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Strategic Formulary Design in Medicare Part D Plans[†]

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The design of Medicare Part D causes most beneficiaries to receive fragmented health insurance, with drug and medical coverage separated. Fragmentation is potentially inefficient since separate insurers optimize over only one component of healthcare spending, despite complementarities and substitutabilities between healthcare types. Fragmentation of only some plans can also lead to market distortions due to differential adverse selection, as integrated plans may use drug formularies to induce enrollment by patients that are profitable in the medical insurance market. We study the design of insurance plans in Medicare Part D and find that formularies reflect these two differences in incentives. (*JEL* D82, G22, H51, I13, I18, L65)

A growing share of all public expenditures on health insurance in the United States is paid to private companies that deliver public health insurance benefits. Medicare Advantage (MA), the private alternative to traditional Medicare, and Medicare's Part D prescription drug coverage together cause about one-third of all Medicare expenses to be delivered entirely by private companies. Similarly, Medicaid is highly dependent on delivery by private managed-care organizations in most states (Paradise 2014). Although a frequently cited goal of privatization is increased 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 have the potential to reduce efficiency and increase total costs.

First, the decision to privately deliver Part D prescription drug benefits led to fragmentation of insurance for enrollees in traditional Medicare. These beneficiaries receive public hospital and physician insurance, but their private drug insurance is delivered by firms that have no incentive to consider the complementarity or substitutability between different classes of medical treatment options when designing insurance plans. A minority (about 30 percent) of beneficiaries are enrolled in MA plans, and have integrated private insurance that bundles together hospital, physician, and prescription drug coverage, creating an incentive for insurers to internalize spillovers across these categories. Empirical evidence from other

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insurance settings—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 such spillovers was a key stated reason for the creation of Medicare Part D.[1]

Second, the fragmentation of some plans but not others can lead to market distortions due to differential adverse selection. In addition to any selection incentives faced uniformly by Part D plans, MA Part D (MAPD) plans are incentivized to design their formularies to induce enrollment by beneficiaries from whom they expect to earn profits in the Medicare hospital and physician insurance market (Parts A and B), while stand-alone Part D plans are not. This creates selection incentives that differ across plans competing in the same market. In contrast to the relatively coarse cost-sharing rules in medical insurance, cost-sharing decisions in drug plans are made at the drug level,[2] providing a mechanism to precisely alter the attractiveness of a plan for individuals with conditions that are associated with specific drugs.

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 ways in which private insurers designed Medicare plans to take advantage of these two relationships between drug and nondrug medical spending. We test whether integrated plans choose more generous formulary rules for drugs taken by patients that tend to be profitable in Medicare Parts A and B, empirically evaluating the type of selection-based insurance design distortions described by Rothschild and Stiglitz (1976).[3] In addition, we test whether integrated plans set cost-sharing rules in ways that internalize spillovers between drug and nondrug 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 co-payments 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 potential implications for the efficient allocation of medical spending across major classes of medical care. Considering these two incentive differences jointly could be important to the extent that there is tension between them.

Many papers have studied adverse selection in health insurance markets, including theoretical discussions such as Rothschild and Stiglitz (1976) and empirical studies

[1] On the thirty-eighth anniversary of Medicare, President George W. Bush (2003) 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."

[2] This is done in part by choosing whether to include a drug on the formulary, and if it is included, by choosing on which cost-sharing tier to place it. In addition, there are certain non-price components of prescription drug formularies, which we discuss in more detail in Section IVF.

[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. Decarolis (2015) finds that Part D plans strategically manipulate premiums to increase profits in the low-income subsidy segment of the market. These studies are consistent with plans making strategic formulary design choices.

such as Handel (2013) and Polyakova (2015). Until very recently, however, few studies had empirically tested how adverse selection affects the design of insurance plans. Lustig (2010) 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: whether plans design insurance formularies differently in response to the potential for enhancing advantageous selection. Our study is related to Carey (2017), which finds evidence of plan design distortions in response to selection incentives within stand-alone Part D, as opposed to selection into MA.

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 nonrandom self-selection, or advertise to targeted audiences. In addition, Medicare uses risk adjustment of payments, with the conceptual goal of equating the expected profit of each potential enrollee. In practice, however, risk adjustment does not completely eliminate selection incentives either. 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 strategy from selecting beneficiaries with the lowest total cost to selecting the lowest-cost beneficiaries conditional on medical diagnoses. As a result, they find that these efforts to improve the risk-adjustment formula had little effect on overpayments to MA plans. Carey (2017) 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 in Part D.

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, calculate what the MA capitation payment would have been if the individual had been in an MA plan instead, and compare this to the actual FFS expenditures of that individual. Since the risk-adjustment formula is designed to equate expected profits across medical conditions, but is estimated using only FFS enrollees, any systematic variation in the difference between capitation payments and FFS expenditures by medical condition suggests that beneficiaries who switch into MA plans are not randomly selected from the pool of FFS beneficiaries.

Next, we use claims data from the 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. These joint probability distributions are used to calculate the expected

risk-adjusted selection incentive of MA plans by drug active ingredient,[4] and 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.

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 nondrug healthcare spending, especially among the elderly and individuals with chronic conditions. Chandra, Gruber, and McKnight (2010) find that 20 percent of the savings from increasing co-payments for prescription drugs and physician visits are offset by increases in hospital costs, and 43 percent 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, 204), who assembled a team of physicians and pharmacists to create drug groups for this purpose. They define spillover drugs—henceforth, CGM spillover—as those that "if not taken, will increase the probability of an adverse health event within the year."[5] We also use the list from Tamblyn et al. (2001, 422), who define classes of "essential" drugs—henceforth, Tamblyn essential—as "medications that prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis." We rely on medical expertise in constructing these lists because we are not aware of an alternative statistical approach for quantifying the causal effects of drug consumption on subsequent medical costs for every drug. One limitation with this approach is a loss of precision from using a binary measure of spillover incentives.

Although MAPD and SAPD plans have similar generosity levels on average, we show the average masks considerable differences in generosity across classes of drugs used to treat different medical conditions. For example, an MA beneficiary purchasing ACE inhibitors, beta-blockers, or coronary vasodilators would pay a 32–38 percent higher share of the total costs on average than a beneficiary in an SAPD would pay, while the same share would be about 11 percent lower for antipsychotic and antimanic drugs.

These coverage differences are not random. We find that a 1 standard deviation increase in a drug's MA switcher surplus ($151 annually) is associated with beneficiaries paying on average 7.4 percent less out-of-pocket for the same product (National Drug Code (NDC)) in MAPDs relative to SAPDs during open enrollment, when the selection incentive is strongest. We also provide direct

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

[5] Chandra, Gruber, and McKnight (2010) created two lists, an Acute list with a shorter 1–2 month adverse event horizon, and a Chronic list with a one year horizon. We combine these into a single list for simplicity.

evidence that the effects are driven by a roughly equal combination of differences in formulary tier choices and differences in cost-sharing rules across tiers. Moreover, these differences remain about the same when comparing MAPD and SAPD plans owned by the same parent organization, suggesting the generosity differences are strategic, rather than due to information differences or firm-level design strategies.

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 6 percent lower in MAPD plans for CGM spillover drugs, and about 8 percent lower for Tamblyn essential drugs. Moreover, the selection and spillover incentives interact in ways that are consistent with intuition. We show that MAPD plans set higher cost-sharing during open enrollment for spillover drugs that have low switcher surplus, but then increase generosity after open enrollment when the selection risk subsides and the spillover incentive prevails. All of these effects persist when we compare generosity across plans and within drug class, or within exact NDCs. MA plans are also less likely to use non-price formulary hurdles like prior authorization requirements and step therapy restrictions on CGM 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, this study estimates that MA enrollment causes beneficiary spending on drugs to increase, and that the effects are largest for CGM drugs. The study's 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 percent in SAPDs. Our paper instead focuses on the supply-side responses to spillover incentives in formulary design and also incorporates selection incentives.

We study insurer behavior in responding to these Part D incentives when designing plans, and not on the resulting consumer behavior or net welfare effects.[6] The welfare effects of plan integration are ambiguous—although the selection effects we identify clearly increase costs for Medicare, MA plans also internalize spillover incentives, potentially reducing total costs. 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]

I. Medicare Part D Background

Several important institutional details and regulations governing plan design and reimbursement in Medicare Part D affect how incentives could possibly manifest

[6] See Han and Lavetti (2017) and Starc and Town (2016) for more on beneficiary responses to these plan differences.

[7] However, several studies have shown that similar types of cost savings are retained by insurers, and only around 20 percent is passed through to consumers (see Cabral, Geruso, and Mahoney 2014; Curto et al. 2015; Duggan, Starc, and Vabson 2014). In addition, 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.

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, 2006b), Hoadley and Simon (2010), and in the public law itself (Medicare Prescription Drug, Improvement, and Modernization Act of 2003).[8]

A. *Plan Design*

Beginning in 2006, Medicare Part D has provided prescription drug insurance to Medicare beneficiaries,[9] who face a choice between traditional Medicare with a private stand-alone drug plan or integrated private coverage of all medical and drug care through an MA plan. MAPDs and SAPDs receive a subsidy for each beneficiary to whom they provide drug coverage, and the subsidies are risk-adjusted based on the demographics and diagnosed illnesses of the beneficiary. Plans are forbidden from declining to insure anyone eligible. As of 2015, 15 million people received 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 set by Medicare, beneficiaries pay the first $310 of annual drug costs (the deductible), then a 25 percent coinsurance on the next $2,520 spent, then 100 percent of the cost for the next $3,526 (the "doughnut hole"), and 5 percent of all costs beyond that (the "catastrophic zone").

Although there was very active debate about the design of the standard benefit structure,[10] 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 percent of MAPDs (enrollment weighted) offered the standard drug benefit (Hoadley, Cubanski, and Neuman 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" (Centers for Medicare and Medicaid Services (CMS) 2007).[11] 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 October 15 and December 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

[8] Medicare Prescription Drug, Improvement, and Modernization Act of 2003, Pub. L. No. 108–173, 117 Stat. 2066 (2003).

[9] One caveat is that prescription drugs directly administered by physicians, including many drugs used to treat cancer, are covered under Medicare Part B.

[10] See Newhouse (2004).

[11] See Hoadley (2005) and Hoadley et al. (2006, 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.

coverage without prior approval. In Section IIIC we discuss empirical evidence on within-year changes in plan formularies.

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.

B. *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 future demand for drugs than for other types of medical care.[12] 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 MA market prior to Part D. Lustig (2010) finds that insurers responded to adverse selection by constraining plan design, leading to a 14.5 percent reduction in the economic surpluses created by MA between 2000–2003.

Several factors 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 the hierarchical condition category system (MedPAC 2006a), whereas prior rates were only adjusted for geographic and demographic factors.[13] However, there is evidence that even after condition-based risk adjustment was fully introduced in 2007, MA plans are still able to profit by favorably selecting healthier patients conditional on risk scores.[14] MedPAC (2006a) explains that these risk-adjustment changes were intended in part to encourage participation by private insurers in traditionally under-served rural

[12] See Berndt (2004).
[13] See MedPAC (2008).
[14] See Brown et al. (2014) and Carey (2017).

areas of the country. Whereas SAPD plans operate regionally, with 34 regions in the country, most MAPD plans operate at the county level, and are able to enter the market in urban counties without necessarily entering nearby rural counties.

Within Part D there are several features that attenuate selection incentives for both MA and SA plans. First, Medicare pays Part D insurers on a risk-adjusted basis using a formula that accounts for the average difference in drug spending among FFS Medicare beneficiaries with different medical conditions. Carey (2017) finds that there are substantial imperfections in this risk-adjustment formula. For MA plans, Part D payments (and the risk-adjustment formula) are separate from medical insurance payments.

Second, Part D has risk-corridors to prevent plans from earning excessive profits or losses, and a reinsurance feature that subsidizes plans if any enrollee's costs exceed a certain threshold. During our study period, the impact of risk-corridors was small. Since 2008, Part D plans have received risk-corridor payments that subsidize 50 percent of losses whenever drug spending exceeds plan bids by 5 to 10 percent, and cover 80 percent of losses that exceed bids by more than 10 percent. The risk-corridors are symmetric, imposing a large effective tax rate on profits that exceed 5 percent of bids. 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 United States earned profit margins of about 5.3 percent in small group markets and 3.8 percent in large group markets.[15] Consistent with this pattern, MedPAC (2015) reports that in 2013, insurers with profits greater than 5 percent paid CMS a total of $737 million as a result of this tax, but 70 percent of these payments came from just two parent organizations, suggesting that most plans are within the normal industry profit range.[16] Reinsurance payments, however, affect many insurers. Although these payments were fairly stable during the time period we study, in subsequent years reinsurance payments have rapidly increased, and represented 37 percent of all Part D expenditures by 2015.[17]

Conceptually, both risk corridors and reinsurance attenuate the responsiveness of profits to selection, although they do not eliminate the incentive for plans to maximize profits. Thus, these risk-protection features may make the selection incentive we study more important to MA insurers relative to selection within Part D alone. They may also lead MA insurers to be more aggressive in pursuing spillover incentives, knowing that they are protected against large losses caused by high drug spending.

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 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

[15] See CMS (2013).
[16] Risk corridor payments are not published at the plan level, only at the parent organization level.
[17] See Medicare Trustees Report (2016).

on out-of-pocket costs fell by 55 percent in subsequent years, suggesting that consumer learning may have increased responsiveness of plan choice to generosity. They also find direct evidence that the potential savings associated with switching plans greatly increased the probability of switching.

If consumers are sufficiently responsive to cost-sharing rules when choosing insurance plans, they presumably must also respond to costs when making drug purchase choices. There is a large body of evidence consistent with this, although there is variation in estimates. Duggan and Scott Morton (2010) estimate the price elasticity of demand for prescription drugs under Medicare Part D to be −0.38, Lichtenberg and Sun (2007) estimate it to be about −0.7, and Einav, Finkelstein, and Polyakova (2016) estimate the average elasticity across drugs in Part D to be −0.24, with substantial drug-level heterogeneity. 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.[18]

II. Conceptual Framework

To help clarify our empirical objects of interest, we start with a 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 a drug's total cost that is covered by the insurer, r_d. The SAPD profit function is

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

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

$$\left[\frac{\partial P(r_d)}{\partial r_1} + \frac{\partial S(r_d)}{\partial r_1} - \frac{\partial c(r_d)}{\partial r_1}\right] Q + \left[P(r_d) + S(r_d) - c(r_d)\right] \frac{\partial Q}{\partial r_1} = 0.$$

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:

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

[18] See Simon, Tennyson, and Hudman (2009) for evidence in the case of state Medicaid pharmacy restrictions.

where $MAR(r_d)$ is the average risk-adjusted revenue that an MA plan receives 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 nondrug 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:

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

$$+ \left[P(r_d) + S(r_d) - c(r_d) + MAR(r_d) - MAc(r_d)\right] \frac{\partial Q}{\partial r_1} = 0.$$

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 spillover and Tamblyn essential drug 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

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

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. 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. Although we do not have evidence on each of these terms, one possibility is that as plans grow larger the derivative of enrollment with respect to cost-sharing, $\partial Q/\partial r_1$, becomes smaller relative to enrollment levels, Q, which could cause the spillover effect to increase in importance relative to the

selection effect. We return to this point in the empirical analyses, where we test for differential responses to the two incentives by plan market share.

Of course, our conceptual framework contains simplified versions of much more complicated profit functions faced by plans. A potential interpretation concern could arise if there are other factors that cause elements of the FOCs to differ between MAPD and SAPDs. Two parameters in the model deserve particular attention in this regard. The first is the moral hazard parameter, $\partial c(r_d)/\partial r_1$. If MAPD and SAPD enrollees have different price elasticities of demand, this term could differ and potentially confound the interpretation of our parameters of interest. However, there are a few pieces of empirical evidence that alleviate this concern. Einav, Finkelstein, and Polyakova (2016) estimate this price elasticity of demand for drugs in Part D, and find that for an average drug it is -0.24, but the standard deviation of the drug-level distribution of elasticities is 0.59, reflecting substantial across-drug heterogeneity. In our empirical specifications, we compare estimates from models that include drug NDC fixed effects, which absorb all of this across-drug variation in elasticities of demand, to models that do not, and find that our estimates are not sensitive to whether we condition on drug classifications or NDCs. If differences in average elasticity of demand of enrollees were an important factor, one would expect that the substantial differences in elasticity across drugs should also matter, but these differences do not appear to be strongly correlated with the selection and spillover incentive variables.

Geruso, Layton, and Prinz (2017) also directly estimate whether risk-adjustment errors in Affordable Care Act (ACA) exchange plans, which use a similar risk-adjustment formula developed for Medicare, are correlated with the drug-level elasticity of demand estimates from Einav, Finkelstein, and Polyakova (2016). Although their empirical approach is different than ours, it is based on similar intuition. They find no clear empirical relationship between selection incentives and drug elasticities of demand.

A second potential concern may be that $\partial Q/\partial r_1$, the derivative of enrollment with respect to coverage generosity for a particular drug, could differ between plan types. For example, since MA plans consist of a broader bundle of products, including medical and drug insurance, beneficiaries may be less responsive to drug formulary changes with respect to enrollment choices in MA plans than in SA plans. This term affects the selection incentive in our conceptual framework, and could attenuate the scope for inducing selection into MA plans using drug formularies, which would make it more difficult to observe significant formulary differences in response to selection incentives. However, as we show, there are significant formulary differences across plan types that are related to the selection incentive. Han and Lavetti (2017) also provide direct evidence that beneficiaries responded to our measure of MA switcher surplus, and estimate that the drug formulary mechanism we discuss increased the probability of an average Medicare beneficiary enrolling in an MA plan by 7.1 percent after Part D was introduced.

III. Data and Empirical Methods

There are several steps required to construct the key variables used in our analyses, and to link them to Part D plan formulary data. We begin by describing how we

calculate the MA switcher surplus variable for each drug, our measure of MA plans' selection incentives. This calculation requires first estimating the difference between risk-adjusted MA revenue and expenditures by medical condition, and then mapping these average differences to the drug level using data on the joint distribution of drug purchases and medical diagnoses. This provides a drug-level estimate of the MA switcher surplus, which we merge at the NDC level to the plan formulary data. Next, we describe the Medicare Part D formulary data that we use, and provide summary statistics on the data. We then discuss the lists of drugs that we use from the literature to identify spillover incentives, and the steps required to link these lists to formulary data. The third set of explanatory variables that we link to the formulary data are Part D-specific estimates of risk-adjustment errors from Carey (2017), which come from a different risk-adjustment formula than the one we study. Before presenting the main empirical specification and identification strategy, we provide an illustrative example of the sources of variation used in our analyses.

A. *Medicare Advantage Risk Adjustment and Selection*

The selection incentive we study arises because risk adjustment in Medicare Parts A and 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, for each beneficiary that was in FFS Medicare for the full prior calendar year we 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 nonrandomly selected, the average annual spending of the population of FFS beneficiaries who subsequently choose to switch to MA plans (the estimated value of parameter $\hat{\beta}$ in equation (1)) is \$902 [SE \$28] 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 \$1,030 using data from the early 1990s.

Using this difference, counterfactual MA capitation payments minus FFS expenditures, as a dependent variable, we estimate the average surplus associated with each of the 70 medical conditions in the risk-adjustment formula using the following fixed effects regression:

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

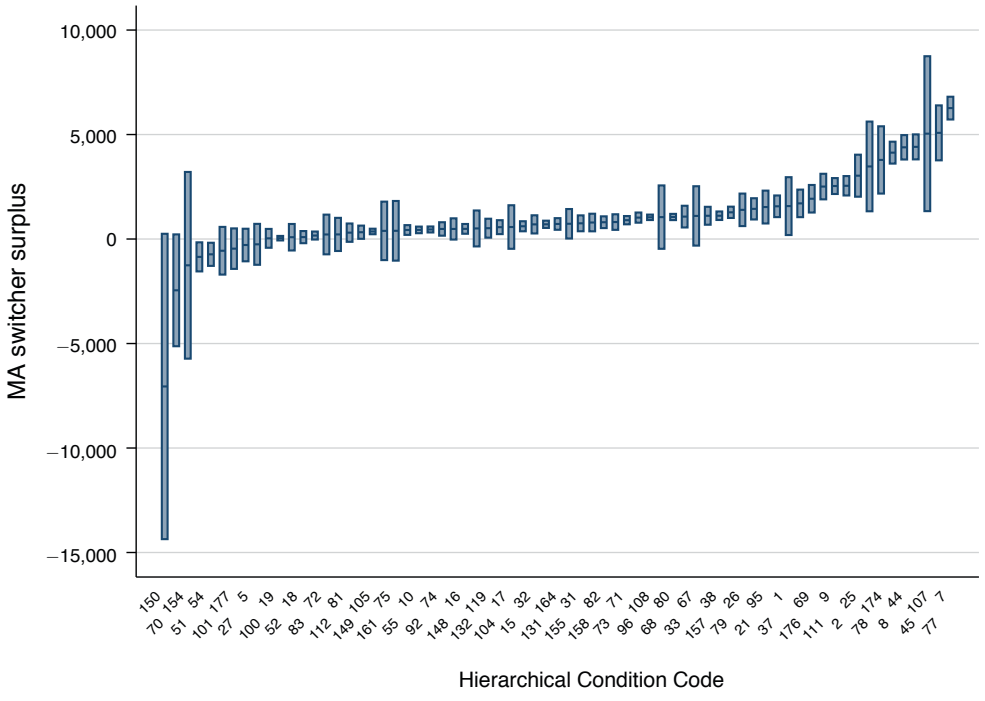

FIGURE 1. MA SWITCHER SURPLUS BY HIERARCHICAL CONDITION CODE

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 percent confidence interval for each estimate. HCC 130 (end-stage renal disease with dialysis) is dropped because Medicare rules restrict beneficiaries with this condition from switching into MA plans.

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.

The key parameters of interest from this model are the 70 estimated values of γ_k, which capture the average deviation from the mean MA switcher surplus for each of the 70 medical conditions, k. If there were no heterogeneity in patterns of switching into MA plans by HCC, these values would all be zero. Figure 1 shows the distribution of these estimates, along with the 95 percent confidence intervals.[19] 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

[19] The confidence intervals depicted in the figure do not adjust for the fact that these are exact population means. We return to this point in Section IIIF.

positive, suggesting that lower cost beneficiaries within these HCCs are more likely to switch into MA plans.

This evidence is consistent with the findings of Brown et al. (2014), who point out that because the variance of medical expenditures tends to increase with the expected mean, if plans are able to avoid beneficiaries in the upper tail of the expenditure distribution, they can potentially obtain large overpayments from enrolling beneficiaries with medical conditions that are on average more costly. They show that after HCC-based risk adjustment was introduced, the difference in baseline medical expenditures between MA switchers and FFS stayers was larger for beneficiaries with higher risk-scores. This implies overpayments to MA plans are larger for beneficiaries with medical conditions (HCCs) that tend to be associated with higher spending. Similarly, we find substantial variation in overpayments across HCCs, which is the variation captured by the γ_ks and depicted in Figure 1.

To be clear, these estimates do not necessarily equal MA plan profit for several reasons. The general approach in the literature of studying selection based on switching behavior (Morgan et al. 1997; Batata 2004; Brown et al. 2014), which we follow conceptually in estimating equation (1), is limited to the extent that the flow of switchers may be different than the stock of enrollees in any given plan. This is difficult to account for, because data on utilization and expenditures of individual MA enrollees are not generally available to researchers. Somewhat reassuringly, however, Brown et al. (2014) estimate that 75 percent of MA enrollees were switchers from FFS at some point, whereas only 25 percent joined an MA plan at the point of initial eligibility. They also find, using administrative risk scores linked to MCBS data, that the average risk score of the stock of MA enrollees increased over time at a rate that closely corresponded to the patterns observed for switchers. Although both of these findings suggest that studying switching choices may be informative about selection in MA plans more broadly, it is possible that some of the difference in average expenditures between switchers and stayers at the time of a switch may not persist.

The costs of treating beneficiaries in MA plans may also differ from the costs under FFS, regardless of risk scores, and this cost difference is not included in our calculation since we have no data on beneficiary utilization in MA plans. In addition, as discussed by Geruso and Layton (2015), 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.

B. *Mapping Medical Conditions to Drug Purchases*

The final step of the switcher surplus calculation, and the step in which we diverge from previous research studying switchers into MA plans, 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 order to connect 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 to its active ingredient using the NDC product database.[20] Beginning with the universe of Medicare Part D claims data from 2008–2010, we link each NDC 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 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 condition codes used in the Medicare Advantage risk-adjustment formula. Formally,

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

This set of equations gives a $d \times h$ matrix of coefficients, ν, where d is the top 431 most frequently purchased active ingredients,[21] and h is 70, corresponding to the number of HCC codes. The dhth element in this matrix equals the marginal effect of HCC h on the probability of purchasing a drug with active ingredient d.

For each estimated $\hat{\nu}_h$ 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

$$MA\ Switcher\ Surp_d = \sum_{h=1}^{70} \hat{\nu}_{dh} \times \hat{\gamma}_h, \tag{3}$$

where $\hat{\gamma}_h$ are the estimated coefficients from equation (1) and $\hat{\nu}_{dh}$ 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. Intuitively, we can describe the two dimensions that contribute to variation in MA switcher surplus in equation (3) as follows. First, drugs whose use is more strongly predicted by a medical condition that is associated with overpayments to MA plans increase drug-level MA switcher

[20] http://www.nber.org/data/national-drug-code-data-ndc.html.
[21] We exclude drugs with fewer than 38,000 prescriptions filled in the data for computational reasons.

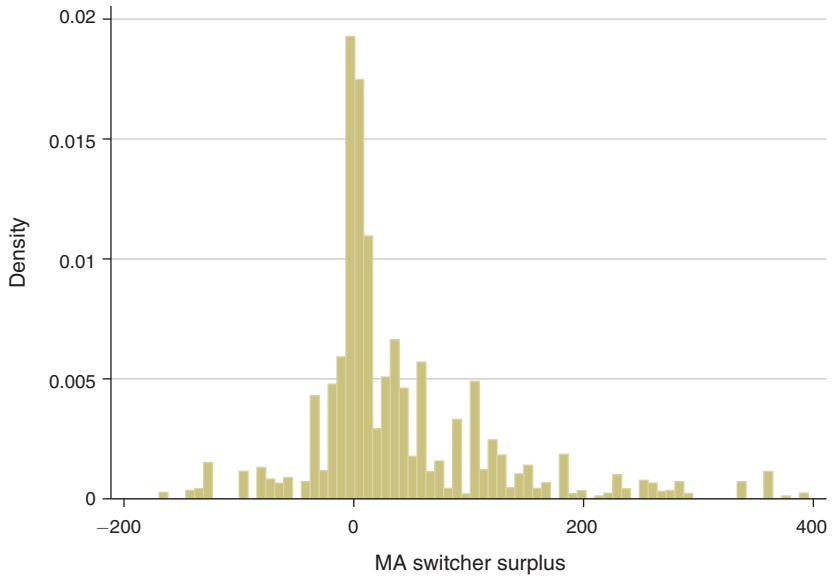

FIGURE 2. DISTRIBUTION OF MA SWITCHER SURPLUS BY DRUG ACTIVE INGREDIENT

Notes: This figure plots the distribution of values of $\sum_{h=1}^{70} \hat{\nu}_{dh} \times \hat{\gamma}_h$ from equation (3) corresponding to each of the 431 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 of \$1,615.

surplus because they have higher values of $\hat{\nu}_{dh}$. Loosely, one can think of this term as capturing the strength of the information signal that connects an HCC to demand for a drug. Second, holding $\hat{\nu}_{dh}$ fixed, if the magnitude of HCC-level overpayments $(\hat{\gamma}_h)$ increases, so too does the magnitude of the expected drug-level MA switcher surplus for all associated drugs.

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

C. *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,

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%	12%
Step therapy	2%	2%
Number of plan-formularies	6,973	4,317
Number of plan-drug pairs	26,417,085	15,854,699

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 and plan formulary pairs, and refers only to drugs that are on-formulary. "Percent of drugs on formulary" is calculated as the share of NDCs that each plan covers among the full set of NDCs that were covered by at least one plan in the same quarter.

but the cost of the drug to the insurance company was unknown, making it difficult to calculate the percentage of the total cost that the consumer must pay for drugs with fixed co-payments. 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. In total, the sample contains 2,588 unique drug NDCs and 5,530 unique plans.

One caveat associated with studying formulary design is that many Medicare enrollees are dually eligible for Medicaid, and receive additional low-income subsidies that reduce both premiums and cost-sharing (see Decarolis 2015). For beneficiaries with incomes below 135 percent of the federal poverty line, subsidies reduce cost-sharing to nearly zero in all plans,[22] which effectively reduces or eliminates coverage generosity differences between MAPD and SAPD plans. This could potentially attenuate the differences in plans' incentives somewhat, although the majority of Part D enrollees (70 percent) do not receive these subsidies (Hoadley, Cubanski, and Neuman 2015). The cost-sharing rules included in the formulary files, which we focus on in our analyses, are those relevant to non-dual-eligible beneficiaries.

We find that there are negligible differences in negotiated drug prices for MAPD and SAPD plans. For the same NDC, the average price paid by MAPD plans is within 1 percent of the average price paid by SAPDs. There also does not appear to be any meaningful correlation between differences in negotiated prices and MA switcher surplus. A $100 increase in MA switcher surplus is associated with about a 0.06 percent difference between MAPD and SAPD prices.

[22] Medicare beneficiaries who qualify for full Medicaid benefits and are in nursing homes have zero cost-sharing (Summer, Hoadley, and Hargrave 2010).

As described in Section IA, there are asymmetric restrictions on changes in plan design within years, permitting changes that increase generosity but not vice versa. One hypothesis we test is whether plans strategically alter their formularies within plan-years, since the selection incentive is theoretically strongest during the open enrollment period. Before directly testing this hypothesis, we look for summary evidence of changes to formulary designs within plan-years. To do this, we construct a balanced panel for each plan-year, which contains the set of all NDCs that the plan covers at any point during the plan year. On the extensive margin, we find that of the drugs covered by a plan at some point during the year, on average 11.5 percent of these drugs are excluded from the formulary during open enrollment, compared to only 5.2 percent, 3.4 percent, and 2.5 percent of drugs excluded during the other three quarters of the year. This pattern appears to be similar for MAPD and SAPD plans. On the intensive margin, however, we find evidence of relative differences in formulary changes for MA plans. To avoid the impacts of potential changes in negotiated prices, which could alter out-of-pocket costs for drugs with variable coinsurance, we calculate the fraction of drugs in the balanced plan-year panel for which the cost-sharing rule itself changes within the year. Consistent with regulatory restrictions, we find that only 0.4 percent of plan-drug-quarter observations that remain on a formulary have changes in cost-sharing rules that reduce generosity. However, in the other direction we calculate that 6.4 percent of plan-drug-quarter observations have changes in cost-sharing rules within the plan-year that increase plan generosity, and MAPD plans are about 23 percent more likely than SAPDs to make such changes.

We connect the formulary data by drug to two lists of spillover drugs to test the spillover hypothesis. The first list is the categorization of acute and chronic spillover drugs developed by Chandra, Gruber, and McKnight (2010). Since their categories were developed using a drug classification system from 1995, it cannot be linked to some more recent NDCs. We developed a mapping that links their categories to the current classification system used by CMS (the United States Pharmacopeia Classification System (USP)). 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 percent of the Acute and 72 percent of the Chronic classes.[23]

The second list we use was developed by Tamblyn et al. (2001, 422), 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 list, they are not directly overlapping, and both indicator variables can be included in regressions without causing substantial collinearity.

[23] The unmatched drug classes on the CGM Acute Care Drug list include: adrenal corticosteroids, anaphylaxis treatment kit, antiasthmatics/bronchodilators, antitoxins/antivenins, chloramphenicol/derivatives, DNA damaging drugs, hypotension/shock drugs, ocular anti-infective/anti-inflammator, polymyxins, and vascular disorders/cerebral/peripheral 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, hemostatics, neurologics, and enteral/parenteral nutrition agents.

D. *Part D Risk Adjustment*

In addition to the selection incentive described above that MA plans face, all Part D plans face separate selection incentives caused by differences in Part D profitability across medical conditions. Carey (2017) shows that this incentive arose primarily because the risk-adjustment formula did not quickly adjust following new drug entry or the onset of generic competition, which changed treatment costs. 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 this source of potential omitted variable bias, 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 (2017). Carey constructs these profitability measures in two steps using data from a 5 percent sample of Medicare claims. The first step is to link each drug in the formulary files to the mostly likely medical diagnosis associated with that drug. This model is identical to our equation (2), but Carey (2017) uses the largest estimated probit coefficient from the model to indicate the most likely diagnosis, whereas we use the entire matrix of coefficients that describe the full joint distribution. 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. This step is analogous to our equation (1), except that we also control for county fixed effects and demographic characteristics of beneficiaries. Carey (2017) 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 test for 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, 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.

E. *Illustrative Example: Fentanyl*

To give a specific example of the steps used in our analysis, we consider a case study of the drug fentanyl. Fentanyl is the most commonly prescribed synthetic opioid pain reliever in the United States. It is extremely potent, and 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 NDCs corresponding to fentanyl, and over 164,000 plan-drug-year observations.

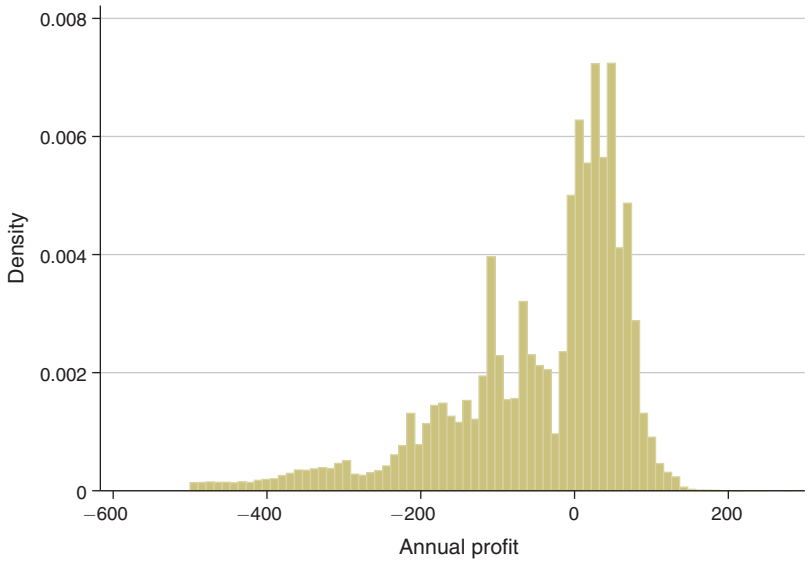

Figure 3. Distribution of Part D Risk-Adjusted Profit by Drug

Notes: This figure plots the histogram of Part D profits from Carey (2017) by drug NDC for all drugs on Part D formularies between 2009:I to 2011:III. Observations are at the plan formulary by quarter by drug level, and the distribution is truncated at −500 and +500.

Based on our analysis using Medicare claims data of the mapping between drug active ingredients and HCC codes, we statistically estimate that the condition that is most predictive of fentanyl use is HCC 7, metastatic cancer and acute leukemia, and the second most predictive condition is HCC 157, vertebral fractures without spinal cord injury. We chose Fentanyl as a case study example because there are only two primary medical conditions associated with the drug, making it relatively simple to explain. 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 with the same HCC 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 with the same HCC. 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. Thus, the selection incentive associated with fentanyl should

Table 2—Generosity of Fentanyl Coverage by NDC

Product	Meda Pharma. 12 mcg/ hour patch	Meda Pharma. 100 mcg/ hour 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	21,318	21,318	21,318	21,318
SAPD number of plan-drug pairs	12,730	12,754	12,754	12,754	12,754

Note: Calculations based on CMS Quarterly Pricing Files data.

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 above-average in profitability for MA plans.

In the formulary data there are 5 NDCs (out of 11 total) that represent 94 percent of fentanyl observations. As shown in Table 2, MAPD plans more generously cover all five of these NDCs. On average, beneficiaries in MAPD plans pay about 80 percent 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 percent of MAPD plan-drug observations for these five NDCs are on tier 1, the tier of most generously covered drugs, compared to just 53.7 percent of SAPDs. Only 6.5 percent of MAPD observations are on tier 3 or above, compared to 12.1 percent for SAPDs.

Within NDCs, unconditional out-of-pocket costs for fentanyl are 92 percent less in MAPDs. After conditioning on plan-level negotiated prices with pharmacies, plan deductible, premium, Carey (2017) 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. This case study is only meant to assist in conceptually illustrating the identifying variation in our analyses—the main empirical specification uses this same type of information, but aggregates results for all drugs.

F. *Empirical Model*

Table 3 summarizes the extensive margin dimensions of variation that we study. The difference in spillover incentives between MAPDs and SAPDs occurs year-round, and we identify the drugs for which these incentives apply using the CGM spillover and Tamblyn essential drug lists. We expect the selection incentive for MA plans to be strongest during the open enrollment period, when beneficiaries are free to choose new plans. To the extent that Medicare rules limit the ability of plans to decrease generosity within-year, the selection incentive may affect MA formularies year-round. On the intensive margin, we quantify the strength of the selection incentive using the drug-level MA switcher surplus described above.

Table 3—Identification of Parts A and 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

Table 4—Formulary Coverage Generosity by Drug Class

Dependent variable:	log OOP cost	
MA plan × antipsychotics/antimanics	−0.115	−0.093
	[0.007]	[0.006]
MA plan × antidepressants	0.024	−0.053
	[0.010]	[0.008]
MA plan × anthelmintics	−0.061	−0.052
	[0.007]	[0.007]
MA plan × penicillins	0.007	−0.008
	[0.011]	[0.011]
MA plan × antineoplastics	−0.009	0.000
	[0.007]	[0.007]
MA plan × Alzheimer/dementia drugs	0.022	0.003
	[0.008]	[0.008]
MA plan × respiratory tract drugs	0.036	0.010
	[0.010]	[0.008]
MA plan × blood glucose regulators	0.034	0.015
	[0.008]	[0.008]
MA plan × antianginals	0.018	0.027
	[0.012]	[0.011]
MA plan × anticonvulsants	0.093	0.073
	[0.007]	[0.006]
MA plan × antiarrhythmics	0.160	0.100
	[0.010]	[0.009]
MA plan × ace inhibitors	0.379	0.164
	[0.019]	[0.014]
MA plan × beta blockers	0.319	0.205
	[0.014]	[0.011]
MA plan × coronary vasodilators	0.347	0.256
	[0.012]	[0.010]
Observations	119,083,552	119,083,552
R^2	0.670	0.789
Drug NDC effects	No	Yes

Notes: Dependent variable is the log of the out-of-pocket cost that the beneficiary must pay in the initial coverage range and after any deductible has been met. All models include fifth 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.

Table 4 presents summary statistics that are suggestive of differences in formulary design. The coefficients shown are the average differences in log out-of-pocket costs paid by beneficiaries in MAPD plans relative to SAPD plans, by drug class. Although Table 1 showed that the average generosity of drug coverage in MAPD plans is similar to that in SAPD plans, Table 4 shows that this

masks substantial heterogeneity in generosity across different classes of drugs. For example, the MAPD enrollees pay 11.5 percent less out-of-pocket for antipsychotic and antimanic drugs. However, they pay about 32–38 percent 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 even for the exact same drug NDC, as shown in column 2. These generosity differences are all conditional on any differences in plan premiums, deductibles, and negotiated drug prices.

The empirical model we use to test the main hypotheses is

$$
\begin{aligned}
(4)\ \ LogOOPCost_{jdt} \ = \ & \alpha + \beta_1 X_{jdt} + \beta_2 MA\ Switcher\ Surp_d \\
& + \beta_3 MA\ Switcher\ Surp_d \times OE_t + \beta_4 MA\ Switcher\ Surp_d \\
& \times MA_j + \beta_5 MA\ Switcher\ Surp_d \times OE_t \times MA_j \\
& + \beta_6 Spillover\ Drug_d + \beta_7 Spillover\ Drug_d \times MA_j + \epsilon_{jdt},
\end{aligned}
$$

where $LogOOPCost_{jdt}$ is the log of out-of-pocket costs for drug d in plan j in quarter t,[24] X_{jdt} includes a polynomial in drug cost, an MA indicator, the monthly plan premium and annual deductible, estimated Part D profitability from Carey (2017) and an interaction with the MA indicator, an open enrollment indicator and interaction with MA, and quarter-by-year effects. Here, $Spillover\ Drug_d$ is a pair of indicator variables for the CGM spillover and Tamblyn essential drug lists. The unit of observation in this model is a product (drug NDC) by plan by quarter, and observations are weighted by drug cost to capture the fact that consumers are likely to be more concerned about the generosity of coverage for expensive drugs than they are for drugs with very low prices. One limitation is that we are unable to link quantities from the claims data to observations in the formulary data, so we cannot weight by total spending, although our analyses only include the most frequently purchased drugs with at least 38,000 prescriptions filled (for computational reasons).

The spillover effect 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. There are two selection hypotheses. The first is $\beta_4 < 0$, which would occur if drugs that tend to be taken by beneficiaries with HCCs that on average result in larger risk-adjusted overpayments to MA plans (i.e., higher values of MA switcher surplus), are covered more generously on MA drug formularies. The second hypothesis is $\beta_5 < 0$, which would indicate especially strong selection effects during open enrollment (OE).

Separately identifying these effects in the same model requires that MA switcher surplus is not collinear with the spillover drug variables. Empirically, the correlations between the MA switcher surplus and CGM spillover and Tamblyn essential variables are 0.03 and 0.05, respectively. Moreover, the data generating processes

[24] A Box-Cox test strongly favors the log specification over a linear specification, with a parameter estimate of 0.027, where zero is a log specification and one is linear. Online Appendix Table A13 shows that there is little impact on the estimates from omitting observations with zero cost-sharing.

associated with the variation in these measures are quite different. The selection incentive relevant to each drug stems from the fact that MA enrollees with certain medical conditions cost less than the risk-adjusted reimbursement, as documented by Brown et al. (2014). Although the exact mechanism that leads to this pattern of selection is not fully understood in the literature, nonrandom selection into MA plans may be driven by factors related to health insurance supply and demand, plan design choices, or advertising strategies.[25] In contrast, the spillover variables capture information about a physiological relationship between a drug and medical treatments for a condition. For example, failure by a patient with asthma to appropriately use an inhaler may lead to hospitalization due to the physiology of asthma symptoms and the ability of inhaled corticosteroids to prevent the complications that would lead to hospitalization. This combination of technology and physiology yields a data generating process that represents variation in spillover effects, which is conceptually very distinct from the data generating process that leads to errors in risk adjustment. We rely on medical experts to interpret and distill this data generating process into a list of spillover drugs that capture these effects.

There is an important caveat regarding inference and the interpretation of parameters from equation (4). As described in Section IV, the MA switcher surplus is a generated regressor that is estimated in equation (1), and inference in this case would generally require standard error correction. Although there are computational limitations to doing this (the steps in Sections IIIA and IIIB took several months to estimate once), since the generated regressor is estimated using the 100 percent population of Medicare beneficiaries this variable contains exact population statistics, and has effectively no sampling error. We implicitly use a finite-population standard error correction in the first stage, and doing so requires careful attention to the interpretation of the parameter estimates, as discussed by Abadie et al. (2014). To be consistent with population statistics, our MA switcher surplus variable can only be interpreted as data on the realized Medicare program, and does not reflect possible outcomes that could have occurred for different alternative populations, for example the population that may have existed if Medicare had different eligibility rules, or if medical or pharmaceutical technology had differed. As long as our estimates are appropriately interpreted as descriptive of the realized Medicare program and setting, then the estimation error in the first stage is zero, and the standard errors we report are equivalent to those that would be obtained using two-step correction for generated regressors.

IV. Results

A. *Selection Effects*

Estimates from equation (4), our main specification, are shown in Table 5. The key variables of interest for testing the selection hypotheses are "MA Switcher

[25] For example, Brown et al. (2014) note that race, ethnicity, and income are several demographic variables that are correlated with health costs but are excluded from the CMS risk-adjustment formula, and are relatively easy for MA plans to select on through targeted advertising.

Table 5—Effects of Selection and Spillover Incentives on Coverage Generosity

	Dependent variable: log OOP cost				
	(1)	(2)	(3)	(4)	(5)
MA switcher surplus	−0.804	0.180	−0.815	0.159	
	[0.015]	[0.016]	[0.016]	[0.016]	
MA switcher surplus × MA	−0.302	−0.289	−0.280	−0.271	−0.240
	[0.020]	[0.020]	[0.020]	[0.020]	[0.019]
MA switcher surplus × OE			0.136	0.261	0.321
			[0.021]	[0.021]	[0.020]
MA switcher surplus × OE × MA			−0.244	−0.233	−0.253
			[0.027]	[0.027]	[0.026]
CGM spillover drug	0.413	0.115	0.413	0.115	
	[0.005]	[0.006]	[0.005]	[0.006]	
CGM spillover drug × MA	−0.099	−0.112	−0.098	−0.112	−0.057
	[0.007]	[0.007]	[0.007]	[0.007]	[0.006]
Tamblyn essential drug	−0.149		−0.149		
	[0.004]		[0.004]		
Tamblyn essential drug × MA	−0.073	−0.077	−0.073	−0.077	−0.081
	[0.006]	[0.005]	[0.006]	[0.005]	[0.005]
log 30 day cost	0.882	0.860	0.882	0.860	0.292
	[0.004]	[0.004]	[0.004]	[0.004]	[0.007]
MA plan	−0.028	0.050	−0.032	0.046	−0.050
	[0.011]	[0.011]	[0.011]	[0.011]	[0.010]
OE × MA			0.049	0.054	0.042
			[0.011]	[0.011]	[0.010]
Part D surplus	−0.651	0.266	−0.651	0.266	
	[0.009]	[0.014]	[0.009]	[0.014]	
Part D surplus × MA	−0.102	0.215	−0.101	0.216	0.090
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
Observations	38,322,097	38,322,097	38,322,097	38,322,097	38,322,097
R^2	0.550	0.673	0.550	0.673	0.764
Drug class effects	No	Yes	No	Yes	Yes
Drug NDC effects	No	No	No	No	Yes

Notes: All models include fifth order orthogonalized polynomial in ln(30 day cost), quarter-by-year effects, plan premium, and plan deductible, and are weighted by drug cost. CGM spillover drug refers to drugs designated by Chandra, Gruber, and McKnight (2010, 204) as those that, "if not taken, will increase the probability of an adverse health event within a year." Tamblyn essential refers to drugs designated by Tamblyn et al. (2001, 422) 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 thousands of dollars. Standard errors, in brackets, are clustered by insurance plan.

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 3.0 percent 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 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 2.7 to 2.8 percent reduction in out-of-pocket

costs in MAPD plans outside of open enrollment, but a 5.0 to 5.2 percent difference during open enrollment. The evidence of selection effects outside of open enrollment suggests that plans may be somewhat constrained in their ability to change generosity within a year, 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 our preferred main estimates from a similar model that includes drug NDC effects, rather than drug class effects. The full drug NDC is similar 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 variation in generosity occurs within drugs, rather than potentially being due to substitution across different forms of similar drugs. Within NDC, MAPD beneficiaries pay 2.4 percent less out-of-pocket per $100 in switcher surplus outside of open enrollment, and 4.9 percent less during open enrollment.

Comparing the estimates from columns 4 and 5 is also informative. One limitation of the NDC effects model is that it does not capture differences in the choices of which drugs to include on the formulary. If two substitutable drugs are in the same class, but one has a higher MA switcher surplus, we might expect MA plans to put that drug on the formulary and omit the other. This is potentially important given evidence from Sacks (2015), who finds HMO plans spend about 19 percent less on statin drugs largely because these plans incentivize physicians to prescribe cheaper drugs within the class. To the extent this incentive is captured in formulary designs as well, the estimates shown in column 4 allow these across-drug within-class differences to be part of the formulary mechanism that may be used to induce selection, whereas in column 5 all of this variation is absorbed by fixed effects and does not contribute to identification of the selection parameters. It is therefore informative that we find little difference in the parameter estimates across these specifications.

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 (2017), we find that a $100 increase in risk-adjusted Part D profits (about 0.60 standard deviations) is associated with 6.5 percent reduction in out-of-pocket costs on average in SAPD plans, and about 7.5 percent in MAPDs. Since the Part D selection incentives, conditional on Parts A and B selection incentives and spillover incentives, are uniform across plans, the similarity of these two estimates was expected. However, there appears to be some difference in the substitution patterns of drug generosity across, as opposed to within, drug classes. When we include fixed drug class effects the estimates become positive—out-of-pocket costs are 2.7 percent higher for SAPDs and 4.8 percent 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. Column 5 shows that within drug NDCs, both plan types are similarly responsive to Part D profits.[26]

[26] In this specification, the base Part D Surplus term is absorbed by NDC effects because it is time-invariant.

B. *Spillover Effects in Integrated Plans*

In addition to the evidence on selection described above, we also find strong and consistent evidence that integrated MAPD plans internalize spillovers when designing drug formularies. Columns 1–4 in Table 5 show that for CGM spillover drugs, out-of-pocket costs are 10–11 percent lower in MAPDs than in SAPDs. The result also holds within NDCs, with a 6 percent difference in costs. Although the Tamblyn and CGM drug lists overlap somewhat, which could attenuate estimates when both variables are included in the same model, the results suggest consistently lower out-of-pocket costs in MAPD plans for each drug list. We find that out-of-pocket costs are 7–8 percent lower in MAPD plans for Tamblyn essential drugs, conditional on the CGM list, and this result is almost entirely due to within-NDC differences in generosity across plan types. As shown in online Appendix Table A2, the estimated CGM spillover effect increases in magnitude when the Tamblyn essential variables are excluded from the model. This evidence is consistent with Starc and Town (2016) who show that enrollment in an MAPD causally increases drug expenditures.

C. *Within Parent Organization Estimates*

Our main estimates treat MAPD and SAPD plans as separate entities, although in some cases they are owned by the same parent company. For example, the top ten national firms represented about 85 percent of total PDP enrollment in 2009, and MAPD enrollment was also highly skewed (Hoadley and Simon 2010). Table 6 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. The coefficients in the models containing parent organization effects are similar to the baseline estimates, and when parent by NDC effects are included all of the key coefficients remain statistically significant. Column 4 suggests, for example, that MAPD plans require beneficiaries to pay about 3 percent 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 substantial differences in the generosity of coverage of Tamblyn essential Drugs, with MAPDs charging about 6.7 percent less out-of-pocket for the same NDC.

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. To the extent that insurers use the same pharmacy benefit managers (PBMs) for all of their plans, this specification also removes the impacts of potential heterogeneity across PBMs, which could include unobserved rebate incentives.

D. *Interactions between Selection and Spillover Incentives*

One interesting extension of our main analyses is to test for interaction effects between spillover and selection incentives. The idea behind this test is that, to the extent plans have incentives to change formularies after open enrollment, this is

Table 6—Variation in Formularies within Parent Organization

	Dependent variable: log OOP cost			
	(1)	(2)	(3)	(4)
MA switcher surplus	−0.809		−0.818	
	[0.015]		[0.016]	
MA switcher surplus × MA	−0.306	−0.304	−0.291	−0.297
	[0.020]	[0.019]	[0.020]	[0.019]
MA switcher surplus × OE			0.107	0.189
			[0.021]	[0.018]
MA switcher surplus × OE × MA			−0.201	−0.059
			[0.029]	[0.023]
CGM spillover drug	0.426		0.426	
	[0.005]		[0.005]	
CGM spillover drug × MA	−0.099	−0.011	−0.099	−0.010
	[0.007]	[0.005]	[0.007]	[0.005]
Tamblyn essential drug	−0.151		−0.151	
	[0.004]		[0.004]	
Tamblyn essential drug × MA	−0.071	−0.067	−0.070	−0.067
	[0.006]	[0.005]	[0.006]	[0.005]
log 30 day cost	0.876	0.218	0.876	0.221
	[0.004]	[0.007]	[0.004]	[0.007]
MA plan	0.022	−0.029	0.017	−0.034
	[0.011]	[0.009]	[0.011]	[0.009]
OE × MA			0.063	0.051
			[0.009]	[0.008]
Part D surplus	−0.640		−0.640	
	[0.008]		[0.008]	
Part D surplus × MA	−0.137	−0.088	−0.137	−0.087
	[0.013]	[0.011]	[0.013]	[0.011]
Observations	36,198,688	36,198,688	36,198,688	36,198,688
R^2	0.568	0.888	0.568	0.888
Parent org. effects	Yes	Yes	Yes	Yes
Parent org. by NDC effects	No	Yes	No	Yes

Notes: All models include parent organization effects, a fifth order orthogonalized polynomial in ln(30 day cost), quarter-by-year effects, plan premium, and plan deductible, and are weighted by drug cost. CGM spillover drug refers to drugs designated by Chandra, Gruber, and McKnight (2010, 204) as those that, "if not taken, will increase the probability of an adverse health event within a year." Tamblyn essential refers to drugs designated by Tamblyn et al. (2001, 422) 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 thousands of dollars. Standard errors, in brackets, are clustered by plan.

likely to be driven by opposing selection and spillover incentives. For example, if a drug has a strongly negative selection incentive but also has spillover effects, MA plans have incentives to temporarily set high out-of-pocket costs during open enrollment, but then increase generosity for these drugs after open enrollment to avoid medical expenses associated with underutilization. However, if the same drug has no spillover effect it is less clear why a plan would increase coverage generosity after open enrollment. This suggests that for drugs with low selection incentives, variation in generosity within MA plans before and after open enrollment should be concentrated largely among spillover drugs.

To test this hypothesis, we collapse the data to plan-drug averages and estimate the following fixed effects regression:

$$(5)\quad \ln(OOP_{jd,OE}) - \ln(OOP_{jd,Non\text{-}OE}) = \alpha + \beta_1 X_{jd} + \beta_2 I(Low\ MA\ Switcher\ Surp_d) \times MA_j + \beta_3 Spillover\ Drug_d \times MA_j + \beta_4 I(Low\ MA\ Switcher\ Surp_d) \times Spillover\ Drug_d \times MA_j + \theta_d + \epsilon_{jd},$$

where $\ln(OOP_{jd,OE})$ is the average log out-of-pocket cost for drug d in plan j during open enrollment, $\ln(OOP_{jd,Non\text{-}OE})$ is the average log out-of-pocket cost outside of open enrollment, X_{jd} includes a polynomial in drug cost averaged over all quarters, an MA indicator, the average monthly plan premium, average deductible, estimated Part D profitability from Carey (2017), and an interaction with the MA indicator. Further, $I(Low\ MA\ Switcher\ Surp_d)$ is an indicator variable for low values of MA switcher surplus, defined as either the bottom quartile or bottom decile of the distribution; $Spillover\ Drug_d$ is an indicator variable for the CGM spillover and Tamblyn essential drug lists; θ_d is a fixed drug NDC effect. The hypothesis we test is that $\beta_4 > 0$, which would indicate that MA plans charge higher out-of-pocket costs for drugs with low switcher surplus and spillover incentives during open enrollment, and then increase generosity for these drugs afterwards.

The estimates shown in Table 7 are consistent with this hypothesis. Among drugs in the bottom quartile of MA switcher surplus that also appear on the CGM spillover list, MA plans set about 6.6 percent higher out-of-pocket costs during open enrollment relative to outside of open enrollment for drugs with the same NDC code. Among Tamblyn essential drugs the difference is 11.2 percent, and among drugs in the bottom decile of switcher surplus, with even less favorable selection incentives, each of these estimated differences increases in magnitude. This pattern in consistent with plans attempting to deter unprofitable enrollees using intertemporal variation in plan design.

E. *Tier Assignment and Cost-Sharing Rules*

In order to generate these differences in drug-level coverage generosity, plans must make different decisions with respect to some margin of plan design. Drug insurance formularies generally have tier-based structures, in which all drugs assigned to the same tier share a common cost-sharing rule, as opposed to setting completely flexible rules for each drug. Still, this leaves a large amount of choice at the drug level: plans choose whether to include each drug on their formulary, they choose the tier on which to place the drug, they choose how many tiers to use overall, and they choose the cost-sharing rules for each tier. In this section we investigate which of these dimensions of plan choice explains the variation in coverage generosity that we observe.

Table 7—Intertemporal Variation and Interactions between Selection and Spillover Incentives

Dependent variable:	$\ln(OOP_{OE}) - \ln(OOP_{Non\text{-}OE})$		
	(1)	(2)	(3)
Bottom quartile MA switcher surplus × CGM × MA	0.066		−0.000
	[0.012]		[0.010]
Bottom quartile MA switcher surplus × Tamblyn × MA		0.112	0.102
		[0.010]	[0.009]
Observations	12,334,646	12,334,646	12,334,646
R^2	0.511	0.511	0.511
NDC effects	Yes	Yes	Yes
Bottom decile MA switcher surplus × CGM × MA	0.121		−0.010
	[0.014]		[0.011]
Bottom decile MA switcher surplus × Tamblyn × MA		0.199	0.195
		[0.011]	[0.011]
Observations	12,334,646	12,334,646	12,334,646
R^2	0.511	0.511	0.511
NDC effects	Yes	Yes	Yes

Notes: Dependent variable is the difference in average log OOP costs for each drug-plan pair during open enrollment versus outside of open enrollment. All specifications include drug NDC effects, a fifth order orthogonalized polynomial in ln(30 day cost), plan premium, plan deductible, Carey Part D selection control interacted with MA, and all sub-combinations of each interaction term reported above. Standard errors, in brackets, are clustered by plan formulary level.

To determine how much of the variation can be explained by tier assignment, we regress the log of out-of-pocket costs on a set of seven dummy variables, one for each tier number observed in Part D formularies, as well as a specialty tier dummy. This regression reveals that 96 percent of all variation in log out-of-pocket costs can be explained by tier choice. The remaining 4 percent of unexplained variation is due to the fact that tier numbers mean different things for different insurers. We then use the parameters from this regression to predict log out-of-pocket costs based only on tier assignment, and re-run the main specifications using the tier-based prediction of the dependent variable. We find that tier assignment is not the primary dimension of formulary choice that leads to the results from Table 5. Estimates from these models are presented in online Appendix Table A3. Despite explaining most of the out-of-pocket cost variation overall, differences in tier assignment explain less than half of the main selection effect. Tier differences can explain the spillover effects with respect to Tamblyn essential drugs, but there are more complicated patterns for CGM spillover drugs.

Since the key explanatory variation is only partly driven by assigning drugs to different tier numbers in MA plans, what is the remaining source of variation? First, we find that within each tier number there are differences between MA plans and stand-alone plans in the choice of cost-sharing rules. Fourteen percent of MA observations use coinsurance rules, as opposed to a fixed co-payment, compared to 21 percent of stand-alone observations. These differences are most pronounced in higher tiers. In tiers 3 and 4, for example, SAPD plans are 14 percentage points more likely than MA plans to use variable coinsurance cost-sharing rules. These differences within tier numbers in the structure of cost-sharing rules

Table 8—Differences between MA and SAPD Plans in Out-of-Pocket Costs by Tier

Dependent variable:	log OOP cost
Tier 1 × MA	0.04
	[0.00]
Tier 2 × MA	–0.06
	[0.00]
Tier 3 × MA	–0.01
	[0.00]
Tier 4 × MA	–0.03
	[0.00]
Tier 5 × MA	–0.27
	[0.00]
Tier 6 × MA	–0.35
	[0.01]
Specialty × MA	0.16
	[0.00]
Observations	38,322,097
R^2	0.823
NDC effects	Yes

Notes: Model also includes dummy variables for Tiers 2–7, and a specialty tier indicator. An MA plan indicator is not included, but the interaction terms sum to one for MA plans. There are no observations in Tier 7 in MA plans.

lead to differences in the average generosity of coverage within tiers. As Table 8 shows, on average tier 1 drugs cost about 4 percent more out-of-pocket in MA plans, while drugs on tiers 2–5 cost less in MA plans, by 6 percent, 1 percent, 3 percent, and 27 percent, respectively. Specialty drugs cost on average 16 percent more in MA plans.

Second, the cost of spillover drugs is significantly higher than the cost of non-spillover drugs. The average prices of 30-day prescriptions for CGM Acute, CGM Chronic, and Tamblyn essential drugs are 71 percent, 87 percent, and 62 percent higher, respectively, than the average price of a non-spillover drug. Of course, our regressions control for polynomials in the cost of drugs, so these price differences alone cannot explain our results.

This combination of tier choice and cost-sharing rules differentially affects the generosity of MA coverage for spillover drugs. To see this, online Appendix Table A4 shows estimates from regressions of log out-of-pocket costs on triple interactions between tier effects, spillover drug effects, and an MA plan effect (with all combinations of single and pairwise effects included), along with the same control variables included in the main specifications. The coefficients show that CGM spillover drug effects are driven by the choice of MA plans to assign these drugs to tiers with fixed co-payments (especially tiers 2–3), which disproportionately impact these drugs beyond the interactions between tier effects and the MA dummy. The Tamblyn spillover effects (conditional on the CGM effects) are driven more by differences in cost-sharing rules in higher tiers.

Table 9—Use of Non-price Formulary Restrictions, logit Odds Ratios

	Quantity limit	Prior authorization	Step therapy
MA switcher surplus	0.049	0.884	0.072
	[0.000]	[0.010]	[0.001]
MA switcher surplus × MA	1.660	1.006	1.609
	[0.017]	[0.015]	[0.039]
MA switcher surplus × OE	0.625	0.406	0.416
	[0.018]	[0.017]	[0.029]
MA switcher surplus × OE × MA	2.018	1.151	1.748
	[0.072]	[0.062]	[0.148]
CGM spillover drug	0.579	1.110	0.732
	[0.001]	[0.004]	[0.003]
CGM spillover drug × MA	0.994	0.812	0.939
	[0.002]	[0.004]	[0.005]
Tamblyn essential drug	1.448	0.555	1.226
	[0.002]	[0.001]	[0.004]
Tamblyn essential drug × MA	0.955	1.060	1.204
	[0.002]	[0.003]	[0.005]
MA plan	0.712	0.903	1.125
	[0.002]	[0.004]	[0.005]
Part D surplus	1.900	0.320	1.717
	[0.007]	[0.002]	[0.017]
Part D surplus × MA	1.845	1.097	3.045
	[0.011]	[0.009]	[0.044]
Observations	38,322,097	38,322,097	38,322,097
R^2	0.111	0.129	0.113

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 spillover drug refers to drugs designated by Chandra, Gruber, and McKnight (2010, 204) as those that, "if not taken, will increase the probability of an adverse health event within a year." Tamblyn essential refers to drugs designated by Tamblyn et al. (2001, 422) 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 thousands of dollars.

These patterns suggest that MA plans achieve the differences in generosity that we document through a combination of different tier assignment than stand-alone plans, as well as differences in choices over cost-sharing rules. The interactions of these choices disproportionately affect drugs with stronger spillover and selection incentives.

F. *Nonmonetary Formulary Generosity*

Table 9 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 obtain permission from the insurer before a given drug will be covered, adding both a transaction cost and

potential ambiguity to the expected generosity of coverage. Step therapy restrictions require beneficiaries to try the most cost-effective forms of treatment before they are allowed to purchase more costly treatment options.

Previous research on non-price formulary restrictions by Heiss, McFadden, and Winter (2009) suggests that these restrictions have no impact on plan premiums, but that consumers dislike them, decreasing consumers' valuations of a plan by $1.01 per restriction on average. Given the discrepancy between premium effects and willingness to pay, the authors speculate that these restrictions are likely to decrease in frequency. Consistent with this prediction, Ketcham et al. (2012) find that the fraction of plans requiring prior authorization dropped from 9.6 percent in 2006 to 2.4 percent in 2007.

Table 9 presents log odds ratio estimates from logit models in which the dependent variable equals 1 if the plan-drug-quarter 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 percent, and increases prior authorization and step therapy by 0.1 percent and 6.1 percent, respectively. The gap in coverage restrictions between MAPD and SAPD plans grows even larger during open enrollment, more than doubling in each model. One speculative explanation for these opposing directions of generosity differences is that monetary generosity could potentially be more salient to consumers, or have 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. MAPDs are significantly less likely to impose step therapy or prior authorization for CGM spillover drugs. The effects of Tamblyn essential drugs are mixed, but this is partly due to overlap with the CGM spillover list.

G. *Extensive Margin Formulary Coverage Effects*

Table 10 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.[27] The mean of the dependent variable, shown in Table 1, is about 0.63, and less than 8 percent of observations have predicted probabilities that exceed one or are below zero. As Table 10 shows there are no economically meaningful effects of either incentive on the extensive margin coverage decision. For example, column 3 suggests that a one standard deviation increase in MA switcher surplus is associated with a one in 2,000 increase in the probability of a drug being included on the formulary. This suggests the intensive margin of formulary coverage generosity appears to be the primary mechanism for either inducing enrollment or managing medical cost externalities. This evidence is

[27] Online Appendix Table A10 compares logit estimates to OLS estimates for a similar model specification, and the main estimates are quite similar in the two models.

Table 10—Effects of Selection and Spillover Incentives on Formulary Inclusion

Dependent variable:	Drug on formulary		
	(1)	(2)	(3)
MA switcher surplus	−0.0208	−0.0298	
	[0.0010]	[0.0021]	
MA switcher surplus × MA	0.0082	0.0088	0.0032
	[0.0011]	[0.0011]	[0.0010]
MA switcher surplus × OE	−0.0248	−0.0245	−0.0209
	[0.0014]	[0.0014]	[0.0013]
MA switcher surplus × OE × MA	0.0041	0.0049	0.0028
	[0.0020]	[0.0020]	[0.0019]
CGM spillover drug	−0.0215	0.0004	
	[0.0005]	[0.0010]	
CGM spillover drug × MA	−0.0031	−0.0028	0.0010
	[0.0006]	[0.0006]	[0.0005]
Tamblyn essential drug	−0.0003		
	[0.0005]		
Tamblyn essential drug × MA	−0.0036	−0.0039	−0.0019
	[0.0006]	[0.0006]	[0.0005]
Observations	42,351,879	42,351,879	42,351,879
R^2	0.1198	0.1565	0.3906
Drug class effects	No	Yes	Yes
Drug NDC effects	No	No	Yes

Notes: All models include fifth order orthogonalized polynomial in ln(30 day cost), quarter-by-year effects, plan premium, and plan deductible. Coefficients are OLS estimates. See online Appendix Table A10 for a comparison between OLS and logit estimates. CGM spillover drug refers to drugs designated by Chandra, Gruber, and McKnight (2010) as those that, "if not taken, will increase the probability of an adverse health event within" a year. Tamblyn essential refers to drugs designated by Tamblyn et al. (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 thousands of dollars. Standard errors, in brackets, are clustered by plan formulary level.

consistent with the fairly restrictive constraints imposed by CMS that forbid plans from excluding a substantial number of drugs from formularies.

H. *Plan Enrollment and Market Share*

The theoretical framework in Section II suggests that the relative magnitudes of the spillover and selection effects may change as Q, the number of enrollees, changes relative to $\partial Q/\partial r$, 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. This suggests that selection incentives may decline in relative importance, while the spillover incentive may become larger, as market share increases.

In online Appendix Table A9 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.

V. 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, giving beneficiaries a choice between integrated Medicare Advantage insurance or fragmented medical and drug insurance. 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 understand how this flexibility has affected the design of plans.

We evaluate two ways by which offering a choice between integrated or fragmented plans may have affected the Medicare program. First, stand-alone drug coverage may lead to inefficient cost minimization by failing to internalize spillovers between drugs and medical care. Ideally, to understand the impacts of this incentive 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 nonrandom assignment prevents us from identifying this directly. Instead we examine the drug formularies themselves and look for evidence that firms respond to these incentives when designing coverage. Second, we point out that offering a choice between integrated or fragmented insurance plans creates differential advantageous selection incentives. Integrated MA plans have incentives to design their drug benefits to encourage enrollment by beneficiaries with conditions that are more profitable in the medical insurance market, after risk adjustment; stand-alone drug plans have no similar incentive.

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 conditional on their risk scores. 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, this selection effect would cause a patient with a condition that is one standard deviation less profitable to a Medicare Advantage plan, given the risk-adjustment formula, to pay about 7 percent more out-of-pocket for their drugs if they were to choose an MAPD over an SAPD. We also find that integrated MAPD plans internalize medical spillover effects associated with drug purchases; as a result they cover drugs more generously than stand-alone drug plans, reducing out-of-pocket costs to enrollees by about 6 to 8 percent relative to stand-alone plans for drugs that have spillover effects.

One limitation to focusing on insurance formulary design is that it may be difficult to conceptualize the relative importance of a 6–8 percent change in out-of-pocket costs. To put these effects in perspective, we conduct a simple back-of-the-envelope

calculation using our estimates and estimates from the literature on the elasticity of demand for drugs, which suggests that if the difference in spillover incentives were removed, beneficiaries in SAPD plans would increase their drug spending by about $300 to $485 million annually. This calculation comes from multiplying an average estimate of the spillover effect on out-of-pocket costs in MA plans of about 7 percent, by a range of estimates of the price elasticity of demand for drugs in Part D (-0.24 from Einav, Finkelstein, and Polyakova 2016, and -0.38 from Duggan and Scott Morton 2010), and the estimate from Starc and Town (2016) that about 40 percent of Part D spending is concentrated on CGM drugs: $7\% \times -0.38 \times 40\% \times \$60$ billion annual Part D spending $\times$ 76% SAPD market share in 2010 equals $485 million.

Han and Lavetti (2017) help put the magnitude of our selection estimates in perspective by extending the analyses to study the impacts of formulary differences on beneficiary plan choice and advantageous selection in the MA market. They estimate that for the average Medicare beneficiary, the change in advantageous selection following the introduction of Part D attributed to our measure of MA switcher surplus led to an abrupt 7.1 percent increase in the probability of enrolling in an MA plan, and the drug formulary mechanism we study was responsible for about 16 percent of the total growth in MA market shares between 2002 and 2009. As a back-of-the-envelope calculation, this change in advantageous selection associated with Part D formulary design led to about $735 million in additional Medicare spending in 2009.[28]

This comparison suggests that each of the two incentives we study is important in its own right, although the selection incentive may have had larger short-run effects on spending. Of course, neither of these estimates is directly informative of the welfare effects of formulary design distortions, which remains an important topic for future research. One specific caveat to make clear in attempting to assess the relative importance of these two incentives is that the full impact of spillover effects may not occur immediately, for example if underutilization of preventative drugs has dynamic consequences for the subsequent efficiency of health spending in the medium to long run.

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) suggesting that efforts to remove profit incentives through risk adjustment may have 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 nondrug 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.

[28] This calculation comes from assuming that 23 percent of the 45 million Medicare beneficiaries were enrolled in MA plans in 2009, payments to MA plans were about 10 percent higher than FFS costs per enrollee, and the average spending per beneficiary was about $10,000.

Finally, the results of this research are useful for understanding factors that affect health insurance plan design generally, as the potential for insurers to act upon spillover or selection incentives exists in a broad range of settings. Although it may be difficult to quantify the impacts of spillover incentives on, for example, the design of private employer-provided plans, the Part D market provides a setting in which it is easier to isolate the effects of these incentives. Similarly, risk-adjustment errors provide a measurable form of selection incentive, but simpler forms also exist in the majority of insurance markets in the United States. Moreover, the insurers and third-party administrators making formulary design decisions in Part D are largely the same insurers operating in many other segments of the private market. The more general manifestations of this incentive are only speculative because the literature has not yet been able to identify the impacts of these incentives on plan design outside of markets with risk adjustment; this remains an important topic for future research.

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