MA plans are still able to profit by favorably selecting healthier patients conditional on risk scores.[13]

[11] See Berndt (2004).
[12] See MedPAC (2007).
[13] See Brown et al. 2014 and Carey 2016.

Within Part D there are several features that dull selection incentives for both MA and SA plans. First, Part D pays insurers on a risk-adjusted basis using a formula that accounts for the average difference in drug spending among FFS Medicaid beneficiaries with different medical conditions. The goal of risk-adjustment is to make plans approximately indifferent between randomly selected FFS beneficiaries with different illnesses. Of course, as Brown et al. (2014) show, and we find in our data, selection into MA plans is far from random. Second, Part D has risk-corridors to prevent plans from earning excessive profits or losses. Since 2008 those risk-corridors have been set such that if drug spending is between 5%-10% higher than expected based on the plan's average risk profile, then 50% of the plan's excess spending is returned as a subsidy, and if spending exceeds expectations by more than 10% the subsidy increases to 80%. The risk-corridors are also symmetric, imposing a large effective tax rate on profits that exceed 5% or 10% of expected drug spending in a year. Nonetheless, these corridors leave sufficient opportunity for typical profit margins that are observed in markets without risk-corridors. For example, a 2013 report by CMS estimated that, on average, private insurance companies in the US earned profit margins of about 5.3% in small group markets and 3.8% in large group markets.[14]

The ability to induce self-selection through strategic formulary design also depends on how sensitive beneficiaries are to differences in generosity when choosing insurance plans. The evidence from the literature on choice inconsistencies, including as Abaluck and Gruber (2011), suggests that consumers were far less responsive to out-of-pocket costs than they were to plan premiums in the first year of Medicare Part D. However, Ketcham et al. (2012) find that overspending on out-of-pocket costs fell by 55% in subsequent years, suggesting that consumer learning may have increased responsiveness of plan choice to generosity. There is also a larger body of evidence that consumers are responsive to out-of-pocket costs when purchasing drugs, conditional on plan choice. Although the well-known RAND health insurance experiment estimated the elasticity of demand for medical care to be quite low, about -0.2 (Newhouse et al., 1993), subsequent research focusing on elderly patients has found elasticities of demand for prescription drugs to be much higher. Duggan and Scott Morton (2010) estimate the elasticity of demand for prescription drugs under Medicare Part D to be -0.4, and Lichtenberg and Sun (2007) estimate it to be about -0.7. Non-price formulary hurdles, such as prior authorization requirements or quantity limits, have also been shown to be important predictors of drug use and spending.[15]

[14] See CMS (2013).

[15] See Simon et al. (2009) for evidence in the case of state Medicaid pharmacy restrictions.

3 Conceptual Framework

To help clarify our empirical objects of interest, we start with a very basic theoretical description of the selection and management incentives. For SAPD plans, profit maximization entails choosing a premium bid, which affects the calculation of federal premium subsidies, and choosing the coinsurance rates of each drug. Although Part D formulary coverage schedules tend to be nonlinear (in that coinsurance rates generally change as a function of total spending), we abstract by considering the average share of drug's total cost that is covered by the insurer, r_d. The SAPD profit function is:

$$\max_{P,r_d} \left[P(r_d) + S(r_d) - c(r_d)\right] Q(P, S, r_d)$$

where $P(r_d)$ is the monthly plan premium paid by beneficiaries, which depends on the generosity of the plan's coverage of the set of d drugs, $S(r_d)$ is the monthly federal subsidy payment, which depends on P, $c(r_d)$ is the cost of insuring a beneficiary, and Q is the number of enrollees, which may depend on the plan premium, federal subsidies, and plan generosity.

Consider the decision over the generosity of a single drug with index $d = 1$. The SAPD plan's FOC is:

$$\left[\frac{\partial P(r_d)}{\partial r_1} + \frac{\partial S(r_d)}{\partial r_1} - \frac{\partial c(r_d)}{\partial r_1}\right] Q + \left[P(r_d) + S(r_d) - c(r_d)\right] \frac{\partial Q}{\partial r_1}$$

In contrast, the profit function for an MA plan includes both drug and medical components. Consider the MA plan's problem that takes into account interactions with medical profits.

$$\max_{P,r_d} \left[P(r_d) + S(r_d) - c(r_d) + MAR(r_d) - MAc(r_d)\right] Q(P, S, r_d, MAR, MAc)$$

where $MAR(r_d)$ is the average risk-adjusted revenue that an MA plan gets for Part A and B coverage, which could depend on the drug formulary generosity insofar as formulary design affects the composition of enrollees, and $MAc(r_d)$ is the average non-drug medical cost of enrollees that choose the plan. The difference between these terms is the selection incentive that MAPDs face, but SAPDs do not.

A similar decision over the generosity of coverage of an arbitrary drug with index $d = 1$ is determined by the FOC:

$$\left[\frac{\partial P(r_d)}{\partial r_1} + \frac{\partial S(r_d)}{\partial r_1} - \frac{\partial c(r_d)}{\partial r_1} + \frac{\partial MAR(r_d)}{\partial r_1} - \frac{\partial MAc(r_d)}{\partial r_1}\right] Q + \left[P(r_d) + S(r_d) - c(r_d) + MAR(r_d) - MAc(r_d)\right] \frac{\partial Q}{\partial r_1}$$

There are two sets of terms that cause an MAPD plan's decision over r_1 to potentially differ from an

SAPD's decision. The first is $\frac{\partial MAc(r_d)}{\partial r_1}Q$, which captures the spillover effect between drugs and the cost of medical treatment. For example, if choosing to generously cover asthma inhalers decreases the probability that an enrollee will have an adverse event leading to hospitalization, then this spillover term would be positive, and likely much larger in magnitude than $\frac{\partial c(r_d)}{\partial r_1}$ since the cost of inhalers is very low relative to emergency care. In our empirical application we do not observe the spillover derivative separately for each drug, so we rely on the knowledge of the medical experts that created the CGM Acute Spillover, CGM Chronic Spillover, and Tamblyn Essential Drugs lists to determine which drugs have the most positive derivatives. In theory there could also be drugs with negative average derivatives, for example if medical care like physician checkups are complementary to drug purchases, as may be the case in the treatment of depression.

The second set of terms is:

$$\frac{\partial MAR(r_d)}{\partial r_1}Q + [MAR(r_d) - MAc(r_d)]\frac{\partial Q}{\partial r_1}$$

The first component could be nonzero if the choice of r_1 affects the composition of enrollees in the plan in a way that alters average risk scores. In this case the revenue effect is Q times the change in average medical revenue per enrollee. Since plan enrollment choices depend on many factors, the impact of coverage generosity of any single drug may be quite small for most individuals, in which case this term will be close to zero. Second, the choice of r_1 could affect enrollment decisions of beneficiaries, differentially increasing the profits of an MA plan by the average difference between medical revenue and medical cost times the responsiveness of demand to the generosity of insurance coverage of the drug, r_1. This term differs from zero if the risk-adjustment formula does not fully eliminate the difference between revenue and cost for enrollees in MA plans. As described above, this could occur, for example, if MA plans are successful at attracting lower cost enrollees within medical conditions, consistent with evidence from Brown et al. (2014).

Since the spillover effect term is scaled by Q, while most of the variation in the selection incentive is likely to be come from the term that is scaled by $\frac{\partial Q}{\partial r_1}$, this suggests that the spillover effect should be relatively stronger for MA plans with high market shares, where enrollment is larger relative to the potential to gain new enrollees. We return to this point in the empirical analyses, where we test for differential effects of the spillover and selection hypotheses in MA plans with larger market shares.

4 Data and Empirical Methods

In order to test the key selection and spillover hypotheses, we first construct empirical analogues of the terms in the first order conditions above. We begin by estimating the difference between risk-adjusted revenue and costs for the medical component of MA plans. We then describe the data and methods used to test each of the hypotheses by combining the risk-adjustment estimates for each drug with data on plan formularies, Medicare claims data on drug purchases and medical conditions, negotiated drug prices, and plan-level enrollment data. Finally, we discuss risk-adjustment in Part D, which is calculated separately from Parts A & B risk-adjustment.

4.1 Medicare Advantage Risk-Adjustment and Selection

The primary selection incentive that we study arises due to the fact that risk-adjustment in Medicare Parts A & B does not eliminate the potential for plans to profit through selection, as shown by Brown et al. (2014). The first step of our analyses is to quantify the magnitude of the selection incentives that MA plans face for each medical condition in the risk-adjustment formula. To do this, we use claims data from the universe of fee-for-service Medicare beneficiaries from 2008-2010. Using Medicare's internal calculations of patient risk-scores, we calculate the counterfactual capitation payment that an MA plan would receive for each beneficiary, if they were to enroll in MA. For each year from 2009-2010, and for each beneficiary that was in FFS Medicare for the full prior calendar year, we then calculate the difference between the actual observed FFS spending and the counterfactual capitation payment that an MA plan would have received if that beneficiary enrolled. If the entire FFS population were to switch into MA plans at the same time this difference would approximately equal zero due to the risk-adjustment formula. However, since the switchers from FFS to MA are non-randomly selected, the average annual spending of the population of FFS beneficiaries who subsequently choose to switch to MA plans is $902 less than the spending of those who remain in FFS, conditional on medical diagnoses and other characteristics included in the risk-adjustment formula. This finding is consistent with advantageous selection of beneficiaries into MA plans as in Brown et al. (2014), and is very close to the similar statistic estimated by Batata (2004) of $1030 using data from the early 1990s. For brevity, we refer to this difference throughout the paper as the expected 'MA switcher surplus.'

Using the MA switcher surplus as a dependent variable, we estimate the surplus associated with each of

the 70 medical conditions in the risk-adjustment formula using the the following fixed effects regression:

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

where $MA\ Switch_{it}$ is an indicator that equals one if person i switched from FFS into an MA plan in year t, $\mathbf{1}\left[HCC_{it-1} = k\right]$ is an indicator that equals one if person i had a diagnosis associated with Medicare Hierarchical Condition Code (HCC) k in the prior year, and X_{it} is a vector of control variables that includes year effects, age effects, race effects, a gender effect, interactions between race effects and an indicator that equals 1 if the individual originally entered Medicare due to a disability, and $\psi_{c(it)}$ is a set of county effects that equals one for the county in which beneficiary i lived in year t. Note that X_{it} contains the set of variables used by CMS for risk-adjustment.

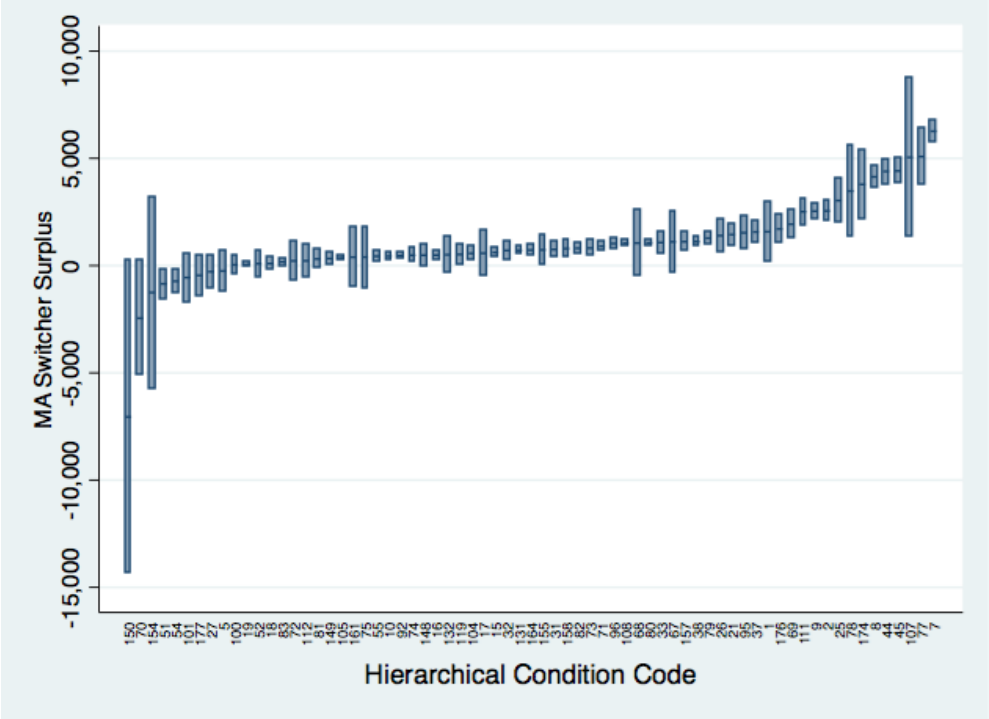
The key parameters of interest from this model are the 70 estimated values of γ_k. Figure 1 shows the distribution of these estimates, along with the 95% confidence intervals. The estimated MA switcher surplus is statistically significantly different from zero for 48 out of 70 HCCs. For 46 of these conditions the estimate is significant and positive, suggesting that lower cost beneficiaries within these HCCs are more likely to switch into MA plans.

To be clear, these estimates do not necessarily equal MA plan profit. The costs of treating beneficiaries in MA plans may differ from the costs under FFS, and is this cost difference is not included in our calculation since we have no data on beneficiary costs in MA plans. In addition, as discussed by Geruso and Layton (2016), to the extent that enrollment in MA plans has a causal effect on risk scores through upcoding, our estimated capitation revenue may understate the revenue that an MA plan would actually receive. The calculation that we use, which is similar to that used by Brown et al. (2014), captures only the selection component of profits. If MA plans are able to select patients with lower medical expenses conditional on their risk score, the difference in costs between the selected patients and the average patients is one component of the total profits of the MA plan.

4.2 Mapping Medical Conditions to Drug Purchases

The final step of the calculation is to use the estimated values γ_k from Equation 1 to calculate the predicted MA switcher surplus by drug active ingredient, rather than by HCC code. The goal is to be able to link each drug on every plan formulary to a measure of the predicted MA surplus that a plan would earn if an average enrollee who takes a drug with that active ingredient were to enroll in the MA plan. In order to connect

Figure 1: MA Switcher Surplus by Hierarchical Condition Code



Notes: This figure plots the estimated values of γ_k from Equation 1 corresponding to each of the 70 Medicare hierarchical condition codes, along with the 95% confidence interval for each estimate. HCC 130 is dropped from the figure because Medicare rules restrict beneficiaries with this condition from switching into MA plans.

this selection incentive to formulary design, we use Medicare claims to construct a complete mapping of all medical conditions used in risk-adjustment calculations to each drug covered by Part D plans. To account for the fact that drugs with the same active ingredient are used to treat the same condition(s), and so they should conceptually have the same selection effect, we link each drug NDC code to its active ingredient using the NDC product database.[16] Beginning with the universe of Medicare Part D claims data from 2008-2010, we link each NDC code in the claims data to its active ingredient, and for each beneficiary-year we construct a set of binary variables indicating whether the beneficiary filled a prescription with that active ingredient in that year. We then link this file to a database of all of the HCC conditions for that beneficiary, which is derived from each of the patient's diagnoses. This provides an individual-year level database of every active ingredient purchased and every medical diagnosis for the population of FFS beneficiaries.

We estimate a separate probit model for each active ingredient in the data. In each model the dependent variable equals one if the beneficiary purchased a drug with the given active ingredient in a given year, and zero otherwise. The independent variables are simply a set of binary variables for each of the 70 HCC

[16] Accessed at http://www.nber.org/data/national-drug-code-data-ndc.html

condition codes used in the Medicare Advantage risk-adjustment formula.

$$\mathbf{1}(ActiveIng_{it}) = \alpha + \sum_{h=1}^{70} \nu_h \mathbf{1}\left[HCC_{it} = h\right] + \epsilon_{it} \tag{2}$$

This set of equations gives a $d \times h$ matrix of coefficients, ν, where d is the top 707 most frequently purchased active ingredients,[17] and h is 70, corresponding to the number of HCC codes.

For each estimated $\widehat{\nu_h}$ we calculate the predicted marginal effect of having HCC_h on the probability of taking a drug with the given active ingredient. We then calculate the predicted MA switcher surplus at the active ingredient level as:

$$MA\ Switcher\ Surp_d = \sum_{h=1}^{70} \widehat{\nu_{dh}} * \widehat{\gamma_h} \tag{3}$$

where $\widehat{\gamma_h}$ are the estimated coefficients from Equation 1 and $\widehat{\nu_{dh}}$ is the row vector from the coefficient matrix from Equation 2 corresponding to the same active ingredient d. Equation 3 gives the probability that a beneficiary takes drug d given their HCC codes times the MA switcher surplus for each of those HCC codes, which equals the expected MA switcher surplus at the active ingredient level, taking into account the full joint distribution of HCC codes and drug active ingredient consumption in the population.

Figure 2 shows the distribution of drug-level MA switcher surpluses, which is the key variable we will use to test the selection hypothesis.[18] The mean of the distribution is \$55, and the standard deviation is \$152.

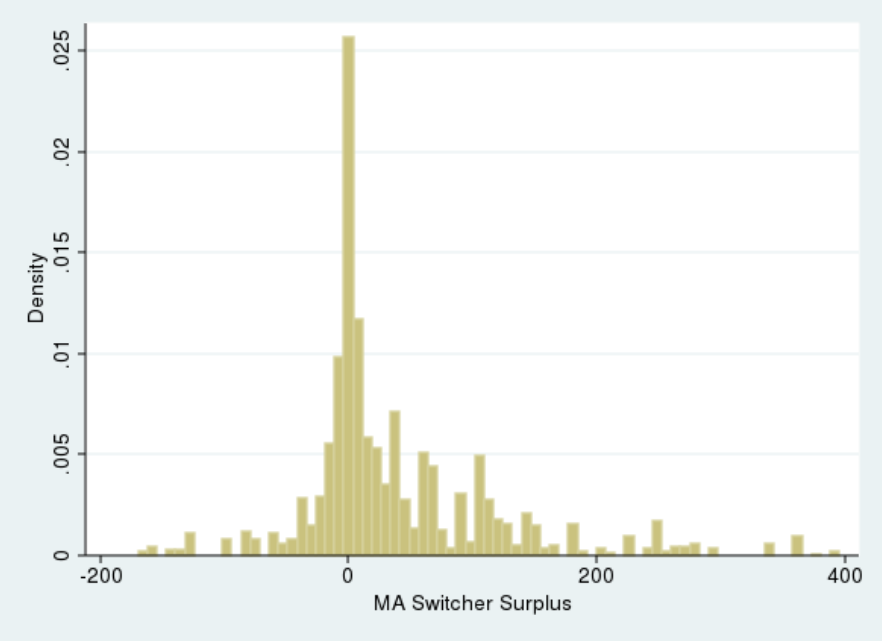
4.3 Part D Formularies and MA Medical Spillover Incentives

We use the CMS Formulary Files and Quarterly Pricing Files to test for differences in Part D formulary designs in SAPD and MAPD plans. The Formulary Files contain monthly data on the universe of MAPD and SAPD plans offered in the country since Part D implementation at the beginning of 2006. In particular, they provide the formulary status of drugs, tier location, whether prior authorization, step therapy and quantity limits are imposed, and limited information about cost sharing policies corresponding to tiers. The Quarterly Pricing Files began being released in 2009, and include data on the average reimbursement prices negotiated between each plan and the in-area retail pharmacies for that plan at the NDC-level. Together, these two files provide complete information about the generosity of the universe of Part D plans. Prior to 2009 the Formulary files contained cost-sharing rules, but the cost of the drug to the insurance company was unknown, making it impossible to calculate the percentage of the total cost that the consumer must pay

[17] We exclude drugs with fewer than 38,000 prescriptions filled in the data for computational reasons.

[18] Ideally one should use a two-step standard error correction to account for that fact that this variable is generated. We cannot do this for practical reasons since one iteration of the full model takes several months to complete. However, since we observe the entire population we know the exact means, so the population-adjusted standard error on the generated variable is zero, in which case our estimates are identical to the two-step corrected estimates.

Figure 2: Distribution of MA Switcher Surplus by Drug Active Ingredient



Notes: This figure plots the distribution of values of $\sum_{h=1}^{70} \widehat{\nu_{dh}} * \widehat{\gamma_h}$ from Equation 3 corresponding to each of the 707 drug active ingredients in the data, weighted by their frequency of coverage on Part D formularies. The distribution is truncated at $400 for ease of presentation, although the full distribution has a longer upper tail with a maximum value is $1615.

for drugs with fixed copayments. We use data on prices from the Quarterly Pricing Files between the first quarter of 2009 and the third quarter of 2011. Table 1 shows summary statistics of our measures of plan generosity from these data sources.

We link into the formulary data the lists of drugs that we use to test the spillover hypothesis. We use the CGM Acute Spillover and CGM Chronic Spillover lists developed by Chandra, Gruber, and McKnight (2010), with the minor caveat that the drug classification system that their lists were based upon, which was developed in 1995, is no longer in use, and therefore cannot be linked perfectly to current NDC codes, many of which did not exist in 1995. As a result we developed a linkage mapping the 1995 standard drug classification system into the classification system that is currently used by CMS, the United States Pharmacopeia Classification System. This mapping was largely straightforward, but there were some classes that were not uniquely matchable to the USP system, so our versions of the lists are subsets of the original lists containing 73% of the Acute and 72% of the Chronic classes.[19]

[19]The unmatched drug classes on the CGM Acute Care Drug list include: Adrenal Corticosteroids, Anaphylaxis Treatment Kit, Antiasthmatics/broncodilators, Antitoxins/antivenins, Chloramphenicol/derivatives, DNA Damaging Drugs, Hypotension/shock drugs, Ocular Anti-infective/anti-inflammator, Polymyxins, and Vascular Disorders/Cerebral/periphera drugs. The unmatched drug classes on the CGM Chronic Care Drug list include: Antidiuretics, Calcium Metabolism drugs, Miscellaneous CNS drugs, Cycloplegics/mydriatics, Deficiency Anemias, Acid/peptic Disorder drugs, Hematopoietic Growth Factors,

Table 1: Summary Statistics on Plan Generosity

	MAPD	SAPD
Initial Coverage Cost-Sharing	36%	34%
Open Enrollment	37%	32%
Percent of Drugs on Formulary	65%	63%
Open Enrollment	64%	61%
CGM Acute Spillover Drug	53%	53%
CGM Chronic Spillover Drug	28%	28%
Tamblyn Essential Drug	42%	42%
Quantity Limit	15%	17%
Prior Authorization	11%	13%
Step Therapy	2%	2%
Number of Plan-Formularies	6,973	4,317
Number of Plan-Drug Pairs	26,417,124	15,854,701

Notes: Summary statistics from formulary pricing files between the first quarter of 2009 and third quarter of 2011. 'Initial Coverage Cost-Sharing' is the out-of-pocket cost divided by the total average cost of the drug. 'Number of Plan-Drug Pairs' is the number of unique NDC code and plan formulary pairs, and refers only to drugs that are on-formulary. 'Percent of Drugs on Formulary' is calculated as the share of NDC codes that each plan covers among the full set of NDC codes that were covered by at least one plan in the same quarter.

A second list that we use is the one developed by Tamblyn et al. (2001), which similarly relied upon clinical experts to classify drugs according to whether they are 'essential,' which was defined as: "medications that prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis." Since the Tamblyn list is based on a different classification system than the CGM lists, they are not directly overlapping, and all three lists can be included simultaneously in our models without causing substantial collinearity problems.

4.4 Part D Risk-Adjustment

In addition to the selection incentive that MA plans face due to the MA switcher surplus, all Part D plans face separate selection incentives caused by differences in Part D profitability across medical conditions. Carey (2016) shows that these risk-adjustment 'errors' have arisen primarily because the risk-adjustment formulas have remained the same while new drug entry and the onset of generic competition changed the cost of treatment for many diagnoses. Although these selection incentives are uniform across all plans that we study, it is possible that by chance they may be correlated with our key variables of interest that measure differential selection and spillover incentives among MAPDs. To remove any potential omitted variable bias caused by these correlations, we control for the Part D selection incentive using the expected profit or loss associated with each drug in the CMS plan formularies, which was calculated by Carey (2016). The profitability measures are based on analyses of the 5% sample of Medicare claims data, and are constructed

Hemostatics, Neurologics, and Enteral/parenteral Nutrition agents.

Table 2: Formulary Coverage Generosity by Drug Class

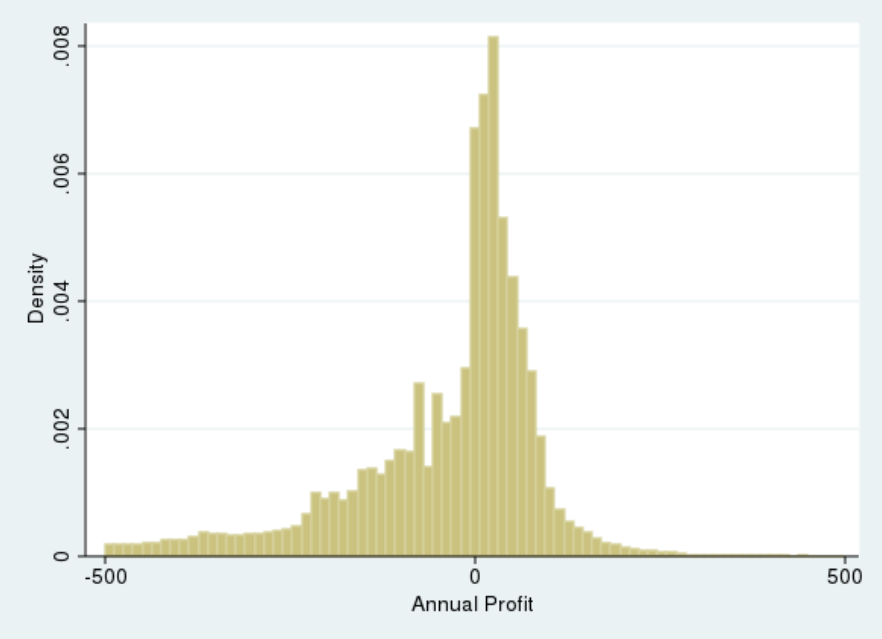
Dependent Variable:	Log OOP Pct	
MA Plan*Penicillins	–0.103*	–0.115*
	[0.014]	[0.014]
MA Plan*Antipsychotics/Antimanics	–0.097*	–0.079*
	[0.007]	[0.007]
MA Plan*Anthelmintics	–0.044*	–0.043*
	[0.007]	[0.007]
MA Plan*Antidepressants	–0.025	–0.072*
	[0.010]	[0.009]
MA Plan*Blood Glucose Regulators	–0.004	–0.032*
	[0.010]	[0.010]
MA Plan*Alzheimer/Dementia Drugs	0.009	–0.015
	[0.009]	[0.009]
MA Plan*Antineoplastics	0.023*	0.025*
	[0.008]	[0.008]
MA Plan*Respiratory Tract Drugs	0.053*	0.025*
	[0.010]	[0.008]
MA Plan*Antianginals	0.057*	0.056*
	[0.012]	[0.012]
MA Plan*Anticonvulsants	0.083*	0.061*
	[0.007]	[0.006]
MA Plan*Antiarrhythmics	0.101*	0.040*
	[0.013]	[0.012]
MA Plan*Beta Blockers	0.199*	0.098*
	[0.018]	[0.016]
MA Plan*Coronary Vasodilators	0.232*	0.151*
	[0.018]	[0.016]
MA Plan*Ace Inhibitors	0.245*	0.047
	[0.023]	[0.019]
N	128,773,526	128,773,526
R-Sq	0.046	0.365
Drug NDC Effects	No	Yes

Notes: Dependent variable is the log of the percentage of drug cost that the beneficiary must pay out-of-pocket in the initial coverage range and after any deductible has been met. All models include 5th order orthogonalized polynomial in ln(30 Day Cost), drug class main effects, plan premium, plan deductible, and quarter-by-year effects. All models are weighted by drug price. Standard errors are clustered at the plan formulary level. * indicates significance at the 0.01 level.

through a two-step process. The first step is to link each drug in the formulary files to the mostly likely medical diagnosis associated with that drug. This is done by separately regressing an indicator of the use of each active ingredient molecule on a set of indicators for medical diagnoses in the claims data, using probit models. The second step is to aggregate treatment costs by patient in the Part D claims data, and regress treatment costs on the set of indicators of predicted diagnoses associated with the drugs taken by each person. Carey (2016) shows that Part D plans respond to these Part D selection incentives in the design of their formularies, consistent with the general type of strategic behavior that we investigate in this paper, but she does not suggest or test the differential incentives between integrated and stand-alone drug plans.

The predictions from this model yield expected treatment costs by diagnosis, which can then be compared to the formulaic risk-adjusted payments by diagnosis that are set by Medicare, and the difference between the two is the expected profit or loss associated with each medical condition. Figure 3 shows the distribution of risk-adjusted Part D profits by drug NDC code, for all drugs that appear on Part D formularies. The distribution has a mean value of -$68, but has substantial mass away from zero, suggesting that risk-adjustment has not fully eliminated selection incentives.

Figure 3: Distribution of Part D Risk-Adjusted Profit by Drug



Notes: This figure plots the histogram of Part D profits from Carey (2016) by drug NDC code for all drugs on Part D formularies between Q1 2009 to Q3 2011. Observations are at the plan formulary by quarter by drug level, and the distribution is truncated at -500 and +500.

4.5 Empirical Model

There are several forms of identifying variation that we use in the analyses. On the extensive margin, variation in plan incentives is summarized in Table 3.

Table 3: Identification of Parts A & B Selection and Spillover Incentives

	During Open Enrollment	Outside Open Enrollment
MA Plans	Strong Selection, Spillovers	Weak Selection, Spillovers
SA Plans	No Selection, No Spillovers	No Selection, No Spillovers

The difference in spillover incentives between MAPDs and SAPDs occurs year-round. However, the selection incentive for MA plans (which is specific to Parts A & B) should be strongest during the open-enrollment period, when beneficiaries are free to choose new plans. To the extent that plans are permitted to change plan formularies within a plan year, generosity could differ during open enrollment periods relative to the rest of the year. Of course, Medicare rules limit plans' abilities to decrease the generosity of formularies, so this within-year variation is somewhat constrained. As a result, the selection incentive is likely to affect MA formularies year-round, but there may be some differential effects during open enrollment. On the intensive margins, we quantify the strength of the selection incentive using the drug-level MA switcher surplus calculated above, and use the three lists of spillover drugs as indicators for drugs where the spillover incentive should be strongest. We omit the selection incentives caused by imperfect Part D risk-adjustment from the table, since these incentives are always the same for all plans.

Table 2 presents summary statistics that are suggestive of differences in formulary design. The coefficients are the average differences in the share of drug costs that must be paid out-of-pocket by beneficiaries between MAPD and SAPD plans by drug class. Although Table 1 showed that the average generosity of drug coverage in MAPD plans is similar to SAPD plans, Table 2 shows that this masks substantial heterogeneity in generosity across different classes of drugs. For example, the share of costs paid out of pocket by MAPD enrollees is 11.5% less for Antipsychotic and Antimanic drugs than the share paid by SAPD enrollees. However, MAPD enrollees pay about 32-38% more out of pocket for Beta Blockers, Coronary Vasodilators, and Ace Inhibitors. For the majority of classes, these differences in generosity occur across plan types within the exact same drug NDC code, as shown in column 2. These generosity differences are all conditional on any differences in plan premiums, deductibles, or any differences across plan types in drug prices negotiated with pharmacies.

Next we test our main hypotheses: whether the differences in generosity are explained by the selection and spillover incentives. Our main empirical specification is:

$$\begin{aligned} \text{LogOOPCost}_{jdt} &= \alpha + \beta_1 \text{X}_{jdt} + \beta_2 MA\ Switcher\ Surp_d + \beta_3 MA\ Switcher\ Surp_d * \text{OE}_t \\ &+ \beta_4 MA\ Switcher\ Surp_d * \text{MA}_j + \beta_5 MA\ Switcher\ Surp_d * \text{OE}_t * \text{MA}_j \\ &+ \beta_6 Spillover\ Drug_d + \beta_7 Spillover\ Drug_d * \text{MA}_j + \epsilon_{jdt} \end{aligned} \tag{4}$$

where LogOOPCost_{jdt} is the log of out-of-pocket costs for drug d in plan j in quarter t, X_{jdt} includes a polynomial in drug cost, an MA indicator, the monthly plan premium and annual deductible, estimated Part D profitability from Carey (2016) and an interaction with the MA indicator, an open-enrollment indicator and interaction with MA, and quarter-by-year effects, and $Spillover\ Drug_d$ is a vector of indicators for each of the three lists of drugs with medical spillovers. The unit of observation in this model is a drug NDC by plan.

The spillover effects hypothesis is $\beta_7 < 0$, which would indicate that MA plans more generously cover drugs that have the potential to reduce hospital and other medical costs. We test the selection hypotheses two ways. The selection hypothesis is $\beta_4 < 0$, which corresponds to more generous coverage of drugs that tend to be taken by profitable MA beneficiaries. There is also a secondary question in the selection hypothesis, corresponding to $\beta_5 < 0$. This would indicate especially strong selection effects during open enrollment, when out-of-pocket costs for drugs may have the strongest effects on consumer plan choices. We test both the selection and spillover hypotheses in the same model to account for any potential correlation between the selection and spillover variables. For example, if a drug has both a high MA switcher surplus and high spillover potential, testing the hypotheses in separate models could bias the estimates.

5 Results

5.1 Selection Effects

Estimates from Equation 4, our main specification, are shown in Table 4. The key variables of interest for testing that selection hypothesis are 'MA Switcher Surplus*MA' and 'MA Switcher Surplus*MA*OE'. Column 1 shows that when the MA switcher surplus increases by \$100 (about 0.66 standard deviations), out of pocket costs are 3.6% lower in MAPD plans than in SAPD plans. This result is similar within drug classes as it is across classes, as shown in Column 2.

Columns 3 and 4 extend the selection hypothesis further by testing whether the difference in coverage

Table 4: Effects of Selection and Spillover Incentives on Coverage Generosity

	Dependent Variable: Log OOP Cost				
	(1)	(2)	(3)	(4)	(5)
MA Switcher Surplus	–0.740*	0.201*	–0.751*	0.180*	
	[0.015]	[0.016]	[0.016]	[0.016]	
MA Switcher Surplus*MA	–0.360*	–0.330*	–0.340*	–0.313*	–0.276*
	[0.021]	[0.020]	[0.021]	[0.020]	[0.020]
MA Switcher Surplus*OE			0.132*	0.259*	0.320*
			[0.021]	[0.021]	[0.020]
MA Switcher Surplus*OE*MA			–0.240*	–0.229*	–0.250*
			[0.027]	[0.027]	[0.026]
CGM Acute Care Drug	0.436*	–0.281*	0.436*	–0.281*	
	[0.006]	[0.006]	[0.006]	[0.006]	
CGM Acute Care Drug*MA	–0.119*	–0.126*	–0.118*	–0.126*	–0.069*
	[0.008]	[0.008]	[0.008]	[0.008]	[0.006]
CGM Chronic Care Drug	0.341*	0.321*	0.341*	0.321*	
	[0.004]	[0.006]	[0.004]	[0.006]	
CGM Chronic Care Drug*MA	–0.026*	–0.059*	–0.026*	–0.059*	–0.013*
	[0.006]	[0.006]	[0.006]	[0.006]	[0.005]
Tamblyn Essential Drug	–0.152*		–0.152*		
	[0.004]		[0.004]		
Tamblyn Essential Drug*MA	–0.073*	–0.077*	–0.073*	–0.076*	–0.080*
	[0.006]	[0.005]	[0.006]	[0.005]	[0.005]
Log 30 Day Cost	0.874*	0.855*	0.874*	0.855*	0.280*
	[0.003]	[0.003]	[0.003]	[0.003]	[0.006]
MA Plan	–0.022	0.054*	–0.025	0.050*	–0.045*
	[0.011]	[0.011]	[0.011]	[0.011]	[0.010]
OE*MA			0.050*	0.054*	0.043
			[0.011]	[0.011]	[0.010]
Part D Surplus	–0.711*	0.223*	–0.711*	0.223*	
	[0.009]	[0.014]	[0.009]	[0.014]	
Part D Surplus*MA	–0.048*	0.254*	–0.048*	0.255*	0.131*
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
N	38,323,671	38,323,671	38,323,671	38,323,671	38,323,671
R-Sq	0.550	0.674	0.550	0.674	0.765
Drug Class Effects	No	Yes	No	Yes	Yes
Drug NDC Effects	No	No	No	No	Yes

Notes: All models include 5th order orthogonalized polynomial in ln(30 Day Cost), quarter-by-year effects, plan premium, and plan deductible, and are weighted by drug cost. CGM Acute Care Drug refers to drugs designated by Chandra, Gruber, and McKnight (AER 2010) as those that, "if not taken, will increase the probability of an adverse health event within a month or two." CGM Chronic Care Drug refers to drugs "designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year." Tamblyn Essential refers to drugs designated by Tamblyn et al (JAMA 2001) as medications that "prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis." All Part D surplus and MA surplus variables are measured in $1,000s. Standard errors, in brackets, are clustered by insurance plan. * indicates significance at the 0.01 level.

generosity between MAPD and SAPD plans changes during the open enrollment period, relative to the difference across plans outside of open-enrollment. We find substantially larger differences during the open-enrollment period, when the selection incentive should be strongest. A $100 increase in MA switcher surplus is associated with a 3.1%-3.4% reduction in out of pocket costs in MAPD plans outside of open-enrollment, but a 5.4%-5.8% difference during open-enrollment. The stronger selection effects during open-enrollment suggest that plans may be somewhat constrained in their ability to change generosity during open-enrollment, either by CMS plan design rules or by consumers, who may notice and respond to larger generosity changes in general equilibrium. Again, the estimates are very similar within and across drug classes.

Column 5 shows estimates of a similar model that includes drug NDC effects, rather than drug class effects. The full drug NDC code can be thought of similarly to a product bar code–it identifies an exact combination of drug, dosage, packaging, and manufacturer so that products with the same NDC are completely identical. The estimates suggest that the variation in generosity occurs within drugs, rather than potentially being due to substitution across different forms of similar drugs. Within NDC code, MAPD beneficiaries pay 2.8% less out of pocket per $100 in switcher surplus outside of open-enrollment, and 5.3% less during open-enrollment.

In addition to the results pertaining to the main hypotheses in this paper, the estimated effects of Part D surplus on plan generosity are also informative. Consistent with Carey (2016), we find that a $100 increase in risk-adjusted Part D profits (about 0.60 standard deviations) is associated with 7.1% reduction in out-of-pocket costs on average in SAPD plans, and about 7.6% in MAPDs. Since the Part D selection incentives, conditional on Parts A & B selection incentives and spillover incentives, are uniform across plans, the similarity of these two estimates is what we would expect to find. However, there appears to be some difference in the substitution patterns of drug generosity across versus within drug classes. When we include fixed drug class effects we find that the estimates are smaller and differ between plan types: out-of-pocket costs are 2.2% higher for SAPDs and 4.8% higher for MAPDs per $100 increase in Part D surplus. This is consistent with the possibility that plans use formularies to induce selection broadly at the condition level, which may be associated with a class of drugs, rather than by type of drug within a class, where (unobserved) bonus payments from drug manufacturers tied to tier placement may play a role in determining the relative generosity of coverage. Column 5 shows that within drug NDC codes, MA plans are less responsive to Part D profits than SAPD plans. When Part D profits increase over time for a given drug, a $100 increase in Part D profits increases the out of pocket costs in MAPDs relative to SAPDs by 1.3%. This is as expected, since MAPDs have less incentive to care about profits from just the Part D component to the extent that Part D profits may be negatively correlated with profits from the medical component of the plan.

5.2 Case Study: Fentanyl

As an example of the effects of MA selection incentives on formulary design, we consider the case of the drug fentanyl. Fentanyl is the most commonly prescribed synthetic opioid pain reliever in the US. It is extremely potent, hundreds of times more potent than pure pharmaceutical heroin, according to the CDC. It is used primarily for palliative care, including the management of chronic pain, especially pain associated with cancer. Originally developed in 1960, there are several competing manufacturers that produce fentanyl, with a variety of delivery mechanisms, but with the same active ingredient. In the Medicare Part D formulary files, there are 11 unique drug NDC codes corresponding to fentanyl that are covered on plan formularies, and over 164,000 plan-drug-year observations associated with fentanyl in our data.

Based on our analysis using Medicare claims data of the mapping between drug active ingredients and HCC codes, we estimate that the condition that is most predictive of fentanyl use is HCC 7, metastatic cancer and acute leukemia. The second most predictive condition according to our model is HCC 157, vertebral fractures without spinal cord injury. Reassuringly, our estimates are completely consistent with described uses of the drug in the medical literature (see Stanley 2014).

As shown in Figure 1 the Medicare beneficiaries that switch from FFS to MA plans and have metastatic cancer (HCC 7) had significantly lower spending levels than those who do not switch—they spent $6,265 less (SE $278) annually. Similarly, switchers with vertebral fractures (HCC 157) spent $1,113 less (SE $219) annually than non-switchers. Although these two conditions are the most strongly predictive of fentanyl use, it is still used for other conditions as well, where the switcher surplus may not be as large, and in some cases may be negative. As a result, if an MA plan had only a single piece of information, that a beneficiary takes fentanyl, their expectation (based on our model of switcher incentives) is that the total spending of this beneficiary would be $167 below the costs of the FFS beneficiaries who do not switch. This $167 value is calculated by multiplying $6,265 by the marginal effect of HCC 7 on the probability of using fentanyl, plus $1,113 times the marginal effect of HCC 157 on the probability of using fentanyl, plus all of the corresponding terms for the remaining 68 HCCs.

As a result, since capitation payments to MA plans are based on costs of FFS enrollees, the selection incentive associated with fentanyl should increase MA profits by $167 per beneficiary per year, all else equal. For the sake of comparison, $167 is about 0.74 standard deviations above the mean switcher surplus for all drug active ingredients, so fentanyl users are moderately profitable for MA plans relative to users of other drugs.

In the formulary data there are 5 NDC codes (out of 11 total) that represent 94% of fentanyl observations. As shown in Table 5, MAPD plans more generously cover all 5 of these NDC codes. On average, beneficiaries

Table 5: Generosity of Fentanyl Coverage by NDC

Product	Meda Pharma. 12 mcg/hr patch	Meda Pharma. 100 mcg/hr patch	Activis Pharma. 25 mcg 5 units	Activis Pharma. 50 mcg 5 units	Activis Pharma. 75 mcg 5 units
Average Negotiated Price (30 Day)	$1,737	$189	$54	$95	$145
MAPD Log OOP Cost	1.50	1.27	1.14	1.20	1.24
SAPD Log OOP Cost	2.59	2.23	2.04	2.13	2.19
MAPD Number of Plan-Drug Pairs	21,173	21,173	21,831	21,831	21,831
SAPD Number of Plan-Drug Pairs	12,730	12,754	12,754	12,754	12,754

Notes: Calculations based on CMS Quarterly Pricing Files data.

in MAPD plans pay about 80% less out-of-pocket for fentanyl than do beneficiaries in SAPDs. These differences in coverage generosity are largely caused by MAPDs choosing to place fentanyl on lower coverage tiers. 61.5% of MAPD plan-drug observations for these 5 NDC codes are on tier 1, the tier of most generously covered drugs, compared to just 53.7% of SAPDs. Only 6.5% of MAPD observations are on tier 3 or above, compared to 12.1% for SAPDs.

Within NDC codes, unconditional out-of-pocket costs for fentanyl are 92% less in MAPDs. After conditioning on plan-level negotiated prices with pharmacies, plan deductible, premium, Carey Part D risk-adjustment errors, and quarter-by-year effects, the conditional difference between MAPD and SAPD plans is about three times larger than the unconditional difference. Our main empirical specification uses this same form of analysis, but aggregates results for all drugs.

5.3 Spillover Effects in Integrated Plans

We also find strong and consistent evidence that integrated MAPD plans internalize spillovers when designing drug formularies. Columns 1-4 in Table 4 show that for Chandra, Gruber, and McKnight's (CGM) Acute Spillover drugs, that will increase the probability of an adverse health event within 1-2 months if not taken, out-of-pocket costs are 12-13% lower in MAPDs than in SAPDs. The result also holds within NDC codes, with a 7% difference in costs. As expected, there is a significant but smaller effect for CGM Chronic Spillover drugs, that will increase the probability of an adverse health event within one year if not taken. Out of pocket costs are 3-6% lower in MAPDs for these drugs, and 1% lower within NDC codes, suggesting that the majority of this effect is driven by substitution in formulary coverage or generosity across drugs rather than being driven by differences across plan within NDC. Although the Tamblyn essential drugs list overlaps with the CGM lists, which could attenuate estimates somewhat, the results suggest consistently lower out of pocket costs in MAPD plans for all three lists even when they are all included in the model at the same time. We find that out of pocket costs are 7-8% lower in MAPD plans for Tamblyn essential drugs, conditional on CGM Lists, and this result is almost entirely due to within NDC differences in generosity across plan types.

As shown in Appendix Table 11, the estimated CGM Acute and Chronic Spillover effects both increase in magnitude when the Tamblyn Essential variables are excluded from the model. This evidence is consistent with Starc and Town (2016), who build on this analysis of formulary differences to study consumer choice, and show that enrollment in an MAPD causally increases drug expenditures.

5.4 Heterogeneity in Selection Effects

One important question given the above estimates on the selection effects of integrated MAPD plans on formulary designs is: are these differences in formulary generosity designed primarily to induce enrollment by profitable beneficiaries, to deter enrollment by unprofitable enrollees, or both?

In Table 6 we test for evidence to answer this question by splitting the variation in MA switcher surplus into tertiles, and testing for heterogeneity in selection effects by tertile. Since about one third of plan-drug observations have negative MA switcher surplus, the lowest tertile can be thought of as drugs with unprofitable selection incentives. In the table the omitted category is the middle tertile, which has modest positive MA switcher spillover values. The estimates show that MA plans cover drugs in the top tertile significantly more generously, with 6% lower out of pocket costs than SAPDs, and 5% lower costs within NDC codes. Column 3 shows that this effect increases to a 9% difference in out of pocket costs in MAPDs during open enrollment. This evidence suggests a 'pulling' inducement effect: relative to drugs associated with more modest selection profits, those with larger switcher surpluses are covered significantly more generously.

However, we find little evidence of a 'pushing' or discouraging effect for unprofitable beneficiaries. Relative to modestly profitable drugs, those with negative switcher surpluses have about 1.6% higher costs in MAPDs according to column 2, but there is no significant effect according to the models presented in columns 1 and three. Moreover, there is no change in the relative generosity of coverage during the open enrollment period. Both the estimated baseline MA generosity difference and the open enrollment effect are fairly precisely zero within drug NDCs.

5.5 Non-Price Formulary Generosity

Table 7 tests whether these differences in plan design incentives affect other dimensions of coverage generosity, including non-price measures like the use of quantity limits, prior authorization, and step therapy restrictions. Each of these formulary dimensions limits beneficiaries' coverage in some way. Quantity limits impose a cap on how many prescriptions or days of prescriptions a beneficiary can purchase. Prior authorization requires the beneficiary to get permission from the insurer before a given drug will be covered, adding both a hassle cost and potential ambiguity to the expected generosity of coverage. Step therapy restrictions require

Table 6: Heterogeneity in Selection Effects

	Dependent Variable: Log OOP Cost		
MA Switcher Surplus Highest Tertile	–0.150*	–0.146*	
	[0.004]	[0.004]	
MA Switcher Surplus Highest Tertile*MA	–0.061*	–0.062*	–0.047*
	[0.006]	[0.006]	[0.005]
MA Switcher Surplus Highest Tertile*OE		0.032*	0.115*
		[0.005]	[0.005]
MA Switcher Surplus Highest Tertile*OE*MA		–0.016	–0.043*
		[0.009]	[0.008]
MA Switcher Surplus Lowest Tertile	–0.136*	–0.133*	
	[0.004]	[0.004]	
MA Switcher Surplus Lowest Tertile*MA	0.015	0.016*	–0.006
	[0.006]	[0.006]	[0.006]
MA Switcher Surplus Lowest Tertile*OE		–0.049*	0.033*
		[0.008]	[0.007]
MA Switcher Surplus Lowest Tertile*OE*MA		0.019	–0.002
		[0.010]	[0.010]
CGM Acute Spillover	0.468*	0.458*	
	[0.006]	[0.006]	
CGM Acute Spillover*MA	–0.117*	–0.117*	–0.065*
	[0.008]	[0.008]	[0.006]
CGM Chronic Spillover	0.324*	0.313*	
	[0.004]	[0.004]	
CGM Chronic Spillover*MA	–0.028*	–0.027*	–0.019*
	[0.006]	[0.006]	[0.005]
Tamblyn Essential	–0.152*	–0.146*	
	[0.004]	[0.004]	
Tamblyn Essential*MA	–0.071*	–0.075*	–0.079*
	[0.005]	[0.005]	[0.005]
Log 30 Day Cost	0.872*	0.878*	0.280*
	[0.003]	[0.003]	[0.006]
MA Plan	–0.022	–0.023	–0.042*
	[0.011]	[0.011]	[0.010]
OE*MA		0.038*	0.044*
		[0.012]	[0.012]
Part D Surplus	–0.747*	–0.740*	
	[0.009]	[0.009]	
Part D Surplus*MA	–0.046*	–0.049*	0.134*
	[0.013]	[0.013]	[0.013]
N	35,043,161	38,323,671	38,323,671
R-Sq	0.545	0.548	0.764
Drug NDC Effects	No	No	Yes

Notes: All models include 5th order orthogonalized polynomial in ln(30 Day Cost), quarter-by-year effects, plan premium, and plan deductible, and are weighted by drug cost. Column 1 includes only non-open enrollment data. CGM Acute Care Drug refers to drugs designated by Chandra, Gruber, and McKnight (AER 2010) as those that, "if not taken, will increase the probability of an adverse health event within a month or two." CGM Chronic Care Drug refers to drugs "designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year." Tamblyn Essential refers to drugs designated by Tamblyn et al (JAMA 2001) as medications that "prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis." All Part D surplus and MA surplus variables are measured in $1,000s. Standard errors, in brackets, are clustered by drug class. * indicates significance at the 0.01 level.

beneficiaries to try the most cost-effective forms of treatment before they are allowed to purchase more costly treatment options.

Table 7 presents log odds ratio estimates from logit models in which the dependent variable equals 1 if the plan-drug observation has each of these three formulary hurdles. The estimates show that MAPD plans partially offset the higher monetary generosity of coverage for drugs with high switcher surplus values by imposing more non-price restrictions. For example, a $100 increase in MA switcher surplus increases the probability that a drug in an MAPD plan will have a quantity limit by 6.6%, and increases prior authorization and step therapy by 2.4% and 4.6%, respectively. The gap in coverage restrictions between MAPD and SAPD plans grows even larger during open-enrollment, more than doubling in the case of quantity limits and step therapy. One explanation for these opposing directions of generosity differences is that monetary generosity is more salient to consumers or has a larger effect on selection.

Also consistent with expectations, MA plans are less likely to make beneficiaries face these hurdles to acquire drugs that could lead to adverse medical events if not taken. MAPD are significantly less likely to impose step therapy or prior authorization for both CGM Acute and Chronic spillover drugs. In the case of quantity limits there is no meaningful effect of CGM Acute Spillover drugs, and there is a modest reduction in use for CGM Chronic Spillover drugs. The effects of Tamblyn Essential drugs are mixed, but this may be due to the fact that the list overlaps somewhat with the CGM spillover lists.

5.6 Extensive Margin Formulary Coverage Effects

Table 8 also presents estimates from models in which the dependent variable is an indicator for the inclusion of a drug on the formulary. The estimates shown are from OLS linear probability models, due to computational convergence problems with logit specifications given the large sample.[20] The mean of the dependent variable, shown in Table 1, is about 0.63, and less than 8% of observations have predicted probabilities that exceed one or are below zero. As Table 8 shows there are no economically meaningful effects of either incentive on the extensive margin coverage decision. As a result, the intensive margin of formulary coverage generosity appears to be the primary mechanism for either inducing enrollment or managing medical cost externalities. This finding could also suggest that the CMS rules forbidding plans from excluding too many drugs from their formulary are binding constraints on formulary design.

[20] Appendix Table 13 compares logit estimates to OLS estimates for a similar model specification, and the main estimates are quite similar in the two model.

Table 7: Use of Non-Price Formulary Restrictions, Logit Odds Ratios

Dependent Variable	Quantity Limit	Prior Authorization	Step Therapy
Log(30 Day Cost)	3.810*	0.612*	83.595*
	[0.006]	[0.001]	[0.645]
MA Plan	0.700*	0.895*	1.112*
	[0.002]	[0.004]	[0.005]
Part D Surplus	1.948*	0.322*	1.802*
	[0.008]	[0.002]	[0.017]
Part D Surplus*MA	1.840*	1.041*	2.880*
	[0.011]	[0.008]	[0.042]
MA Switcher Surplus	0.051*	0.921*	0.077*
	[0.000]	[0.010]	[0.001]
MA Switcher Surplus*OE	0.644*	0.410*	0.411*
	[0.018]	[0.018]	[0.029]
MA Switcher Surplus*MA	1.660*	1.238*	1.459*
	[0.017]	[0.018]	[0.033]
MA Switcher Surplus*OE*MA	1.930*	1.147*	1.723*
	[0.067]	[0.060]	[0.143]
CGM Acute Care Drug	0.571*	1.109*	0.800*
	[0.001]	[0.004]	[0.003]
CGM Acute Care Drug*MA	1.008*	0.839*	0.969*
	[0.002]	[0.004]	[0.005]
CGM Chronic Care Drug	0.576*	1.192*	0.606*
	[0.001]	[0.005]	[0.003]
CGM Chronic Care Drug*MA	0.969*	0.741*	0.857*
	[0.002]	[0.004]	[0.005]
Tamblyn Essential Drug	1.461*	0.557*	1.206*
	[0.002]	[0.001]	[0.004]
Tamblyn Essential Drug*MA	0.959*	1.059*	1.177*
	[0.002]	[0.003]	[0.005]
N	41,958,670	41,958,670	41,958,670
R-Sq	0.114	0.130	0.117

Notes: Logit odds ratios reported. All models include a quadratic in Log 30 Day Cost, quarter-by-year effects, open enrollment interacted with MA plan, plan premium, and plan deductible, and are weighted by drug cost. CGM Acute Care Drug refers to drugs designated by Chandra, Gruber, and McKnight (AER 2010) as those that, "if not taken, will increase the probability of an adverse health event within a month or two." CGM Chronic Care Drug refers to drugs "designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year." Tamblyn Essential refers to drugs designated by Tamblyn et al (JAMA 2001) as medications that "prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis." All Part D surplus and MA surplus variables are measured in $1,000s. * indicates significance at the 0.01 level.

Table 8: Effects of Selection and Management Incentives on Formulary Inclusion

Dependent Variable:	Drug On Formulary	
	(1)	(2)
MA Switcher Surplus	0.005*	–0.029*
	[0.002]	[0.003]
MA Switcher Surplus*OE	–0.000	0.002
	[0.002]	[0.002]
MA Switcher Surplus*MA	–0.002	–0.001
	[0.002]	[0.002]
MA Switcher Surplus*OE*MA	–0.015*	–0.015*
	[0.003]	[0.003]
CGM Acute Care Drug	–0.025*	0.004*
	[0.001]	[0.002]
CGM Acute Care Drug*MA	–0.004*	–0.004*
	[0.001]	[0.001]
CGM Chronic Care Drug	–0.021*	–0.010*
	[0.000]	[0.002]
CGM Chronic Care Drug*MA	0.001	0.001
	[0.001]	[0.001]
Tamblyn Essential Drug	–0.001	
	[0.001]	
Tamblyn Essential Drug*MA	–0.003*	–0.003*
	[0.001]	[0.001]
Log 30 Day Cost	0.082*	0.082*
	[0.001]	[0.001]
MA Plan	–0.048*	–0.050*
	[0.004]	[0.004]
OE*MA	–0.030*	–0.030*
	[0.003]	[0.003]
Part D Surplus	–0.012*	–0.080*
	[0.002]	[0.002]
Part D Surplus*MA Plan	–0.040*	–0.061*
	[0.003]	[0.003]
N	41,958,670	41,958,670
R-Sq	0.120	0.157
Drug Class Effects	No	Yes

Notes: All models include 5th order orthogonalized polynomial in ln(30 Day Cost), quarter-by-year effects, plan premium, and plan deductible. Coefficients are OLS estimates. See Appendix Table 13 for a comparison between OLS and Logit estimates. CGM Acute Care Drug refers to drugs designated by Chandra, Gruber, and McKnight (AER 2010) as those that, "if not taken, will increase the probability of an adverse health event within a month or two." CGM Chronic Care Drug refers to drugs "designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year." Tamblyn Essential refers to drugs designated by Tamblyn et al (JAMA 2001) as medications that "prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis." All Part D surplus and MA surplus variables are measured in $1,000s. Standard errors, in brackets, are clustered by plan formulary level. * indicates significance at the 0.01 level.

5.7 Do These Effects Occur Across Plans With the Same Owner?

Our previous estimates have treated MAPD and SAPD plans as separate entities, although in some cases they are owned by the same parent company. For example, thirteen national firms represent about 84% of total PDP enrollment and about 42% of MAPD enrollment (Hoadley and Simon 2010). Table 9 presents estimates of the effect of plan integration on formulary design across plans owned by the same parent organization. Columns 1 and 3 in the table include fixed parent organization effects, and columns 2 and 4 include fixed parent organization by NDC effects. Although the standard errors are somewhat larger when we cluster by parent organization, the coefficients are similar in magnitude to the baseline estimates, and many remain statistically significant at the 0.05 level. For example, MAPD plans require beneficiaries to pay about 3.1% less out of pocket per $100 in switcher surplus for the exact same drug with the same NDC relative to SAPD plans owned by the same company. There are also significant differences in the generosity of coverage of Tamblyn Essential Drugs, with MAPDs charging about 6.7% less out of pocket for the same NDC.

Returning to the fentanyl case study, for example the parent organization Bravo Health Insurance offers several Part D plans in Texas. Their MA plan called Bravo Classic Plus (offered by Bravo Health Texas, with CMS Contract ID H4528 and Plan ID 001) was available in the first quarter of 2010 for $0 premium, and had $0 deductible. Bravo also offered a regional PDP for the state of Texas under the name Bravo Health Insurance (with CMS Contract ID S5998 and Plan ID 038). This plan however had a $29.80 monthly premium and a $310 deductible. In the case of fentanyl, for the Meda Pharmaceuticals 12 mcg/hr patch the Bravo MA plan had a $3 fixed copayment, compared to base price of $1651, so consumers paid less than 1% of the total cost out of pocket. In contrast the Bravo PDP plan, for the exact same NDC code in the same region, had a 25% coinsurance rate, so that consumers paid about $413 out of pocket per 30-day supply, despite paying a higher premium and higher deductible for this plan.

These findings suggest that the effects documented cannot be explained, for example, by differences in information or data available to different insurance companies, or to differences across firms in insurance design strategies.

5.8 Plan Enrollment and Market Share

The theoretical framework in Section 3 suggests that the relative magnitudes of the spillover and selection effects may change as Q, the number of enrollees, changes relative to $\frac{\partial Q}{\partial r}$, the change in enrollment in response to a change in formulary generosity. Intuitively, if a plan already has a very large market share, there is little scope for inducing further enrollment, and we have found evidence that plans do not appear to design

Table 9: Variation in Formularies within Parent Organization

	Dependent Variable: Log OOP Cost			
	(1)	(2)	(3)	(4)
MA Switcher Surplus	–0.751*		–0.758*	
	[0.144]		[0.156]	
MA Switcher Surplus*MA	–0.360*	–0.316*	–0.345	–0.310*
	[0.171]	[0.127]	[0.180]	[0.125]
MA Switcher Surplus*OE			0.104	0.191
			[0.190]	[0.108]
MA Switcher Surplus*OE*MA			–0.198	–0.063
			[0.183]	[0.105]
CGM Acute Care Drug	0.446*		0.446*	
	[0.058]		[0.058]	
CGM Acute Care Drug*MA	–0.117	–0.014	–0.117	–0.014
	[0.060]	[0.017]	[0.060]	[0.017]
CGM Chronic Care Drug	0.358*		0.358*	
	[0.035]		[0.035]	
CGM Chronic Care Drug*MA	–0.033	0.002	–0.033	0.003
	[0.037]	[0.024]	[0.037]	[0.023]
Tamblyn Essential Drug	–0.153*		–0.153*	
	[0.022]		[0.022]	
Tamblyn Essential Drug*MA	–0.070	–0.067*	–0.070	–0.067*
	[0.042]	[0.028]	[0.042]	[0.028]
Log 30 Day Cost	0.871*	0.205*	0.871*	0.204*
	[0.020]	[0.035]	[0.020]	[0.035]
MA Plan	0.027	–0.029	0.023	–0.032
	[0.067]	[0.044]	[0.066]	[0.043]
OE*MA			0.062	0.050
			[0.048]	[0.039]
Part D Surplus	–0.696*		–0.696*	
	[0.088]		[0.088]	
Part D Surplus*MA	–0.088	–0.074	–0.088	–0.073
	[0.078]	[0.048]	[0.078]	[0.048]
N	36,200,201	36,200,201	36,200,201	36,200,201
R-Sq	0.569	0.889	0.569	0.889
Parent Org. Effects	Yes	Yes	Yes	Yes
Parent Org. by NDC Effects	No	Yes	No	Yes

Notes: All models include parent organization effects, a 5th order orthogonalized polynomial in ln(30 Day Cost), quarter-by-year effects, plan premium, and plan deductible, and are weighted by drug cost. CGM Acute Care Drug refers to drugs designated by Chandra, Gruber, and McKnight (AER 2010) as those that, "if not taken, will increase the probability of an adverse health event within a month or two." CGM Chronic Care Drug refers to drugs "designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year." Tamblyn Essential refers to drugs designated by Tamblyn et al (JAMA 2001) as medications that "prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis." All Part D surplus and MA surplus variables are measured in $1,000s. Standard errors, in brackets, are clustered by parent organization. * indicates significance at the 0.05 level.

formularies to encourage disenrollment of unprofitable beneficiaries. As a result, the spillover incentive in this case should be larger, while the selection incentive should decrease.

In Appendix Table 12 we test for evidence that plans with larger market shares place more emphasis on the medical spillover incentive. We find no significant or meaningful difference in the generosity of coverage of drugs on any of the three spillover lists when plan market shares are larger. This finding holds both across plans on average, and within plans. The conclusion is also the same when plan enrollment levels are used rather than market shares.

6 Summary and Discussion

The introduction of Part D was the first time in the history of Medicare that beneficiaries were required to receive benefits exclusively from private plans. Despite guidelines that constrain certain aspects of plan design, plans are allowed considerable flexibility in designing their coverage formularies. It is important for future Part D public policy decisions to know how this flexibility has affected the design of plans.

We evaluate one aspect of the extent to which Part D is achieving this goal of reducing costs by integrating coverage. The fundamental question of interest is whether the option to provide stand-alone drug coverage leads to inefficient cost minimization that does not account for spillovers between drugs and medical care. Ideally, we would like to know whether exogenously assigned enrollees have higher total costs when they are covered by separate insurance plans, but the problem of non-random assignment prevents us from identifying this directly. Instead we examine the drug formularies directly and look for evidence that firms respond to these incentives when designing coverage formularies. Starc and Town (2016) and Han and Lavetti (2016) build on this idea to show that consumers indeed respond to the formulary differences that we find, and that the introduction of Medicare Part D in 2006 increased MA plans' ability to advantageously select enrollees.

Using data on the universe of Medicare Part D formularies between 2009-2011 and the universe of fee-for-service Medicare claims data from 2008-2010, we test the hypotheses that integrated plans design their formularies differently than stand-alone plans to internalize spillovers between drug and medical costs, and that integrated plans design formularies to discourage enrollment by people with high medical costs. We find strong and consistent empirical support for both hypotheses when comparing the out-of-pocket costs that consumers would face for the same drugs in different types of plans. MAPDs cover drugs more generously when the medical conditions treated by those drugs tend to be more profitable, consistent with the selection hypothesis. For example, a patient with a condition that happens to be one standard deviations less profitable to a Medicare Advantage plan, given the risk-adjustment formula, would have to pay about 5% - 9% more out of pocket for their drugs if they were to choose an MAPD over an SAPD, because of this selection effect.

We also find that integrated MAPD plans internalize medical spillover effects associated with drug purchases, and as result they cover drugs more generously than stand-alone drug plans, reducing out-of-pocket costs to enrollees by up to 13% relative to stand-alone plans for drugs that have short-run spillover effects within 1-2 months.

These results are significant for current Part D debates about whether to change the flexibility given to plans. They also provide information about the extent to which risk-adjustment and Medicare rules affect the incentive and ability of Medicare Advantage plans to select healthier patients, and build upon evidence from Brown et al. (2014) that efforts to remove profit incentives through risk-adjustment have simply resulted in changes in the targets of selection, rather than a net reduction in the incentive. The results are also relevant to a practical issue of reimbursement cuts for MA plans for non-drug care, which has been proposed as a potential source of cost-savings. Evidence that integrated MAPDs increase welfare relative to stand-alone plans by more effectively minimizing health care costs may be of direct relevance for the way that MA plans are compensated overall. Finally, the results of this research are useful for understanding the extent to which the fragmentation of health insurance generally affects plan design, which is the primary channel through which adverse or advantageous selection is likely to arise in insurance markets.

References

[1] Abaluck, Jason and Jonathan Gruber (2011), "Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program," *American Economic Review*, Vol. 101, No. 4, (June 2011), pp. 1180-1210.

[2] Afendulis, Christopher C, Michael E Chernew and Daniel P Kessler (2013), "The Effect of Medicare Advantage on Hospital Admissions and Mortality," NBER Working Paper No. 19101.

[3] Batata, Amber, (2004), "The Effect of HMOs on Fee-For-Service Health Care Expenditures: Evidence from Medicare Revisited, *Journal of Health Economics*, Vol. 23, (2004), pp. 951-963.

[4] Berndt, E., (2004), Unique Issues Raised By Drug Benefit Design, *Health Affairs*, Vol. 23, No. 1.

[5] Brown, Jason, Mark Duggan, Illyana Kuziemko, and William Woolston (Brown et al. 2014). "How Does Risk Selection Respond to Risk Adjustment? New Evidence from the Medicare Advantage Program" *American Economic Review*, Vol. 104, No. 10, (Oct. 2014), pp 3335-64.

[6] Cabral, Marika, Michael Geruso, and Neale Mahoney (2014) "Does Privatized Health Insurance Benefit Patients or Producers? Evidence from Medicare Advantage" NBER Working Paper No. 20470, 2014.

[7] Carey, Colleen (2016), "Technological Change and Risk Adjustment: Benefit Design Incentives in Medicare Part D," Forthcoming at *American Economic Journal: Economic Policy*, 2016.

[8] Centers for Medicare and Medicaid Services (CMS), 2007 Medicare Modernization Act 2007 Final Guidelines Formularies, available at `http://www.cms.hhs.gov/PrescriptionDrugCovContra/Downloads/CY07FormularyGuidance.pdf` (accessed August 13, 2007)

[9] Centers for Medicare and Medicaid Services (CMS), 2008 Medicare Part D Manual-Chapter 6, Part D Drugs and Formulary Requirements, available at `http://www.cms.hhs.gov/PrescriptionDrugCovContra/Downloads/PDBMChap6FormularyReqrmts_03.09.07.pdf`

[10] Centers for Medicare and Medicaid Services (CMS), 2013 "The 80/20 Rule: How Insurers Spend Your Health Insurance Premiums," available at `https://www.cms.gov/CCIIO/Resources/Files/Downloads/mlr-report-02-15-2013.pdf`

[11] Chandra, Amitabh, Jonathan Gruber, and Robin McKnight (2010) "Patient Cost-Sharing, Hospitalization Offsets, and the Design of Optimal Health Insurance for the Elderly," *American Economic Review* Vol. 100, No. 1, (2010), pp. 193-213.

[12] Curto, Vilsa, Liran Einav, Jonathan Levin and Jay Bhattacharya. 2015. "Can Health Insurance Competition Work? Evidence from Medicare Advantage" NBER Working Paper No. 20818, 2015.

[13] Duggan, Mark and Fiona Scott Morton (2010) "The Effect of Medicare Part D on Pharmaceutical Prices and Utilization," American Economic Review, Vol. 100, No. 1, (March 2010), pp. 590-607.

[14] Duggan, Mark and Amanda Starc, and Boris Vabson (2015) "Who Benefits when the Government Pays More? Pass-Through in the Medicare Advantage Program," NBER Working Paper 19989, March 2014.

[15] Einav, Liran, Amy Finkelstein, and Maria Polykova (2016), "Private Provision of Social Insurance: Drug-Specific Price Elasticities and Cost Sharing in Medicare Part D," Working paper, 2016.

[16] Fendrick AM, Smith DG, Chernew ME, Shah SN. 2001. A benefit-based copayment for prescription drugs: patient contribution based on total benefits, not drug acquisition cost. American Journal of Managed Care.pp.861-867.

[17] Geruso, Michael and Timothy Layton (2016) "Upcoding or Selection? Evidence from Medicare on Squishy Risk Adjustment" Working Paper.

[18] Goldman, Dana and Tomas Philipson. 2007. Integrated Insurance Design in the Presence of Multiple Medical Technologies, American Economic Review Papers and Proceedings, 97 (2) May pp. 427-432.

[19] Han, Shijie and Kurt Lavetti (2016) "The Effect of Part D on Medicare Advantage Selection" Working Paper.

[20] Handel, Benjamin (2013) "Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts," *American Economic Review*, Vol. 103, No. 7, (2013), pp. 2643-82.

[21] Hoadley, Jack 2005. The Effect of Formularies and Other Cost Management Tools on Access to Medications: An Analysis of the MMA and the Final Rule, Kaiser Family Foundation, March 2005, available at http://www.kff.org/medicare/7299.cfm

[22] Hoadley, J. et al., 2006. An In-Depth Examination of Formularies and Other Features of Medicare Drug Plans, April, available at http://www.kff.org/medicare/upload/7489.pdf(accessedAugust19, 2007)

[23] Hoadley, Jack, Elizabeth Hargrave, Katie Merrell, Juliette Cubanski, and Tricia Neuman, 2008. Medicare Part D 2008 Data Spotlight: Formularies, The Kaiser Family Foundation, January, Available at http://www.kff.org/medicare/upload/7734.pdf.

[24] Hoadley, Jack, Juliette Cubanski, and Tricia Neuman, 2015 (Hoadley et al. 2015). Medicare Part D at Ten Years: The 2015 Marketplace and Key Trends, 2006-2015, The Kaiser Family Foundation, Oct. 2015, Available at http://kff.org/medicare/report/medicare-part-d-at-ten-years-the-2015-marketplace-and-key-trends-2006-2015/.

[25] Hoadley, J. and K. Simon. 2010. "Medicare Part D Turns Four: Trends in Plan Design, Enrollment, and the Impact of the Program on Beneficiaries" in Avi Dor edited Advances in Health Economics and Health Services Research Vol. 22.

[26] Kaiser Family Foundation 2014 (KFF 2014). Key Findings on Medicaid Managed Care: Highlights from the Medicaid Managed Care Market Tracker, December 2014, available at http://files.kff.org/attachment/key-findings-on-medicaid-managed-care-highlights-from-the-medicaid-managed-care-market-tracker-report (accessed May, 2016).

[27] Jonathan Ketcham, Claudio Lucarelli, Eugenio Miravete and M. Christopher Roebuck, (Ketcham et al. 2012), "Sinking, Swimming, or Learning to Swim in Medicare Part D," *American Economic Review*, Vol. 102, No. 6, (2012) pp. 2639-73.

[28] Lichtenberg, Frank R. and Shawn X. Sun, "The Impact Of Medicare Part D On Prescription Drug Use By The Elderly" Health Affairs 26, no.6 (2007):1735-1744.

[29] Lucarelli, Claudio, Jeff Prince and K. Simon, (2012) "The Welfare Impact of Reducing Choice in Medicare Part D: A Comparison of Two Regulatory Strategies," *International Economic Review*, Vol. 53, No. 4, (Nov. 2012), pp. 1155-77.

[30] Lustig, J. 2010. The Welfare Effects of Adverse Selection in Privatized Medicare, Yale University, Working Paper.

[31] Medicare Payment Advisory Commission (MedPAC). 2005.Report to the Congress: Issues in a modernized Medicare program, June 2005.

[32] Medicare Payment Advisory Commission (MedPAC). 2006a. Report to the Congress: Increasing the value of Medicare, June 2006.

[33] Medicare Payment Advisory Commission (MedPAC), 2006b. Medicare Advantage Program Payment System, September, available at http://www.medpac.gov/publications/other_reports/Sept06_MedPAC_Payment_Basics_MA.pdf

[34] Medicare Payment Advisory Commission (MedPAC). 2007. Report to the Congress: Update on the Medicare Advantage Program Implementation of Past Recommendations, March 2007.

[35] Newhouse, J. 2004 How Much Should Medicare Pay for Drugs? Health Affairs. Vol 23, N 1, pp.89-102

[36] Newhouse, J. P., and the Insurance Experiment Team. 1993. Free for All? Lessons from the RAND Health Insurance Experiment, Cambridge, MA: Harvard University Press.

[37] Pauly, Mark, and Yuhui Zeng, 2004. Adverse Selection and the Challenges to Stand-Alone Prescription Drug Insurance, Forum for Health Economics and Policy, Vol. 7, Article 3

[38] Polyakova, Maria (2015) "Regulation of Insurance with Adverse Selection and Switching Costs: Evidence from Medicare Part D" NBER Working Paper No. 21541.

[39] Rothschild, M., and J. Stiglitz. 1976. Equilibrium in Competitive Insurance Markets: An Essay in the Economics of Imperfect Competition, Quarterly Journal of Economics, Vol 90, p.629-49.

[40] Simon, K., S. Tennyson and J. Hudman, 2009, What Policies are States Using to Control Medicaid Prescription Drug Spending, and How Effective are They? Risk Management and Insurance Review. Vol 12, issue 1

[41] Stanley, Theodore (2014) "The Fentanyl Story" *The Journal of Pain*, Vol. 15, No. 12, (Dec. 2014), pp. 1215-26.

[42] Starc, Amanda and Robert J Town (2016) "Internalizing Behavioral Externalities: Benefit Integration in Health Insurance" Working Paper.

[43] Tamblyn, Robyn, Rejean Laprise, James Hanley, Michael Abrahamowicz, Susan Scott, Nancy Mayo, Jerry Hurley, Roland Grad, Eric Latimer, Robert Perreault, Peter McLeod, Allen Huang, Pierre Larochelle, and Louise Mallet . 2001. Adverse Events Associated with Prescription Drug Cost-Sharing Among Poor and Elderly Persons. Journal of the American Medical Association 285(4):42129.

[44] U.S. Congress. 2003 Public Law 108-173. Medicare Prescription Drug, Improvement, and Modernization Act of 2003.

Appendix: Supporting Tables

Table 10: Average Plan Generosity and Changes over Time

	Dependent Variable: ln(OOP Cost)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(30 Day Cost)	0.704	0.645	1.002	0.715	1.027	0.738
MA Plan	0.099	0.110	−0.013	0.002	0.276	0.274
Local MA Plan	−0.044	−0.049	−0.203	−0.203	−0.202	−0.203
1st Quarter	−0.014	−0.017	−0.071	−0.068	−0.071	−0.068
2nd Quarter	−0.011	−0.015	−0.011	−0.034	−0.011	−0.035
3rd Quarter	−0.033	−0.037	−0.027	−0.051	−0.027	−0.051
Year 2009	−0.009	−0.008	−0.174	−0.168	−0.174	−0.168
Year 2010	−0.006	−0.007	−0.025	−0.050	−0.026	−0.051
Plan Monthly Premium	0.001	0.001	−0.002	−0.002	−0.002	−0.002
MA Plan*ln(30 Day Cost)					−0.040	−0.038
Constant	−0.089	0.164	−1.470	0.608	−1.650	0.440
N	77,551,704	77,551,704	77,551,704	77,551,704	77,551,704	77,551,704
R-Sq	0.555	0.603	0.685	0.752	0.685	0.752
Drug Class Effects	No	Yes	No	Yes	No	Yes
Weighted (Cost)	No	No	Yes	Yes	Yes	Yes

Table 11: Alternative Model Specifications

	Dependent Variable: Log OOP Cost							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MA Switcher Surplus	–0.066*	0.188*	–0.431*	–0.061*	–0.073*	0.166*	–0.434*	–0.070*
	[0.006]	[0.016]	[0.007]	[0.008]	[0.007]	[0.016]	[0.007]	[0.008]
MA Switcher Surplus*MA	–0.207*	–0.334*	–0.150*	–0.156*	–0.197*	–0.317*	–0.141*	–0.147*
	[0.009]	[0.020]	[0.010]	[0.010]	[0.009]	[0.020]	[0.010]	[0.010]
MA Switcher Surplus*OE					0.092*	0.268*	0.038*	0.111*
					[0.010]	[0.021]	[0.012]	[0.012]
MA Switcher Surplus*OE*MA					–0.123*	–0.233*	–0.102*	–0.116*
					[0.013]	[0.027]	[0.015]	[0.015]
CGM Acute Care Drug	0.371*	0.052*			0.371*	0.052*		
	[0.005]	[0.007]			[0.005]	[0.007]		
CGM Acute Care Drug*MA	–0.133*	–0.136*			–0.133*	–0.136*		
	[0.007]	[0.008]			[0.007]	[0.008]		
CGM Chronic Care Drug	0.293*	0.388*			0.293*	0.388*		
	[0.004]	[0.006]			[0.004]	[0.006]		
CGM Chronic Care Drug*MA	–0.061*	–0.070*			–0.061*	–0.070*		
	[0.005]	[0.006]			[0.005]	[0.006]		
Tamblyn Essential Drug			–0.146*				–0.146*	
			[0.004]				[0.004]	
Tamblyn Essential Drug*MA			–0.075*	–0.080*			–0.075*	–0.080*
			[0.005]	[0.005]			[0.005]	[0.005]
Log 30 Day Cost	0.856*	0.853*	0.878*	0.855*	0.856*	0.852*	0.878*	0.855*
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
MA Plan	–0.022	0.034*	–0.125*	–0.053*	–0.026	0.030*	–0.128*	–0.056*
	[0.010]	[0.011]	[0.010]	[0.010]	[0.010]	[0.011]	[0.010]	[0.010]
OE*MA					0.050*	0.056*	0.039*	0.048*
					[0.011]	[0.011]	[0.011]	[0.011]
Part D Surplus	–0.569*	0.252*	–0.677*	0.246*	–0.569*	0.252*	–0.677*	0.246*
	[0.008]	[0.014]	[0.008]	[0.014]	[0.008]	[0.014]	[0.008]	[0.014]
Part D Surplus*MA	0.018	0.262*	–0.100*	0.229*	0.018	0.263*	–0.100*	0.230*
	[0.012]	[0.013]	[0.013]	[0.013]	[0.012]	[0.013]	[0.013]	[0.013]
N	48,350,532	39,204,663	38,706,488	38,706,488	48,350,532	39,204,663	38,706,488	38,706,488
R-Sq	0.537	0.674	0.544	0.672	0.537	0.674	0.544	0.672
Drug Class Effects	No	Yes	No	Yes	No	Yes	No	Yes

Notes: All models include 5th order orthogonalized polynomial in ln(30 Day Cost), quarter-by-year effects, plan premium, and plan deductible, and are weighted by drug cost. CGM Acute Care Drug refers to drugs designated by Chandra, Gruber, and McKnight (AER 2010) as those that, 'if not taken, will increase the probability of an adverse health event within a month or two.' CGM Chronic Care Drug refers to drugs 'designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year.' Tamblyn Essential Drug refers to drugs designated by Tamblyn et al (JAMA 2001) as medications that 'prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis.' All Part D surplus and MA surplus variables are measured in $1,000s. Standard errors, in brackets, are clustered by plan formulary level. * indicates significance at the 0.01 level.

Table 12: Effects of Plan Market Share on Spillover Incentive

	Dependent Variable: Log OOP Cost				
	(1)	(2)	(3)	(4)	(5)
	All	All	MAPD	SAPD	All
CGM Acute Care Drug	0.447*	0.448*	0.373*	0.393*	0.457*
	[0.006]	[0.006]	[0.005]	[0.004]	[0.005]
CGM Acute Care Drug*MA	–0.126*	–0.126*			–0.117*
	[0.009]	[0.009]			[0.008]
CGM Acute Care Drug*Market Share	–0.003*	–0.003*	–0.004	–0.004*	–0.004*
	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
CGM Acute Care Drug*Market Share*MA	0.002	0.002			0.002
	[0.002]	[0.002]			[0.002]
CGM Chronic Care Drug	0.353*	0.353*	0.345*	0.345*	0.365*
	[0.005]	[0.005]	[0.005]	[0.004]	[0.005]
CGM Chronic Care Drug*MA	–0.029*	–0.029*			–0.027*
	[0.007]	[0.007]			[0.007]
CGM Chronic Care Drug*Market Share	–0.004*	–0.004*	–0.007*	–0.005*	–0.005*
	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
CGM Chronic Care Drug*Market Share*MA	–0.000	–0.000			–0.001
	[0.002]	[0.002]			[0.002]
Tamblyn Essential Drug	–0.154*	–0.154*	–0.235*	–0.129*	–0.156*
	[0.005]	[0.005]	[0.004]	[0.004]	[0.005]
Tamblyn Essential Drug*MA	–0.066*	–0.066*			–0.064*
	[0.006]	[0.006]			[0.007]
Tamblyn Essential Drug*Market Share	0.001	0.001	–0.001	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Tamblyn Essential Drug*Market Share*MA	–0.003	–0.003			–0.003
	[0.002]	[0.002]			[0.002]
Market Share	0.010*	0.010*	0.004	0.001	0.002
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Market Share*MA	–0.003	–0.003			0.001
	[0.002]	[0.002]			[0.002]
MA Switcher Surplus	–0.759*	–0.766*	–1.016*	–0.873*	–0.743*
	[0.016]	[0.016]	[0.011]	[0.014]	[0.015]
MA Switcher Surplus*MA	–0.364*	–0.349*			–0.350*
	[0.021]	[0.021]			[0.020]
MA Switcher Surplus*OE		0.099*	–0.093*	0.083*	0.075*
		[0.022]	[0.019]	[0.021]	[0.021]
MA Switcher Surplus*OE*MA		–0.194*			–0.165*
		[0.029]			[0.029]
Log 30 Day Cost	0.871*	0.871*	0.829*	0.899*	0.858*
	[0.003]	[0.003]	[0.004]	[0.005]	[0.003]
MA Plan	–0.019	–0.022			
	[0.012]	[0.012]			
OE*MA		0.041*			0.021*
		[0.012]			[0.004]
Part D Surplus	–0.713*	–0.713*	–0.899*	–0.570*	–0.707*
	[0.009]	[0.009]	[0.012]	[0.009]	[0.009]
Part D Surplus*MA Plan	–0.048*	–0.047*			–0.076*
	[0.014]	[0.014]			[0.014]
N	35,691,734	35,691,734	21,823,719	13,868,015	35,691,734
R-Sq	0.550	0.550	0.565	0.634	0.592
Drug Plan Effects	No	No	Yes	Yes	Yes

Notes: All models include 5th order orthogonalized polynomial in ln(30 Day Cost), quarter-by-year effects, plan premium, and plan deductible, and are weighted by drug cost. Columns 1, 2, and 5 include the full sample, while column 3 includes only MAPD plans and column 4 includes only SAPD plans. CGM Acute Care Drug refers to drugs designated by Chandra, Gruber, and McKnight (AER 2010) as those that, 'if not taken, will increase the probability of an adverse health event within a month or two.' CGM Chronic Care Drug refers to drugs 'designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year.' Tamblyn Essential Drug refers to drugs designated by Tamblyn et al (JAMA 2001) as medications that 'prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis.' All Part D surplus and MA surplus variables are measured in $1,000s. Standard errors, in brackets, are clustered by plan formulary level. * indicates significance at the 0.01 level.

Table 13: Effects of Selection and Management Incentives on Formulary Inclusion: Comparison of Logit and OLS Estimates

Dependent Variable:	Drug On Formulary	
	Logit	OLS
MA Plan	–0.043*	–0.051*
	[0.000]	[0.000]
Part D Surplus	–0.035*	–0.024*
	[0.000]	[0.000]
Part D Surplus*MA	–0.014*	–0.049*
	[0.001]	[0.001]
MA Switcher Surplus	–0.013*	–0.005*
	[0.001]	[0.001]
MA Switcher Surplus*OE	0.000	–0.004
	[0.002]	[0.003]
MA Switcher Surplus*MA	0.005*	–0.000
	[0.001]	[0.001]
MA Switcher Surplus*OE*MA	–0.012*	–0.014*
	[0.003]	[0.003]
CGM Acute Care Drug	–0.019*	–0.020*
	[0.000]	[0.000]
CGM Acute Care Drug*MA	0.001*	–0.003*
	[0.000]	[0.000]
CGM Chronic Care Drug	–0.015*	–0.018*
	[0.000]	[0.000]
CGM Chronic Care Drug*MA	0.003*	0.000
	[0.000]	[0.000]
Tamblyn Essential Drug	0.001*	–0.001*
	[0.000]	[0.000]
Tamblyn Essential Drug*MA	–0.001*	–0.003*
	[0.000]	[0.000]
N	41,958,670	41,958,670
R-Sq	0.133	0.098

Notes: Column one reports logit estimates of the marginal effects at means. Column two reports OLS estimates. All models include quadratic in log 30 Day Cost, quarter-by-year effects, plan premium, plan deductible, and open enrollment interacted with MA plan. CGM Acute Care Drug refers to drugs designated by Chandra, Gruber, and McKnight (AER 2010) as those that, 'if not taken, will increase the probability of an adverse health event within a month or two.' CGM Chronic Care Drug refers to drugs 'designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year.' Tamblyn Essential Drug refers to drugs designated by Tamblyn et al (JAMA 2001) as medications that 'prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis.' All Part D surplus and MA surplus variables are measured in $1,000s. * indicates significance at the 0.01 level.