Externalities and Benefit Design in Health Insurance

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Abstract

Insurance benefit design has important implications for consumer welfare. In this paper, we model insurer behavior in the Medicare prescription drug coverage market and show that strategic private insurer incentives impose a fiscal externality on the traditional Medicare program. We document that plans covering medical expenses have more generous drug coverage than plans that are only responsible for prescription drug spending, which translates into higher drug utilization by enrollees. The effect is driven by drugs that reduce medical expenditure and treat chronic conditions. Our equilibrium model of benefit design endogenizes plan characteristics and accounts for asymmetric information; the model estimates confirm that differential incentives to internalize medical care offsets can explain disparities across plans. Counterfactuals show that strategic insurer incentives are as important as asymmetric information in determining benefit design.

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1 Introduction

The welfare generated by private health insurance critically depends on the structure of benefits offered by insurers. More generous benefits provide increased enrollee risk protection but are costly to the risk-bearing insurer. Increasing generosity mechanically increases plan expenditures and, more important from a welfare perspective, increases the likelihood of moral hazard and adverse selection. An optimal insurance plan must balance these gains from risk protection against inefficiencies due to asymmetric information.

While this theoretical trade-off is well-understood, most recent empirical models of equilibrium insurer behavior focus exclusively on the pricing behavior of insurers holding benefit design fixed (Handel (2013); Starc (2015); Town and Liu (2003); Tebaldi (2017); Ericson and Starc (2015); Decarolis, Polyakova and Ryan (Forthcoming)). The literature highlights the important role of imperfect competition and strategic insurer behavior – in addition to asymmetric information – in driving equilibrium outcomes. In this paper, we develop and estimate a tractable oligopoly model of premium setting and benefit design. We use our model to quantify the impact of both asymmetric information and strategic incentives on premium setting and benefit design. To study the role of insurers' strategic incentives in shaping benefit design, we examine the impact of an important friction in benefit design in our setting: externalities due to incentive misalignment. We find that this externality plays as important of a role as asymmetric information in affecting equilibrium plan benefit design.

Patient care often spans different treatment modalities (e.g., inpatient, office visits, outpatient surgery, specialist care, pharmaceuticals), and coverage for one type of care may interact and spill over to other services, creating the potential for an externality (Goldman and Philipson (2007); McGuire (2011); Goldman, Joyce and Zheng (2007)). We focus on the classic example of drug offsets: a substantial body of evidence shows that more generous drug coverage increases drug adherence, preventing future inpatient utilization. Unless insurers are responsible for coverage across linked treatment modalities, they will have limited incentives to internalize this externality in their benefit design decisions. The welfare impact of these benefit design decisions are potentially large, as the level and composition of consumption of health care services depend on insurer benefit design. We model the benefit design decisions of insurers and estimate the impact of this externality by studying the mandated separation of covered benefits categories for private insurers providing services in the United States Medicare system in Medicare Part D.

The Medicare Part D program provides prescription drug coverage to beneficiaries through private plans that are publicly financed. In 2015, over 39 million Medicare beneficiaries signed up for a Part D plan, accounting for $137 billion in drug spending. Under the Medicare Part D program, there are two major categories of drug plans: stand-alone prescription drug plans (PDPs) and Medicare Advantage Prescription Drug (MA-PD) plans. Stand-alone PDPs are mandated to cover only pharmaceutical expenditures, while MA-PD plans cover both drug and medical expenditures. These differences imply that the two types of plans face different benefit design incentives. Stand-alone

PDPs have an incentive to minimize drug expenditures, ignoring the impact on medical spending, while MA-PD plans have an incentive to minimize overall medical and drug expenditures, taking externalities from drug consumption to medical care utilization into account. As a result, MA-PD plans have an incentive to provide more generous coverage for drugs – particularly for those drugs for which increased adherence reduces medical expenditures.

Our primary data source is the rich Medicare Part D prescription drug claims data. We observe every prescription fill for the years 2006-2009 for a random 10% sample of all Medicare eligibles. These data contain information on the specific drug filled, retail price, enrollee out-of-pocket cost, and fill date for over 123 million drug claim events. We supplement claims data with information on beneficiary and plan characteristics. The beneficiary data contain information on enrollee demographics and the plan enrollment details. The plan data contain detailed information on the premiums and benefit design (e.g., which drugs are on each benefit tier and the coinsurance/co-payment structures of each tier).

We begin the empirical analysis by comparing the benefit designs of PDPs and MA-PD plans. The comparison is challenging because there are over 35,000 unique pharmaceutical products for which plans need to determine coverage, and plans generally employ a complex nonlinear plan design. Over our sample period, the Part D standard benefit package included a deductible, an initial coverage region where enrollee costs are limited, the donut hole where the enrollee is responsible for 100% of the cost of their drugs, and finally the catastrophic region where the enrollee is responsible for only a small fraction of drug cost. Using the detailed prescription level data with over 123 million claims, we estimate that MA-PD plan enrollees spend between 8 and 11 percent less on average for an identical bundle of drugs. The differences across plan type are larger for sicker enrollees. Furthermore, consistent with externalities playing a key role, the expenditure differentials are largely driven by drugs that have been explicitly identified as having large medical care offsets and treat chronic conditions like asthma, diabetes, and high cholesterol.

We then turn to the main empirical exercise: specifying and estimating the structural parameters of an oligopoly model of premium and benefit design choice. To capture insurer incentives, we model both consumer plan choice and insurer benefit design. Importantly, the model allows for drug expenditures and preferences to vary across consumers, and captures the extent to which differences in generosity by plan type can be rationalized by consumer demand and asymmetric information. We also allow strategic insurer incentives to vary by plan type. The model recovers cost and demand side parameters, enabling us to understand the economic rationale behind increased prescription drug benefit generosity in MA-PD plans. Consistent with previous work, the demand side estimates imply that consumer responsiveness to plan generosity when choosing plans is modest. Consistent with the importance of offsets, the supply side estimates show that MA-PD plans find it less costly to increase generosity than their stand-alone counterparts. Taken together, the model parameters imply that the increased generosity of MA-PD plans is driven by both asymmetric information and insurer cost side incentives.

Using the model and parameter estimates, we measure the impact of various economic forces on benefit design,

including the effect of plans internalizing the externalities generated by offsets. We find substantial medical care offsets in MA-PD plans: a $1 increase in prescription drug spending reduces non-drug expenditure by approximately 27 cents.[1] If stand-alone PDPs were forced to account for this externality in their premiums and benefit design behavior, insurer drug spending would increase by 7%. Based on these estimates, we find that stand-alone PDPs impose a $378 million externality (-.8% of Part D spending) on traditional Medicare each year.

In addition to explicitly modeling incentives to internalize offsets, the model allows for and explores the impact of asymmetric information. Specifically, we account for selection and screening incentives (Geruso, Layton and Prinz (Forthcoming); Carey (2017); Lavetti and Simon (2018)) and moral hazard (Einav, Finkelstein and Polyakova (2016)).[2] Critically, we show that asymmetric information also has an impact on benefit design: absent selection and moral hazard, insurer drug spending would increase by an additional 7%. In contrast to a large literature focused on the dead-weight loss due to moral hazard and over-consumption of medical services, our paper finds evidence of potential under-consumption. Our analysis further shows that strategic incentives are equally important determinants of benefit design. Given market imperfections, benefit design in both MA-PD and stand-alone PDPs is unlikely to be socially optimal. However, our approach helps us better understand insurer incentives, explore the implications of endogenous product benefit design in the Medicare Part D marke, and provide a framework for future researchers.

Our work also expands on the recent literature examining insurer competition in private Medicare markets (e.g. Decarolis, Polyakova and Ryan (Forthcoming); Curto et al. (2015)); more broadly, we contribute to a recent, growing literature on endogenous product design (see Fan (2013) and Crawford (2012) for a review).[3] The paper is organized as follows. Section 2 describes the market. Section 3 presents the reduced form estimations. Section 4 describes and estimates our model of firm behavior. Section 5 presents counterfactual exercises that put the magnitude of our effect in context, and Section 6 concludes.

2 Empirical Setting and Data

In this section, we describe the role of private insurers within Medicare, which provides health insurance to the elderly in the United States.[4] Private insurers play an important role in administering benefits; as a result, our setting is a data

[1] These offsets of medical care costs are viewed as sufficiently important to be included in government budget forecasts of health care expenditures, and are consistent with previous estimates. This estimate aligns with previous work by Chandra, Gruber and McKnight (2010), who examine offsets using demand-side consumption. We cannot employ a similar strategy because we do not observe medical claims for enrollees in MA-PD plans.

[2] We also explore the impact of behavioral biases including inertia (Ho, Hogan and Scott Morton (2015); Polyakova (2016)), and explore the impact of choice frictions and the under-utilization of cost-effective care (Abaluck and Gruber (2011); Ketcham et al. (2012)) and Manning et al. (1987), Brot-Goldberg et al. (2017)). Critically, our modeling approach accounts for imperfect competition among insurers (Decarolis, Polyakova and Ryan (Forthcoming)) and extends existing models that endogenize prices but hold product characteristics fixed (Handel (2013); Lustig (2010); Starc (2015); Town and Liu (2003); Tebaldi (2017); Ericson and Starc (2015)).

[3] Fan (2013) is the closest to our setting, as she explores continuous quality attributes. See also Draganska, Mazzeo and Seim (2009); Eizenberg (2014); Sweeting (2010); Wollman (2018).

[4] Medicare also provides health insurance coverage for the disabled and those with End Stage Renal Disease. We do not focus on those populations in this paper.

rich – if institutionally complex – laboratory in which to explore endogenous product design. Medicare Parts A and B are publicly administered and cover inpatient and outpatient services, respectively. Medicare Advantage (Part C) and Part D are administered by private insurers. Medicare Advantage is an alternative to traditional Medicare under Parts A and B, and Medicare Part D covers prescription drugs. Under both Medicare Advantage and Part D, Medicare beneficiaries are given information on the plan's premiums and benefit design and can select into any of the available plans in the area; competitive pressures should motivate insurers to offer low premium and cost-efficient products.

2.1 Private Plans and Medicare

Medicare Part C, the first broad private insurance option available to Medicare beneficiaries, was created under the Tax Equity and Fiscal Responsibility Act in 1982. Over its history, the program has gone by a variety of names (see McGuire, Newhouse and Sinaiko (2011) for a comprehensive history), and is currently known as Medicare Advantage. Medicare Advantage plans give Medicare beneficiaries the option to forego traditional Medicare and enroll in a private insurance plan for their health care benefits. Medicare Advantage plans are attractive because they typically offer more generous coverage. For each beneficiary that it enrolls, the plan receives a risk-adjusted, per-capita payment from the Centers for Medicare and Medicaid Services (CMS). Insurers also earn revenue from premiums paid directly by enrollees.[5] The program's popularity has waxed and waned over time, coinciding with the level of federal subsidy. As of 2009, the last year of our sample, 24% of all Medicare beneficiaries and 23% of Part D beneficiaries were enrolled in a Medicare Advantage plan.[6] There is significant geographic and demographic heterogeneity in the popularity of MA-PD plans: MA-PD plans are typically more attractive to middle and lower income as well as healthier beneficiaries within a market. Finally, the typical Medicare Advantage market is concentrated. In 2008, the largest four carriers had 45% of total Medicare Advantage enrollment.[7]

Premiums and benefit generosity in Medicare Advantage are determined through the plan's "bid" (the dollar amount the plan estimates will cover Part A and B benefits for a beneficiary in average health) and the county-level benchmark. If the plan's bid is above the benchmark, the payment from the government to the insurer is the benchmark plus the premium, which is the difference between the bid and the benchmark. If the plan's bid is below the benchmark, the payment is their bid plus 75% of the difference between the bid and the benchmark. The insurer must

[5] During our sample period, MA-PD plans received an additional Part D subsidy from the government and a premium payment from the enrollee. In 2009, the vast majority of Medicare Advantage plan beneficiaries (82%) were enrollees in a MA-PD plan.

[6] During our entire sample period, from 2007-2009, approximately 1 in 4 beneficiaries was enrolled in a MA-PD plan. Enrollment rates have continued to grow post-Affordable Care Act (ACA).

[7] The Medicare Advantage program is important from a policy perspective due to its sheer size in terms of enrollees and budget impact, but despite its popularity among beneficiaries, the Medicare Advantage program has always been controversial. There is substantial debate about the level of spending in Medicare Advantage as compared to traditional Medicare; cherry-picking by Medicare Advantage plans could lead to overpayment by the federal government or skew benefit design to attract favorable risks (Brown et al. (2014); Carey (2017)). Furthermore, a more recent literature argues that a substantial portion of the private gains from the Medicare Advantage program accrue to insurers, though the exact magnitude is a matter of debate (see Cabral, Geruso and Mahoney (2018); Curto et al. (2015); Duggan, Starc and Vabson (2016)). By contrast, a number of papers highlight the potential for better medical management under Medicare Advantage (Afendulis et al. (2011)). There is also evidence that the benefits of Medicare Advantage may spill over to traditional Medicare beneficiaries (Baicker, Chernew and Robbins (2013)).

use the payment between the bid and the benchmark (the "rebate") to fund benefit enhancement for enrollees. Benefit enhancements include reductions in medical care costs for enrollees, provision of added, non-Medicare benefits such as dental coverage, increased generosity of the drug benefit, and reduction of additional premiums. The payments made to the insurer are ultimately risk-adjusted based on the expected average cost of the plan's enrollment. MA-PD plans also submit a separate bid for the Part D component, and the payments that flow from that bid follow the Part D rules discussed below.

The Medicare Part D program, enacted under the Medicare Modernization Act in 2003, was introduced in 2006. Medicare beneficiaries can enroll in a private insurance plan that provides prescription drug coverage. For most Medicare beneficiaries, there are two ways to obtain drug coverage. They can enroll in a stand-alone PDP that only covers prescription drugs, or they can enroll in a MA-PD plan. Typically, enrollees in PDPs receive their medical coverage from traditional Medicare. Outside of the direct impact on plan enrollment, the PDPs have little incentive to consider the influence of their benefit design decisions on enrollee medical care utilization. Part D is also heavily subsidized; because of this subsidy it is financially beneficial for most Medicare beneficiaries to enroll in some form of drug coverage.

The program requires insurers to provide drug coverage at least as generous as the standard benefit, which has a nonlinear structure in which the beneficiary pays differing out-of-pocket prices depending on the phase of the benefit design. The deductible in 2008 was $275, followed by 25% cost-sharing in the initial coverage region (ICR) up to $2510 of expenditure, followed by the infamous donut hole phase where the enrollee incurs the entire cost of drug expenditures and, finally, catastrophic coverage where the enrollee faces a 5% coinsurance rate. Despite the large number of plan offerings typically available, markets are typically concentrated. Over 50% of Part D beneficiaries enroll in plans offered by three carriers.

While the strict regulation of Part D plans creates a minimum standard for plans, PDPs and MA-PD plans can provide more generous drug coverage than the minimum. In fact, the majority of plans in our sample offer coverage more generous than the standard benefit. The majority of these plans eliminate the deductible, and nearly one quarter of MA-PD plans had some form of donut hole coverage in 2006.[8] In addition to providing drug coverage that is at least actuarially equivalent to the standard benefit, plans must cover all or substantially all drugs within six protected drug classes and two or more drugs in another 150 categories. The set of PDPs available depends on which of the 34 regions an enrollee lives in, while the set of MA-PD plans available depends on the county of residence. The main focus of this paper is modeling benefit design. All plans feature some form of cost-sharing – consumer payments required at the time of purchase. Cost-sharing can take the form of coinsurance, in which the consumer pays a fixed percentage of the total cost. Cost-sharing can also take the form of fixed co-pays, in which the consumer pays a set dollar amount.

[8] By contrast, only 6% of PDP plans had donut coverage in 2006. The donut hole is being phased out as a part of the ACA. See Hoadley et al. (2014) for additional details.

To consistently model insurer behavior and its effect on consumers, we describe benefit design in terms of annual, expected consumer out-of-pocket costs (OOPC), which are a function of insurer choices. Increases in cost-sharing decrease plan generosity and increase OOPC.

Like Medicare Advantage plans, Part D plan premiums and government payments are determined through plan bids. The premium subsidy, paid by CMS, is also calculated using a formula that averages over plan bids. Premiums are calculated as the difference between the bid and the subsidy paid by CMS. To mitigate adverse selection, CMS employs a three-pillar risk equalization system within Medicare Part D. First, the government provides individual reinsurance during the catastrophic phase of the standard benefit, covering 80% of drug expenditure after an individual has incurred substantial drug costs. Second, risk adjustment attempts to equalize insurer profitability across beneficiaries by increasing subsidies for sicker enrollees. Despite this, there may still be selection conditional on the risk adjustment (Brown et al. (2014); Carey (2017)). Third, risk corridors provide downside protection against plan-level losses and cap plan-level profit margins. Finally, CMS provides additional subsidies to a subset of beneficiaries through the low-income subsidy (LIS) program.[9]

To summarize, during our sample period, a senior eligible for Medicare had multiple private insurance choices. They could opt out of traditional Medicare and into a Medicare Advantage plan and the private Medicare Advantage insurer would be responsible for all medical spending. The federal government pays the insurer a fixed subsidy payment per month for both the medical and prescription drug portion of the plan benefit; enrollees may be required to pay a premium as well. By contrast, the beneficiary could instead remain in traditional fee-for-service (FFS) Medicare and choose to augment Medicare Parts A and B with a stand-alone PDP. The private PDP insurer would cover drug expenditure, while the Medicare program would cover non-drug medical spending directly, including hospitalizations and physician services. The federal government would pay the PDP insurer a fixed subsidy payment per month for the prescription drug benefit; enrollees are required to pay a premium as well. Private insurers in Medicare Advantage have an incentive to take any offsets into account; in this paper, we focus on the behavior of MA-PD plans relative to stand-alone PDPs. As the discussion highlights, the institutional setting in which plans compete for both Medicare Advantage and Part D are complex. Our empirical analysis, in particular our structural demand and supply framework, accounts for this complexity.

[9]LIS eligibles comprise 28% of the total Part D population. They receive a subsidy equivalent to the region specific LIS benchmark and can enroll in any plan. If they enroll in a plan with a premium below the benchmark, they must pay the difference between that benchmark and premium but they still receive the benefit of the subsidized cost-sharing. Importantly, plans that offer premiums below the LIS threshold are eligible for randomized auto-enrollment of LIS beneficiaries. Previous research has highlighted that the presence of the LIS subsidy can distort plan bidding incentives (Decarolis (2015); Decarolis, Polyakova and Ryan (Forthcoming)). Additional information and robustness check are available in Appendix B.

2.2 Pharmaceutical Plan Characteristics and Medical Care Offsets

An underlying premise of our analysis is that increased pharmaceutical cost-sharing leads to reductions in prescription drug consumption, and that decreases in drug consumption leads to an increase in medical care utilization. In this subsection, we review the existing evidence.[10] Numerous studies have documented the presence of medical care offsets as related to changes in drug benefit design and the importance of considering these offsets in optimal insurance design (Goldman and Philipson (2007); McGuire (2011); Goldman, Joyce and Zheng (2007)). The evidence for meaningful offsets spans a variety of settings including employer-sponsored insurance (Gaynor, Li and Vogt (2007)), the Medicare population (Chandra, Gruber and McKnight (2010) and, specifically in the Medicare Part D program, McWilliams, Zaslavsky and Huskamp (2011)). The Congressional Budget Office, based on a survey of the literature, assumes that a 1% increase in drug consumption reduces non-drug medical consumption by 0.2% (CBO (2012)). Cost-sharing can lead to sub-optimal consumption because of discrepancies between private willingness to pay and social marginal cost, for a variety of reasons. There may be asymmetric information about the value of treatment (Manning et al. (1987)) or misalignment across multiple technologies (Ellis, Jiang and Manning (2015); Goldman and Philipson (2007)) or payers (see Cabral and Mahoney (2019)). Underutilization of drugs may also be "due to mistakes or behavior biases," referred to in the literature as behavioral hazard (Baicker, Mullainathan and Schwartzstein (2015)).[11] In sum, there is a large, robust literature documenting that among health care consumers in general and Medicare enrollees specifically, increased enrollee costs decrease drug adherence. Furthermore, this reduction in adherence leads to an increased likelihood of utilization of non-drug medical care.

While the Part D program is complicated, the intuition underlying the expected impact of pharmaceutical offsets on plan benefit design is relatively straightforward to describe and their empirical implications easy to characterize. Part D insurers' average and marginal costs are a function of endogenous plan characteristics. As enrollee costs decrease, the insurer's cost mechanically increases. In setting its benefit design, the insurer considers the trade-off between increasing generosity and hence costs and the benefit of increased demand. In addition, higher generosity plans may attract sicker consumers (adverse selection) and induce existing enrollees to spend more (moral hazard). MA-PD plans face a different set of incentives in designing benefits than stand-alone PDPs. In addition to the factors just discussed, MA-PD plans consider the spillover impact of drug consumption induced by increasing drug benefit generosity on

[10] A long literature, including the RAND health insurance experiment (Manning et al. (1987)), has shown that increased cost-sharing causally leads to a reduction in the consumption of pharmaceuticals. More recent evidence indicates that these reductions in consumption affect both high- and low-value services (Brot-Goldberg et al. (2017); Baicker and Goldman (2011); Maciejewski, Farley, Parker and Wansink (2010); Maciejewski, Bryson, Perkins, Blough, Cunningham, Fortney, Krein, Stroupe, Sharp and Liu (2010)). Within the Medicare Part D setting, multiple papers (including this one) have exploited the non-linear benefit structure to measure the behavioral response to cost-sharing (Abaluck, Gruber and Swanson (2018); Einav, Finkelstein and Schrimpf (2015); Einav, Finkelstein and Polyakova (2016); Dalton, Gowrisankaran and Town (2015)). This literature finds that increased cost-sharing reduces drug consumption and that cost-sharing in the donut hole is especially salient to consumers. Dalton, Gowrisankaran and Town (2015) find enrollees reduce the number of prescriptions filled by 21% upon entering the coverage gap. Furthermore, there is evidence that the introduction of the Part D program is associated with reduced hospital admissions in the Medicare population (Afendulis et al. (2011)).

[11] Within the context of the Part D program, the behavioral bias most frequently explored is myopia (Abaluck, Gruber and Swanson 2018, Dalton, Gowrisankaran and Town 2015).

overall (non-drug) medical expenditures. In the presence of drug offsets, increased average drug consumption reduces (non-drug) medical expenditures. As a result and unlike stand-alone PDPs, MA-PD plans have an incentive to internalize the impact of changes in drug plan generosity on medical care utilization and, all else equal, offer a more generous benefit design. We take this prediction to the data.

2.3 Data

In the Medicare Part D prescription drug claim event data, we observe every prescription fill for the years 2006-2009 for a random 10% sample of all Medicare eligibles. For much of our analysis, we aggregate these data to the enrollee-year level. We supplement these data with information on beneficiary and plan characteristics and merge in Medicare Advantage subsidy payment levels and county and metropolitan demographic information.

We begin the construction of our analytic sample by capturing all beneficiaries that were enrolled in a PDP or MA-PD plan between 2007 and 2009. This gives us 7,597,476 enrollee/year observations. We exclude any enrollees who receive low-income subsidies that negate the impact of benefit design by insurers.[12] This restriction leaves us with 4,802,000 enrollee-year observations. We then drop any enrollees for whom we do not have claims in 2006 to control for previous consumption, leaving us with 3,534,965 enrollee/year observations in the analytical data set.

Summary statistics are presented in Table 1. In the full sample, the average enrollee is 77 years old, 62% are female and 90% are white. Average total annual expenditure is $1763. There is substantial heterogeneity in annual expenditure, as highlighted in Figure A.3, which plots a histogram of annual expenditure in both MA-PD and standalone PDPs in 2008. There are a couple of observations to highlight: first, as expected, there is excess mass at the initial coverage limit, as highlighted by Einav, Finkelstein and Schrimpf (2015). Second, enrollees in MA-PD plans spend substantially less on prescription drugs than PDP enrollees.[13] While we observe rich data on drug spending, we do not observe non-drug medical claims for MA-PD enrollees; an important goal of the structural analysis is to compensate for this data limitation by using the model we develop to infer the level of medical expenditures.[14]

3 Reduced Form Evidence

We begin the empirical analysis by examining whether the differential benefit design incentives between PDP and MA-PD plans translate into differential enrollee expenditures. The initial analysis is at the claim level and compares enrollee out-of-pocket expenditure per day supply on identical drugs across plan type. While the analysis is primarily

[12] While we drop LIS enrollees for our main analysis, we run numerous robustness analyses to test the sensitivity of our findings to supply-side responses to the presence of the LIS population.

[13] We will control for this observed heterogeneity by controlling for lagged consumption in both our reduced form results and consumer demand system.

[14] Given that CMS encrypts the beneficiary identification variable, linking the CMS pharmacy claims to Medicare Advantage claims is not currently feasible.

Table 1: Enrollee Summary Statistics (Means and Standard Deviations)

Total Drug Expenditure	1762.78
	[2620.15]
Insurer Drug Expenditure	1114.65
	[2068.99]
Enrollee Expenditure	648.13
	[879.49]
Total day supply	1302.61
	[875.93]
% in MA-PD	0.40
	[0.49]
Age	76.87
	[7.25]
% Female	0.62
	[0.49]
% White	0.90
	[0.30]
Observations	3,465,139

Notes: Table presents summary statistics describing mean enrollee demographics, coverage, and utilization. The unit of observation is the enrollee-year; therefore, all expenditures are annual averages. Total day supply represents the sum across all drugs, and can therefore total more than 365. Standard deviations are in brackets.

descriptive, estimated differences will be driven by plan benefit design rather than enrollee demographics. Put differently, we are comparing expenditure on 20mg of Lipitor in a MA-PD plan to consumer expenditure on 20mg of Lipitor in a stand-alone PDP. Using claims level data, we estimate the parameters of the following equation using ordinary least squares:

$$Log(PatientPay_{cdjt}) = \alpha_d + \tau_t + \beta 1(MA\text{-}PD_{jt}) + \varepsilon_{cdjt}, \tag{1}$$

where $PatientPay_{cdjt}$ is out-of-pocket expenditure per day supply on prescription claim c for drug d in plan j and year t. The parameters α_d and τ_t are drug and year fixed effects. The drug fixed effects are at the National Drug Code (NDC) level, which capture all of the variation related to the detailed product and package (i.e., 20mg of Lipitor). The coefficient β captures the effect of interest.

Table 2 presents the results. Column 1 presents equation (1) exactly, and includes drug and year fixed effects. In column 2, we control for drug, year, and the phase of the prescription drug standard benefit for two reasons. First, insurers can alter enrollee costs given the benefit structure or alter the benefit structure itself. Second, sicker enrollees may consume more drugs in the donut hole; in this case, our results could be affected by the composition of fills. The results show a consistent pattern. Enrollee expenditure per day supply is 4-7% lower in MA-PD plans than stand-alone PDPs, holding the drug (NDC) constant.[15] The effect is robust and driven by benefit design. Table A.12 shows that

[15]In Appendix Table A.12, we also show some evidence that enrollees in MA-PD plans are more likely to fill 90-day prescriptions, which likely

the total cost per day supply for a given drug is equal across plan types; negotiated prices are not systematically higher or lower for MA-PD plans and do not explain the empirical results.

We also allow the effect to vary based on the type of drug.[16] In Panel B of Table 2, we present regression results in which we interact plan type with drug class indicators. We find statistically larger effects among drugs used to treat diabetes, asthma, and hyperlipidemia (high cholesterol). Enrollee expenditure per day supply in MA-PD plans is approximately 10% lower than in PDPs. However, anti-hypertensives are slightly more expensive in MA-PD plans. In Figure A.4, we show that this is due to heterogeneity across types of anti-hypertensive drugs. Enrollee expenditure per day supply in MA-PD plans is lower for the most cost-effective, recommended initial therapy (non-beta blockers, NICE (2011)). Finally, to examine how these expenditure differences manifest across the benefit phases, we estimate Equation (1) restricting the sample to deductible and ICR claims and donut hole claims. Consistent with Figure 1, which shows that few stand-alone PDPs offer donut hole coverage, Panel C of Table 2 shows that the expenditure differences are most pronounced in the donut hole. Going forward, we will focus on enrollee costs in the initial coverage range – which composes the bulk of fills and represents the effective marginal price for most enrollees – and in the donut hole – where we observe substantial variation and which is especially salient to enrollees.

The substantial difference in enrollee expenditure per day conflates lower costs for identical drugs and a different mix of drugs among MA-PD and PDP enrollees. The latter is especially likely to be important, as Medicare Advantage enrollees tend to be healthier on average and may take lower cost drugs. Therefore, we characterize plans by a drug premium p^D_{jmt} and benefit design x^D_{jmt}. Each element of the vector is defined as a weighted average of enrollee expenditure per day supply using national consumption weights. To create each benefit design variable, we construct an average enrollee cost per day supply for each product d in each phase-plan j specific combination in year t. For the initial coverage range (ICR) of the standard benefit, we denote this variable by x^{ICR}_{jmt}. For the donut hole, we denote this variable by x^{Donut}_{jmt}, such that $x^D_{jmt} = \left[\begin{array}{cc} x^{ICR}_{jmt}, & x^{Donut}_{jmt} \end{array} \right]'$. We then construct plan- and phase-specific enrollee cost measures for each drug, given by $l^{ICR}_{d\,jmt}$ and $l^{Donut}_{d\,jmt}$, by averaging observed enrollee expenditure within each drug-plan-market-phase cell. Critically, $l^{ICR}_{d\,jmt}$ and $l^{Donut}_{d\,jmt}$ do not depend on the composition of enrollee consumption within that plan. To capture average levels of consumption, we average the day supply by drug-year combination at the national level to create weight y_{dt}. The weighting allows us to construct a measure of enrollee cost that does not depend on enrollee behavior, where $x^{ICR}_{jmt} = \sum_d l^{ICR}_{d\,jmt} y_{dt}$ and $x^{Donut}_{jmt} = \sum_d l^{Donut}_{d\,jmt} y_{dt}$. Our measure of plan generosity captures the average enrollee cost for the average Medicare beneficiary. This construction nests formulary inclusion, tiering, coinsurance levels, and any benefit enhancements, but does not allow substitution if, for example, a particular drug

contributes to increased adherence; the estimates imply that 1.4% more prescriptions are 90-day fills under MA-PD plans, making the effect small, but still indicative of differential strategies by plan type. In Appendix Table A.10, we show that the results are not sensitive to the inclusion or exclusion of claims for which we observe third party payments. In Appendix Table A.11, we also show that these results are robust to the inclusion of flexible controls for day supply.

[16] Specifically, we examine the effect for drugs targeted by value-based insurance designs in the commercial insurance market (Chernew, Rosen and Fendrick (2007); Gowrisankaran et al. (2013)).

Table 2: Estimates of the Relationship between Plan Enrollment and Enrollee Expenditure

	Dependent Variable: $Log(PatientPay_{cdjt})$	
Panel A: Main Results	(1)	(2)
1(MA-PD)	-0.069***	-0.042***
	(0.003)	(0.003)
Observations	123,035,098	123,035,098
Adjusted R-Squared	0.610	0.678
Panel B: By High Offset Class		
1(MA-PD)	-0.057***	-0.032***
	(0.0042)	(0.004)
1(MA-PD)*Asthma	-0.075***	-0.083***
	(0.017)	(0.018)
1(MA-PD)*Hypertension	0.026**	0.035***
	(0.0081)	(0.0086)
1(MA-PD)*Diabetes	-0.076***	-0.075***
	(0.012)	(0.012)
1(MA-PD)*Cholesterol	-0.088***	-0.085***
	(0.012)	(0.012)
Observations	123,035,098	123,035,098
Adjusted R-Squared	0.610	0.678
Product Fixed Effects	X	X
Phase Fixed Effects		X
	ICR or Deductible	
Panel C: By Standard Benefit Phase	(Ded Amt. = 0)	Donut Hole
1(MA-PD)	0.00944*	-0.296***
	(0.00367)	(0.00507)
Observations	96,758,755	17,210,240
Adjusted R-Squared	0.680	0.646

Notes: Table presents linear regression models with logged enrollee expenditure per day supply as the dependent variable. The unit of observation is at the fill level (weighted by day supply), for the 2007-2009 period. The original data are obtained from a 10% sample of CMS prescription drug event files. We include year-level indicators and product fixed effects in all specifications. In some specifications, we also control the phase of the standard Part D benefit. Standard errors are clustered at the plan-product level. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table 3: Plan Summary Statistics

	PDP	MA-PD
x^{ICR}	0.50	0.46***
	[0.01]	[0.01]
x^{Donut}	1.93	1.71***
	[0.03]	[0.02]
1(Deductible)	0.191	0.166
	[0.020]	[0.008]
Premium	23.16	12.77***
	[0.55]	[0.32]
Observations	381	1926

Notes: The unit of observation is the year-plan. Mean enrollee cost per prescription and day supply are calculated given observed utilization levels. x^{ICR} and x^{Donut} are calculated for a standardized population using claims data and averaged across plans; for stand-alone PDPs, we aggregate across markets to the contract level. Deductible and premium information is taken from the Part D Plan Characteristics file. Standard deviations are in brackets. Statistically different means at the 1% level denoted by ***.

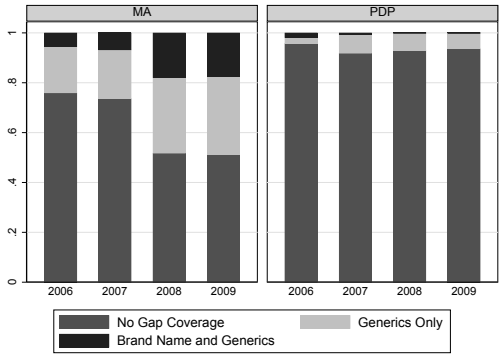
was excluded from an alternative formulary. While formularies are discrete, we create two continuous choice variables for tractability and explore alternative constructions in robustness checks.

Table 3 aggregates to plan-level characteristics. The first two rows show thatenrollee costs are lower in MA-PD plans. The difference is especially pronounced in the donut hole (denoted by x_{jmt}^{Donut}), where the average enrollee cost is 11% lower ($1.71 versus $1.93 for PDPs). The pattern is consistent with Figure 1: the vast majority of stand-alone PDP enrollees do not have any gap coverage, while over half of MA-PD enrollees have at least some gap coverage by the end of our sample. Once we account for the average consumption bundle, enrollee costs are also lower in MA-PD plans in the initial coverage phase (denoted by x_{jmt}^{ICR}). The average MA-PD enrollee pays 46 cents per day, while the average PDP enrollee pays 50 cents per day. These differences are smaller than those that do not correct for the composition of drugs consumed, but also indicate that MA-PD plans are likely to be more generous than their PDP counterparts. Differences in enrollee cost per day supply in each benefit phase lead to statistically and economically different enrollee cost per prescription (approximately $20 in stand-alone PDPs and $16 in MA-PD plans). Figure 2 summarizes the results of benefit design differences between PDP and MA-PD plans. The left panel depicts the standard benefit, and the right panel shows the mean structure by plan type.[17] There are other differences in plan characteristics as well, as highlighted by the third and fourth rows of Table 3; for example, MA-PD plans are slightly less likely to have a deductible, and generous Medicare Advantage subsidies mean that MA-PD plans tend to have significantly lower premiums.

Armed with evidence of meaningful benefit design differentials between PDPs and MA-PD plans, we turn to describing the behavioral response by consumers to these differences. There are several challenges to estimating the demand response, including the potential for enrollee selection and the role of dynamic consumption decisions given

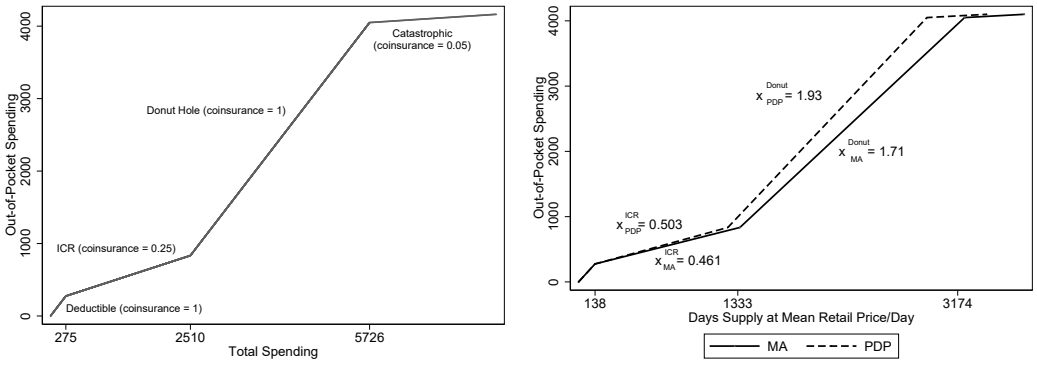
[17] Furthermore, we show in Appendix Table A.1 that it is costly for MA-PD firms to increase the generosity of their drug benefit.

Figure 1: Percentage of Enrollees with Gap Coverage by Plan Type



Notes: Figure constructed from plan characteristics data and author calculations.

Figure 2: Benefit Design



Notes: Figure constructed from plan characteristics data and author calculations. x_{PDP}^{ICR} and x_{PDP}^{Donut} are averages across stand-alone PDPs (and defined analogously for MA-PD plans).

the nonlinear structure of the benefit design. We address these challenges using the approaches outlined in Einav, Finkelstein and Schrimpf (2015), and Dalton, Gowrisankaran and Town (2015). Einav, Finkelstein and Schrimpf (2015) use the large discontinuous increase in cost sharing due to the donut hole to measure the behavioral response to cost sharing. Dalton, Gowrisankaran and Town (2015) show that, given the nonlinear benefit structure they face, Part D enrollees' prescription drug filling behavior is not consistent with standard models of dynamic drug consumption; the authors estimate a dynamic model of consumer price salience that explains this behavior. Both approaches show that consumers respond to higher cost sharing by reducing drug consumption. In Appendix A, we calculate elasticities using the methods described in Einav, Finkelstein and Schrimpf (2015) and Dalton, Gowrisankaran and Town (2015) and the variation described above. We estimate elasticities ranging from -0.53 (stand-alone PDPs) to -0.79 (MA-PD plans). Given that consumers respond to out-of-pocket costs, we expect benefit design to affect drug consumption. Given the Congressional Budget Office estimates of offsets (a 1% increase in drug consumption reduces non-drug medical consumption by 0.2%), we expect that increases in drug consumption reduce medical spending.[18]

Taken together, the results in this section show a consistent pattern. MA-PD plans offer more generous drug coverage than stand-alone PDPs. The difference is concentrated in drugs likely to generate large offsets. To isolate the treatment effect of MA-PD enrollment and abstract from selection, Appendix A leverages quasi-experimental variation in the probability of MA-PD enrollment. Table A.3 shows that the causal effect of MA-PD enrollment is to both decrease overall enrollee expenditure and increase total drug expenditure, as well as the fraction of expenditure paid for by insurers.[19]

4 An Oligopoly Model of Premiums and Benefit Design

In this section, we describe our empirical model of equilibrium insurer benefit design and outline our estimation strategy. We estimate the structural parameters of the model to (1) decompose demand and cost side rationales for MA-PD plans to offer more generous drug coverage; (2) provide estimates of the implied externality of increased drug coverage and the magnitude of the offset; and (3) perform policy counterfactuals. The model is simple enough to be tractable yet rich enough to capture the complexity of equilibrium insurer behavior when setting premiums and designing benefits. We describe the empirical model, then our demand specification and parameter estimates, and then estimate the key supply-side parameters.

[18]There are several caveats to note. First, existing studies ten to use within year variation; random plan reassignment over time may lead to different behavioral results. Second, MA-PD insurers have additional tools to increase consumption; for example, Table A.12 shows suggestive evidence of additional use of 90 day fills in MA-PD plans, which may improve medication adherence.

[19]The effect of MA-PD enrollment on overall utilization is larger in magnitude (13%) but not statistically different from the effect that would be predicted by differences in benefit design alone.

4.1 Empirical Model

We model the behavior of risk neutral, profit maximizing insurers selling prescription drug coverage to heterogeneous Medicare beneficiaries. CMS establishes the minimum plan generosity, $\underline{x}$, plan bidding rules, and risk stabilization programs, which are described in detail in Appendix B. Medicare beneficiaries, indexed by i, choose plans from a menu of $J+1$ plans (including an outside option) indexed by j in county-level market m and year t to maximize indirect utility. Each enrollee i is assigned risk (severity) quintile, q, which is determined by their 2006 drug expenditures. Utility is a function of plan characteristics which include annual drug premiums, p^D_{jmt}, expected annual out-of-pocket cost, $OOPC_{ijmt}$, which is a function of benefit design, and other features that may not be observable to the econometrician, ξ_{jqmt}.[20] As is common in the discrete choice literature, we assume ξ_{jmt} is exogenously given. A plan is defined as a county specific insurance contract. CMS rules imply that drug premiums p^D_{jmt} are a function of the plan's bid, b^D_{jmt}, such that $p^D_{jmt} = max\left\{0, b^D_{jmt} - \overline{b^D_t} + \chi\overline{b^D_t}\right\}$, where $\overline{b^D_t}$ is the enrollment-weighted average bid across all plans and χ is the share of the average bid not covered by the baseline subsidy z^D_t set by CMS.[21] Insurers maximize profits by choosing b^D_{jmt} and plan benefit design. Benefit design consists of a $2x1$ vector, $x^D_{jmt} = \left[\begin{array}{cc} x^{ICR}_{jmt}, & x^{Donut}_{jmt} \end{array}\right]'$, corresponding to the normalized enrollee out-of-pocket prices per days supplied in the initial coverage region and the donut hole.[22]

Plan profits depend on revenues, enrollee drug costs, and market shares, and are a function of the entire vectors of bids and product characteristics in the market: competitor bids affect the benchmark subsidy, while competitor product characteristics affect consumer plan choice and drug costs. The insurer collects the premium, which does not vary by enrollee. Federal subsidies augment consumer premiums. To mitigate adverse selection, CMS risk adjusts the plan subsidies. Insurers incur drug costs net of risk adjustment $c^D_{ijmt}(\mathbf{x^D_{mt}}, r_{it}, \eta_{ijmt})$, where $\mathbf{x^D_{mt}}$ is the $2xJ$ vector of benefit design characteristics in the market, r_{it} is the individual's risk score, and η_{ijmt} is an idiosyncratic error term unknown to the insurer at the time of they design plans and set premiums and, hence, does not affect insurer choices. While $OOPC_{ijmt}$ is a function of the focal plan's benefit design, costs and shares are a function of the entire vector of benefit designs across plans within a market m. We decompose individual drug costs into two additively separable components such that $c^D_{ijmt}(\mathbf{x^D_{mt}}, r_{it}, \eta_{ijmt}) = c^D_{ijmt}(\mathbf{x^D_{mt}}, r_{it}) + \eta_{ijmt}$, where we assume that $c^D_{ijmt}(\mathbf{x^D_{mt}}, r_{it}, \eta_{ijmt})$ is linear in the risk score. Drug costs vary with benefit design. There is a mechanical relationship between benefit design and plan cost, and benefit design can impact the quantity of drugs consumed (moral hazard) as well as selection conditional on risk-adjustment. The idiosyncratic term, η_{ijmt}, represents uncertainty in drug costs and is realized after all insurer decisions. As we describe in more detail below, we capture selection conditional on risk adjustment mechanism via

[20] Throughout, D superscripts refer to the drug portion of the plan, while M superscripts refer to the medical portion of the plan. Te function mapping benefit design to expected annual out-of-pocket cost is described in equation (6).

[21] For example, in 2010, $\chi = 0.36$. The baseline subsidy is equal to $(1-\chi)\overline{b^D_t}$. In practice, subsidies are individual specific and depend on enrollee risk; they aim to make enrollees equally profitable, regardless of type. In our model, individual risk is captured in costs. Therefore, z^D_t is the net of costs risk-adjusted subsidy for plan j in year t, and is not affected by selection.

[22] Other plan characteristics are held fixed (e.g., marketing).

the plan's cost structure.[23]

To aggregate, let B_{mt} be the number of Medicare beneficiaries eligible to enroll in a PDP or MA-PD plan, and A_{jmt} be the set of consumers who purchase plan j, yielding market share $s(\mathbf{b_t^D}, \mathbf{x_{mt}^D}, \xi_{\mathbf{mt}})$, which we will denote s_{jmt}. Average plan costs are given as $\frac{1}{A_{jmt}} \sum_{i \in A_{jmt}} c_{ijmt}^D(\mathbf{x_{mt}^D}, r_{it}, \eta_{ijmt}) = c_{jmt}^D(\mathbf{x_{mt}^D}, \bar{r}_{jmt})$, where $\bar{r}_{jmt}$ is the average risk score. The idiosyncratic error term, η_{ijmt}, enters linearly and is unknown to the insurer; therefore we omit it.

Formally, the post-enrollment expected profit function for stand-alone PDPs is:

$$\Pi_{jmt}^{PDP}(\mathbf{b_t^D}, \mathbf{x_{mt}^D}, \xi_{\mathbf{mt}}) = \left(p_{jmt}^D(\mathbf{b_t^D}) + z_t^D - c_{jmt}^D(\mathbf{x_{mt}^D}, \bar{r}_{jmt})\right) s_{jmt} B_{mt}. \tag{2}$$

The profit function for MA-PD plans is analogous, though plans also submit a bid for non-drug medical coverage, b_{jmt}^M.[24] We write:

$$\Pi_{jmt}^{MA\text{-}PD}(\mathbf{b_t^D}, \mathbf{b_{mt}^M}, \mathbf{x_{mt}^D}, \xi_{\mathbf{mt}}) = (p_{jmt}^D(\mathbf{b_t^D}) + z_t^D - c_{jmt}^D(\mathbf{x_{mt}^D}, \bar{r}_{jmt}) + b_{jmt}^M + z_{mt}^M - c_{jmt}^M(\mathbf{x_{mt}^D}, \bar{r}_{jmt}))) s_{jmt} B_{mt}, \tag{3}$$

where the M superscripts reflect medical ("Part C") bids and costs, and b_{jmt}^M is equal to the Part C bid which maps into Part C premiums as described in Appendix B. The subsidy payment for non-drug medical costs, z_{mt}^M, is paid to MA-PD plans to partially offset the plan's expected net-of-risk adjustment medical cost, $c_{jmt}^M(\mathbf{x_{mt}^D}, \bar{r}_{jmt})$, which is a function of prescription drug benefit design and average risk score. Similar to stand-alone PDPs, MA-PD plans must submit bids, incur costs that depend on individual and plan characteristics, and receive risk-adjusted subsidies. Unlike stand-alone PDPs, drug offsets imply that drug benefit design could increase or decrease drug expenditure, which could, in turn, increase or decrease medical expenditure.

To summarize, we describe the timing of the game and optimization for stand-alone PDPs:

1. CMS sets the minimum plan generosity, $\underline{x}$.
2. Insurers choose benefit design $x_{jmt}^D = \left[\begin{array}{cc} x_{jmt}^{ICR}, & x_{jmt}^{Donut} \end{array} \right]'$ and bids b_{jmt}^D to maximize profits.
3. The average subsidy z_t^D is determined based on the entire vector of bids, $\mathbf{b_t^D}$. The bid and subsidy determine the premium p_{jmt}^D.
4. Medicare beneficiaries choose plans to maximize utility.
5. Enrollees incur claims. The idiosyncratic term, η_{ijmt}, is realized.

[23] Risk adjustment affects insurer costs through $c_{ijmt}^D(\mathbf{x_{mt}^D}, r_{it})$, which is a function of the individual's risk score. Appendix B provides additional details on CMS's risk adjustment approach and the robustness of our results to different assumptions on the impact of risk adjustment.

[24] There are separate subsidies for the non-drug component of MA-PD plans that vary at the market level; we incorporate these explicitly.

6. CMS engages in risk stabilization, as described in the appendix.

Insurers play a Nash-Bertrand game in which beliefs about costs are correct, and both insurer and consumers make decisions to maximize their payoffs (profits or indirect utility) given the strategies of other players. Therefore, stand-alone PDPs choose their bid b^D_{jmt} and benefit design x^D_{jmt} to maximize profit subject to the minimum generosity requirement:

$$\max_{b^D_{jmt}, x^D_{jmt}} \Pi^{PDP}_{jmt}(\mathbf{b^D_t}, \mathbf{x^D_{mt}}, \boldsymbol{\xi}_{\mathbf{mt}}) \, s.t. \, x^D_{jmt} \geq \underline{x}. \tag{4}$$

MA-PD plans optimize over medical bids b^M_{jmt} in addition to drug bids and drug benefit design:

$$\max_{b^M_{jmt}, b^D_{jmt}, x^D_{jmt}} \Pi^{MA\text{-}PD}_{jmt}(\mathbf{b^D_t}, \mathbf{b^M_{mt}}, \mathbf{x^D_{mt}}, \boldsymbol{\xi}_{\mathbf{mt}}) \, s.t. \, x^D_{jmt} \geq \underline{x}. \tag{5}$$

The design of the medical benefit is taken as given.

4.2 Plan Choice

4.2.1 Consumer Behavior

We first flexibly estimate consumer preferences over plans using a nested logit model. We allow preference parameters to vary with severity quintile, q which we can measure using the detailed claims data.

Consumers have preferences over the annual premium, p^D_{jmt}, and annual expected out-of-pocket costs for enrollment in plan j, $OOPC_{ijmt}$. $OOPC_{ijmt}$ is a nonlinear, individual-plan specific function of x^D_{jmt}. For example, a consumer ending the year in the initial coverage phase has $OOPC_{ijmt}$ equal to the deductible (if any) and the number of day supply in the initial coverage phase multiplied by x^{ICR}_{jmt}.[25] The relationship between the structure of the Part D benefit, insurer choice variables, and $OOPC_{ijmt}$ is described in Figure 2: the first panel describes the standard benefit, the second panel describes how the insurer choice variables captured by x^D_{jmt} map into $OOPC_{ijmt}$ and differences across plan types. Premiums are a function of plan bids, as described above.

We divide the sample into five types of consumers, based on quintiles of 2006 total drug spending. We divide plans

[25] Formally, we construct $OOPC_{ijmt}$ by developing a function that maps total drug spending into $OOPC_{ijmt}$, taking insurer cost-sharing, consumer consumption, and the structure of the standard benefit as given. For a consumer i in market m with consumption (day supply) d_{it}, this can be written as:

$$OOPC_{ijmt} = \begin{cases} R_{jt} d \; if \; R_{jt} d_{it} < DED \\ x^{ICR}_{jmt}\left(d - \frac{DED}{R}\right) + DED \; if \; R_{jt} d_{it} \geq DED \; and \; R_{jt} d_{it} < ICL \\ x^{Donut}_{jmt}\left(d - \frac{ICL}{R_{jt}}\right) + DED + \gamma_{ICR}(ICL - DED) \; if \; R_{jt} d_{it} \geq ICL \; and \; R_{jt} d_{it} < CAT \\ .05 R_{jt}\left(d - \frac{CAT}{R_{jt}}\right) + DED + \gamma_{ICR}(ICL - DED) + \gamma_{Donut}(CAT - ICL) \; if \; R_{jt} d_{it} \geq CAT \end{cases}, \tag{6}$$

where d is the day supply, γ represents the average coinsurance in each phase, R_{jt} is the mean retail price for plan j, and DED, ICL, and CAT represent the statutory deductible, initial coverage limit, and catastrophic cap, respectively. For any enrollee and level of consumption, there is a mechanical and monotonic relationship between the insurer's choice variables x^{ICR}_{jmt} and x^{Donut}_{jmt} and enrollee costs $OOPC_{ijmt}$.

into three nests, indexed by g: stand-alone PDPs, MA-PD plans and the outside good. The outside good consists of both no drug coverage and any coverage not associated with a PDP or MA-PD plan (such as an employer-sponsored plan). We aggregate $OOPC_{ijmt}$ to the risk quintile level and allow consumers in each quintile to have different preferences over the unobserved characteristics which we now index by q, ξ_{qjmt}. In each risk quintile q, consumer utility for plan j (which can be either a PDP or a MA-PD plan) in market m at time t is given by:

$$u_{iqjmt} = \overline{\xi_{qj}} + \alpha_q^p p_{jmt}^D + \alpha_q^x OOPC_{qjmt} + \tilde{\xi}_{qjmt} + \zeta_{iqg} + (1-\sigma_q)\varepsilon_{ijmt}, \tag{7}$$

where we decompose ξ_{qjmt} into a time-invariant plan characteristic (i.e., plan fixed effects), $\overline{\xi_{qj}}$, and a mean zero deviation, $\tilde{\xi}_{qjmt}$. The drug premium is given by p_{jmt}^D. Average $OOPC_{qjmt}$ within a quintile (now indexed by q) is a function of benefit design as defined above. Finally, ζ_{iqg} is common to all products in nest g and has a distribution function that depends on σ_q with $0 \leq \sigma_q < 1$. We assume that ε_{ijmt} has an extreme value distribution, which allows us to calculate within quintile shares s_{qjmt} using the standard formula (Train (2009)). Preferences over the time-invariant features of plans, premiums, and generosity are all heterogeneous: we allow unobserved plan quality ξ_{qjmt}, premium and OOPC coefficients α_q^x and α_q^p, and $(1-\sigma_q)$ to vary by risk quintile. We do not directly model the impact of MA-PD non-drug premiums on consumer choice in MA-PD plans.[26]

4.2.2 Demand Estimation

The choice set is defined at the county-year level. While PDPs have identical offerings within the 34 large PDP regions, MA-PD plans can choose which counties to enter within a region. Medicare assigns both "contract IDs" and "plan IDs." In MA-PD plans, the contract ID is typically specific to a geographic market; in stand-alone PDPs, the contract ID is typically national and the plan ID within a contract ID specific to the geographic market. As is standard in the literature, a MA-PD product is defined as a unique Medicare contract ID. If there is more than one Medicare Advantage plan offered by an individual insurer within a carrier contract-county pair, we use the premium of the lowest numbered plan among MA-PD plans (Lustig (2010); Nosal (2011)). A PDP plan is defined as a Medicare contract ID-county combination; we average benefit design parameters within a county. Assuming one Medicare plan ID per county within a contract ID, this is equivalent to defining the product at the Medicare contract ID-plan ID combination.[27]

To capture firm incentives, we must identify the causal impact of premiums and OOPC on plan enrollment. Our estimates will be biased if ξ_{qjmt} is correlated with bids or benefit design. We address this issue via a two-pronged approach. First, we include product fixed effects, $\overline{\xi_{qj}}$, that are allowed to vary with risk quintile: the unobserved

[26] The vast majority of plans have zero (non-drug) premiums, and some rebate a portion of the Part B premium, reducing salience to consumers and making measurement difficult. The supply-side inversion will assume – consistent with a neoclassical model – that the elasticity with respect to drug premiums, non-drug premiums, and subsidies is the same.

[27] In unreported specifications, we confirm that all of our results are robust to defining PDPs as a contract ID-plan ID combination.

product characteristic, $\tilde{\xi}_{qjmt}$, is the deviation from the plan mean for the risk quintile in question. Second, we instrument for the premium, OOPC, and the inside share. The instrument for the inside share is the urban dummy interacted with an MA-PD dummy, which captures the fact that MA-PD plans are more popular in urban counties. Following a series of papers (Afendulis, Chernew and Kessler (2017); Cabral, Geruso and Mahoney (2018); Duggan, Starc and Vabson (2016)), we rely on a statutory discontinuity in MA-PD plan reimbursement. For counties with relatively low FFS spending, payment is set equal to a floor. Beginning in 2003, differential floors were applied to urban and rural counties – approximately two-thirds of counties are floor counties. Higher reimbursement in urban counties led to more plan entry and higher Medicare Advantage penetration rates (Duggan, Starc and Vabson (2016)). The empirical evidence in Afendulis, Chernew and Kessler (2017); Cabral, Geruso and Mahoney (2018) and Duggan, Starc and Vabson (2016) strongly indicates that this variation in Medicare Advantage penetration rates is driven by the differential Medicare Advantage subsidies and is not correlated with individual health risk or other demand side factors.[28]

As is common in this setting, we use Hausman-style instruments for premiums and OOPC: the average premiums and OOPC in all other markets. Conditional on plan and consumer quintile specific means, the exclusion restriction requires that market-specific plan valuations are independent. Correlation in OOPC and premiums within a plan across markets is then due to common marginal costs. For example, consider a plan with coinsurance that is offered in two markets. Suppose that a large pharmacy chain also operates in both markets, while independent pharmacies operate separately in each market. The chain pharmacy and plan negotiate retail drug prices for both markets jointly. Because consumers in both markets pay a percentage of jointly negotiated retail prices, OOPC are correlated across markets. Common marginal costs (negotiated retail prices) – rather than demand shocks – drive the correlation. Common negotiated retail prices will also lead to correlation in premiums within a plan across markets. Common (marginal) administrative costs (e.g., claims processing or broker commissions) will also generate useful variation.[29]

A number of recent papers (Ericson (2014); Heiss et al. (2016); Ho, Hogan and Scott Morton (2015); Miller and Yeo (2014); Polyakova (2016); Wu (2016)) document "stickiness" in plan choice over time. Following Decarolis, Polyakova and Ryan (Forthcoming), we allow for this inertia by including plan vintage – defined by the number of years the plan has been available in a market – in the utility function in our preferred specification.[30] While we allow the dissimilarity term, time-invariant plan quality, and premium and OOPC coefficients to vary by risk quintile, the

[28] The exclusion restriction requires that shocks to consumer utility for a given plan and area are uncorrelated with the CMS's definition of urban and rural counties.

[29] By assumption, premiums in other markets are uncorrelated with the market-specific valuation in the focal market.

[30] They show that their approach corresponds to "an explicit structural model of inattention and choice" (Hortascu, Madanizadeh and Puller (2015)). Because we are not explicitly interested in the effect of switching costs on premiums or benefit design, we do not develop a dynamic model of premium setting or benefit design. Additionally, we do not allow for selection on moral hazard. Put differently, the relationship between $x_{jmt}^{ICR}, x_{jmt}^{Donut}$, and $OOPC_{qjmt}$ is purely mechanical; therefore, the derivative of shares with respect to x_{jmt}^{ICR} and x_{jmt}^{Donut} is given by $\sum_q \frac{\partial s_{qjmt}}{\partial OOPC_{qjmt}} \frac{\partial OOPC_{qjmt}}{\partial x_{jmt}^{ICR}}$ and $\sum_q \frac{\partial s_{qjmt}}{\partial OOPC_{qjmt}} \frac{\partial OOPC_{qjmt}}{\partial x_{jmt}^{Donut}}$, respectively. Differences in drug demand across plan types is consistent with plans attracting different types of consumers on average, but not necessarily selection on moral hazard on the margin. Finally, we do not directly model the impact of the subsidy policy on plan behavior, though we also examine the magnitude of this potential distortion in the robustness checks subsection and find that our conclusions are robust.

nested logit error term, $\zeta_{iqg} + (1-\sigma_q)\varepsilon_{ijmt}$, is the only source of unobserved consumer heterogeneity in the model. In robustness analyses, we allow for additional unobserved consumer heterogeneity with risk quintiles; our main findings are not sensitive to allowing for more flexible patterns of substitution.

4.2.3 Consumer Heterogeneity and Selection

Capturing heterogeneous consumer preferences is a critical component of modeling selection, and the model explicitly accounts for heterogeneity in plan choice. For example, healthier enrollees may prefer MA-PD plans regardless of plan generosity. We account for this possibility through the fixed effects, which can vary by risk quintile. Second and more importantly, a more generous drug plan may attract sicker enrollees. To address potential selection with respect to benefit design, we allow for preferences and drug costs to vary flexibly by risk quintile. As plan characteristics change, plans attract a different mix of enrollees. If benefit design attracts sicker enrollees, we will estimate different behavioral responses $\frac{\partial s_{qjmt}}{\partial x^D_{jmt}}$ by risk quintile. If preferences are correlated with drug costs, changes in benefit design will then affect costs.[31]

Given the literature and reduced form estimates in Table A.3, which show that a MA-PD and risk quintile dummies account for a substantial amount of variation in insurer expenditure, our approach accounts for nearly all of the heterogeneity in drug costs that could be observed or predicted by the insurer. Einav, Finkelstein and Schrimpf (2015) find a raw monthly correlation of drug consumption of 0.5; Hsu et al. (2009) argue that "approaches that include information on prior-year drug use or costs perform markedly better than the current Medicare risk-adjustment approaches."[32] Flexible demand estimates explicitly allow heterogeneity in preferences to be correlated with heterogeneity in costs, and the results are robust to allowing for more heterogeneity by defining finer consumer types and allowing for unobserved consumer heterogeneity.[33]

4.2.4 Demand Parameter Estimates

Demand parameters for each of the five risk quintiles are in Table 4. Panel A describes baseline results that do not account for inertia. Panel B presents our preferred estimates that use plan vintage to account for inertia. Preferences over premiums and OOPC are similar in magnitude across the specifications, but there are two key differences to highlight. First, the nesting parameter is somewhat smaller in Panel A. Second, and more important, the effect of plan vintage differs with consumer characteristics. Consistent with Ho, Hogan and Scott Morton (2015), we find that

[31] We also implicitly allow changes in drug premiums to alter the risk pool the firm attracts because $\frac{\partial s_{qjmt}}{\partial p^D_{jmt}}$ varies by plan quintile.

[32] Furthermore, the degree of selection conditional on risk adjustment in the market is a matter of debate; see Newhouse et al. (2015) and Brown et al. (2014). Our specification allows for consumer heterogeneity in preferences by including flexible plan fixed effects that can vary by risk quintile, which implicitly allows for differential selection into plans based on consumer type.

[33] For example, we explore deciles of 2006 total drug spending, conditioning on demographics, or considering only high offset drugs. Our model does not explicitly accommodate selection with respect to formulary design (Carey (2017); Lavetti and Simon (2018)); we discuss modeling formulary design as an extension.

healthy consumers are unlikely to switch plans. In addition, we find that the sickest consumers are even less likely to switch.

The parameter estimates are sensible. In both specifications, the premium coefficient is negative and significant in all specifications, and sicker consumers are slightly less price sensitive than healthier consumers. Own-premium elasticities are quite sensible and range from -4.6 to -5.7, depending on risk quintile, consistent with the results in Decarolis, Polyakova and Ryan (Forthcoming). Across all quintiles, α_q^x is much smaller in magnitude than α_q^p, consistent with the results in Abaluck and Gruber (2011), and becomes attenuated among sicker consumers. We note that (expected) OOPC is observed with error and its coefficient estimate may be attenuated; while differences across consumer groups may reflect differential preferences, they could also reflect larger measurement error among higher spending enrollees. Finally, across all groups, $(1-\sigma_q)$ indicates that MA-PD plans are much closer substitutes for other MA-PD plans than stand-alone PDPs. Stand-alone PDPs are much closer substitutes for other PDPs than MA-PD plans.

To check the robustness of our results, we estimate three alternative parameterizations of the demand system. Alternative specifications in Table A.8 of Appendix C explore implications of the potential over-weighting of premiums in the demand model. Second, we model plan choice as a function of contract characteristics. In Table A.14, we include premiums and dummies for deductible and donut hole coverage as the observable characteristics; the overall pattern is consistent with our main specification. Finally, in Table A.15, we allow for unobserved consumer heterogeneity; the results are not sensitive to allowing for more flexible patterns of substitution.

4.3 Endogenous Benefit Design

We next combine the data, demand estimates, and the model of insurer behavior to estimate cost parameters. Dropping arguments for simplicity, the profit function can be rewritten as the sum of profits over risk quintiles q:

$$\Pi_{jmt} = \sum_q \left[p_{jmt}^D + z_t^D - c_{qjmt}^D + 1(MA\text{-}PD_{jmt}) * \left(b_{jmt}^M + z_{mt}^M - c_{jmt}^M\right)\right] s_{jqmt} B_{qmt}, \tag{8}$$

where both drug costs and market shares vary by risk quintile. The insurer's first-order conditions with respect to each element of $x_{jmt}^D = [x_{jmt}^{ICR}, x_{jmt}^{Donut}]'$ can then be written as:

$$\sum_q [\left(p_{jmt}^D + z_t^D - c_{qjmt}^D + 1(MA\text{-}PD_{jmt}) \left(b_{jmt}^M + z_{mt}^M - c_{jmt}^M\right)\right) \frac{\partial s_{qjmt}}{\partial x_{jmt}^D} - \frac{\partial c_{qjmt}}{\partial x_{jmt}^D} s_{qjmt}] = 0. \tag{9}$$

Total costs c_{qjmt} in MA-PD plans are equal to $c_{jmt}^M + c_{qjmt}^D$. This formulation explicitly accounts for selection and risk adjustment. For example, if more generous plans disproportionately attract sicker enrollees, $\frac{\partial s_{qjmt}}{\partial x_{jmt}^D}$ will be larger for sicker risk quintiles q, and the insurer will factor in higher costs as the plan becomes more generous: the relative

Table 4: IV Nested Logit Parameter Estimates

Risk Quintile (Lowest to Highest)	(1)	(2)	(3)	(4)	(5)
Panel A: Baseline Estimates					
Premium, α_q^p	-0.191***	-0.187***	-0.246***	-0.230***	-0.208***
	(0.0227)	(0.0207)	(0.0179)	(0.0161)	(0.0145)
OOPC, α_q^x	-0.138***	-0.0974***	-0.0491***	-0.0327***	-0.0157***
	(0.0132)	(0.00920)	(0.00642)	(0.00437)	(0.00263)
$(1-\sigma_q)$	0.506***	0.508***	0.508***	0.532***	0.521***
	(0.0142)	(0.0144)	(0.0144)	(0.0135)	(0.0127)
Adjusted R^2	0.295	0.279	0.272	0.266	0.244
Panel B: Accounting for Inertia					
Premium, α_q^p	-0.198***	-0.189***	-0.237***	-0.224***	-0.198***
	(0.0211)	(0.0193)	(0.0172)	(0.0154)	(0.0140)
OOPC, α_q^x	-0.136***	-0.0939***	-0.0516***	-0.0336***	-0.0151***
	(0.0120)	(0.00844)	(0.00605)	(0.00419)	(0.00255)
$(1-\sigma_q)$	0.439***	0.441***	0.474***	0.472***	0.472***
	(0.0132)	(0.0134)	(0.0130)	(0.0128)	(0.0120)
Plan Vintage	1.136*	1.653***	1.018	1.088*	2.412***
	(0.631)	(0.632)	(0.728)	(0.634)	(0.640)
Adjusted R^2	0.307	0.294	0.288	0.281	0.262
Observations	58,189	58,626	59,885	60,463	61,317

Notes: Table presents instrumental variable regression models as described in Berry (1994). The outside share is constructed as all Medicare eligibles not enrolled in a stand-alone PDP plan or MA-PD plan. In all specifications, we include plan fixed effects. Excluded instruments are an urban county dummy, and premiums and out-of-pocket expenditure in other markets, where a market is defined as a county-year combination. Standard errors are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

weight on drug costs for each risk quintile is proportional to the marginal change in demand.[34]

Table 5 lists the variables used in the estimating equations and categorizes them as either data, implied from the demand estimation, or parameters to be estimated. Bids, subsidies, market shares, and realized drug costs are all observed in the data. To construct expected drug costs, denoted in the model by c^D_{qjmt}, we estimate the regression described in the sixth and final column of Table A.3 on the entire sample.[35] The derivative of shares with respect to drug premiums, $\frac{\partial s_{qjmt}}{\partial p^D_{jmt}}$, is derived from the demand estimates by risk quintile. The derivative of shares with respect to benefit design can be written as $\frac{\partial s_{qjmt}}{\partial x^D_{jmt}} = \frac{\partial s_{qjmt}}{\partial OOPC_{qjmt}} \frac{\partial OOPC_{qjmt}}{\partial x^D_{jmt}}$ and has two components. The derivative of shares with respect to prescription drug OOPC, $\frac{\partial s_{qjmt}}{\partial OOPC_{qjmt}}$, is derived from the demand estimates by risk quintile, while the derivative of prescription drug OOPC with respect to benefit design parameters, $\frac{\partial OOPC_{qjmt}}{\partial x^D_{jmt}}$, is mechanical.[36] The derivative of average insurer costs with respect to benefit design can similarly be rewritten as $\frac{\partial c_{jmt}}{\partial x^D_{jmt}} = \frac{\partial c_{jmt}}{\partial OOPC_{jmt}} \frac{\partial OOPC_{jmt}}{\partial x^D_{jmt}}$. The derivative of average insurer costs with respect to prescription drug OOPC, $\frac{\partial c_{jmt}}{\partial OOPC_{jmt}}$, is the object of interest.[37]

We need to impute one additional object: expected average (over q) medical costs, c^M_{jmt}. We use the fact that we observe separate bids (and, therefore premiums) and subsidies for the medical and drug spending components of Medicare Advantage plans and calculate medical costs separately for each plan, and assume that they are known to the firm in the remainder of the supply-side estimation. We do this by inverting the insurer's first-order condition with respect to the Medicare Advantage bid and assuming firms bid optimally given premium elasticities, bids, subsidies, and observed market shares, as in Curto et al. (2015). Formally, for MA-PD plans,

$$c^M_{jmt} = \frac{1}{5}\sum_q \left[\left(p^D_{jmt} + z^D_t - c^D_{qjmt} + b^M_{jmt} + z^M_{mt} \right) + s_{qjmt} \frac{\partial s_{qjmt}}{\partial b^M_{jmt}}^{-1} \right], \tag{10}$$

where costs c^D_{qjmt}, and shares s_{jqmt} are allowed to vary with risk quintile.[38] For this calculation, we assume that consumers view \$1 in drug premiums as equivalent to \$1 in medical premiums. This assumption is innocuous: premiums are not disaggregated when presented to consumers. We further assume that the expectation of the deviation of medical costs from the average is zero: medical bids do not affect heterogeneous sorting among MA-PD plans, and we do

[34] See Ericson and Starc (2015) for a more detailed discussion). Of course, the mechanical effect only fully captures selection if the average costs net of risk adjustment are either constant across risk quintile or captured by the observable types.

[35] This allows us to abstract from plan selection and allow for "medical management" on the part of MA-PD plans. While we observe point-of-sale drug costs, we do not observe any rebates negotiated by payers, which are unlikely to affect generosity on the margin. A full model of bargaining between manufacturers and pharmacy benefit managers is outside the scope of this paper.

[36] For example, consider a \$1 increase in the ICR cost. For an enrollee with total drug spending below the deductible, the derivative is zero. For an enrollee above the initial coverage limit, the derivative is also zero (though this enrollee will reach the limit earlier in the year). In the ICR, the derivative is equal to the day supply less the day supply required to hit the deductible (the deductible divided by the average retail price). We do not consider cases in which a (small) change in benefit design would push an enrollee into the next phase of the standard benefit, as this effect complicates the analysis substantially and is of second order relevance to the analysis. Furthermore, we do not allow the enrollee to forecast a behavioral response to changes in benefit design.

[37] In the empirical implementation, we average $\frac{\partial OOPC_{qjmt}}{\partial x^D_{jmt}}$ over quintiles to obtain $\frac{\partial OOPC_{jmt}}{\partial x^D_{jmt}}$.

[38] For the supply model, we assume that firms optimize each plan's characteristics, rather than optimizing over their entire portfolio. To minimize the potential bias, we treat the stand-alone PDP contract IDs as the unit of analysis in the supply-side estimation. Given high correlation within nests in the demand system (e.g., a consumer substituting away from a stand-alone plan is most likely to choose another stand-alone PDP offered by a different firm), we believe it is unlikely that a consumer will substitute between the MA-PD and stand-alone PDPs within a single firm; therefore, this assumption seems fairly reasonable. The above expression assumes that the minimum benefits constraint is not binding.

Table 5: Parameters and Identification

Object	Description	Inference
p^D_{jmt}	drug premium	data
b^M_{jmt}	Part C (medical) bid	data
z^M_{mt}, z^D_t	Part C (medical) and D subsidies	data
s_{qjmt}	market share	data
c^D_{qjmt}	drug costs	data*
$\frac{\partial s_{qjmt}}{\partial p^D_{jmt}}$	derivative of market share w/r/t drug premium	calculated from demand estimates, by risk quintile to allow for selection
$\frac{\partial s_{qjmt}}{\partial OOPC_{qjmt}}$	derivative of market share w/r/t prescription drugOOPC	calculated from demand estimates, by risk quintile to allow for selection
$\frac{\partial OOPC_{qjmt}}{\partial x^{ICR}_{jmt}}$, $\frac{\partial OOPC_{qjmt}}{\partial x^{Donut}_{jmt}}$	derivative of out-of-pocket costs w/r/t drug benefit design	calculated from data
c^M_{jmt}	medical cost	inferred from bidding decision**
$\frac{\partial c^D_{jmt}}{\partial OOPC_{jmt}}$	mean derivative of insurer drug costs w/r/t prescription drug OOPC	object of interest to estimate
$\frac{\partial c^M_{jmt}}{\partial OOPC_{jmt}}$	mean derivative of insurer medical costs w/r/t prescription drug OOPC	object of interest to estimate***

Notes:
*We use accounting costs (drug claims), but take the expectation by risk quintile to allow for selection using specification in Table A.3.
**We do not observe medical claims. Therefore, we infer medical costs using Part C bids and subsidies for Medicare Advantage plans only using equation (10).
***Medicare Advantage variable costs are given as $c_{qjmt} = c^D_{jmt} + c^M_{jmt}$; the derivative of MA-PD costs with respect to benefit design parameters can be written as $\frac{\partial c_{qjmt}}{\partial x^D_{jmt}} = \frac{\partial c^D_{qjmt}}{\partial x^D_{jmt}} + \frac{\partial c^M_{jmt}}{\partial x^D_{jmt}}$.

not explicitly model non-drug benefit design except through the determination of the rebates. Therefore, we can take the weighted average across enrollee types. Subsidies are calculated using the formula provided by CMS, averaging 74.5% of bids. We estimate average margins of 14%, similar in magnitude to those obtained by Curto et al. (2015).

4.3.1 Supply-Side Estimation

To understand the role of strategic incentives in affecting equilibrium behavior, we need to parameterize plan costs as a function of benefit design and offsets. We allow plan drug costs to be a linear function of average (over q) $OOPC_{jmt}$ scaled by an average effect across plans θ_1 plus a normally distributed, mean zero plan-specific deviation ψ^D_{jmt}, and an error term ω^D_{jmt} that captures all the exogenous features of the plan that affect its drug costs:

$$c^D_{jmt} = \left(\theta_1 + \psi^D_{jmt}\right) OOPC_{jmt} + \omega^D_{jmt}. \tag{11}$$

Medical costs are parameterized similarly as a linear function of $OOPC_{jmt}$ scaled by an average effect across plans θ_2 plus a normally distributed, mean zero plan-specific deviation ψ^M_{jmt}, and an error term ω^M_{jmt} that captures all the exogenous features of the plan that affect its drug costs:

$$c^M_{jmt} = \left(\theta_2 + \psi^M_{jmt}\right) OOPC_{jmt} + \omega^M_{jmt}. \tag{12}$$

This parameterization yields $\frac{\partial c_{jmt}}{\partial OOPC_{jmt}} = \theta_1 + \theta_2 1(MA\text{-}PD_{jmt}) + \psi^D_{jmt} + \psi^M_{jmt} 1(MA\text{-}PD_{jmt})$. We infer $\frac{\partial c_{jmt}}{\partial OOPC_{jmt}}$ by inverting the insurer's first-order condition in equation (9) and then use OLS to estimate the following equation:

$$\frac{\partial \hat{c}_{jmt}}{\partial OOPC_{jmt}} = \theta_1 + \theta_2 1(MA\text{-}PD_{jmt}) + \psi^D_{jmt} + \psi^M_{jmt} 1(MA\text{-}PD_{jmt}), \tag{13}$$

where $\frac{\partial \hat{c}_{jmt}}{\partial OOPC_{jmt}}$ is the inferred value from the inversion.[39] The projection allows us to recover the key parameters of interest in equations 11 and 12: θ_1 and θ_2. In doing so, the model captures heterogeneity in the relationship between benefit design and insurer costs across plan types.

Asymmetric information affects plan costs both directly and indirectly. There is a direct relationship between benefit design and the average risk quintile of consumers within a plan, which is governed by demand heterogeneity. The relative weight on drug costs for each risk quintile in the first-order condition is proportional to the marginal change in demand (see Ericson and Starc (2015) for a more detailed discussion). This direct, mechanical effect only fully captures the impact of selection on insurer incentives if risk adjustment within quintile captures all the heterogeneity known to the insurer. However, the model is flexible enough to allow for selection conditional on risk adjustment indirectly through our estimates of θ_1. Therefore, while θ_1 and θ_2 are equilibrium objects, they have clear interpretations in specific scenarios. For example, $\theta_1 = -1$ implies that increases in prescription drug OOPC lead to one-for-one decreases in insurer costs in stand-alone PDPs. This rules out both moral hazard and adverse selection conditional on risk adjustment. For simplicity, we describe this as "no asymmetric information." By contrast, if increasing prescription drug OOPC attracts healthier enrollees (conditional on risk adjustment), then a \$1 increase in OOPC will lower insurer costs more than one-for-one. If increasing prescription drug OOPC decreases drug demand, then a \$1 increase in OOPC will lower also insurer costs more than one-for-one. Absent asymmetric information and drug offsets, $\theta_1 = -1$ and $\theta_2 = 0$. If there are offsets and drug demand slopes down, then higher prescription drug OOPC will increase non-drug medical costs, implying $\theta_2 > 0$.

Identification of the key objects of interest – $\frac{\partial c^D_{jmt}}{\partial OOPC_{jmt}}$ and $\frac{\partial c^M_{jmt}}{\partial OOPC_{jmt}}$ – relies on the first-order conditions with respect to benefit design parameters, along with variation across plan types. There is a direct mapping from different values of the key parameters of interest to levels of insurer drug spending. Intuitively, the more "expensive" it is to

[39] Profits are additive across risk quintile and we estimate the relationship between prescription drug OOPC and insurer costs on average: $\frac{\partial c_{jmt}}{\partial OOPC_{jmt}}$ is not allowed to vary by risk quintile.

make plans more generous, the less willing the firm is to increase generosity. Figure A.5 illustrates the basic logic of the identification argument using average values of the derivatives of shares with respect to premiums and prescription drug OOPC.

4.3.2 Supply-Side Parameters

Estimated cost parameters are presented in Table 6. Panel A presents parameters given the baseline demand estimates, while Panel B relies on the demand estimates that account for plan inertia. We first report estimates of $\frac{\partial \hat{c}_{jmt}}{\partial OOPC_{jmt}}$. The estimates in column 1 imply that the average plan would save \$99.73 per member in insurer costs by increasing prescription drug OOPC by \$100 (a 15% increase from the mean prescription drug OOPC). In column 2, we allow the effect to vary between PDPs and MA-PD plans. The impact of changes to prescription drug OOPC in a MA-PD plan is the sum of the two coefficients. The results show that the relationship between benefit design and insurer costs is economically and statistically different across different types of plans. Increasing prescription drug OOPC by \$100 in a MA-PD plan has a smaller impact on the insurer's total cost (by \$35).

The estimates accounting for plan vintage in Panel B imply a larger impact of an increase in prescription drug OOPC on plan costs. This is not surprising as this demand model allows for consumers to have both heterogeneous preferences and different degrees of state dependence. Column 2 implies that a \$100 increase in prescription drug OOPC decreases stand-alone PDP costs by \$134. Heterogeneity in the degree of inertia could also lead to other differences in plan incentives. The offset effect might vary with consumer tenure, as insurers will be more likely to invest in enrollee health (that saves money over time) if enrollees stay in plans for extended periods. To explore the importance of these incentives, we estimate the model allowing θ_2 to vary by degree of inertia within the plan. The results are in column 3 and show that while θ_2 is increasing in average plan retention rates, the effect is not statistically significant. In Appendix D, we explore the extent to which dynamic incentives could impact the results along two other dimensions. Inertia could affect the parameter estimates if it leads us to under- or over-estimate MA-PD medical costs. Following Decarolis, Polyakova and Ryan (Forthcoming) and Miller and Yeo (2014), we re-estimate the model assuming marginal costs equal to the federal subsidy plus a fixed markup. The qualitative results are unchanged. To explore the potential for more complex dynamic strategies, Table A.16 replicates the reduced form results in Ho, Hogan and Scott Morton (2015) that suggest an "invest then harvest" strategy of premium setting. However, we also show that plan generosity, measured by insurer drug spending, does not exhibit the same pattern.

The cost parameters are robust to the exact model of firm behavior, the allowing for additional unobserved consumer heterogeneity, and the regulatory features of the environment. Our model treats insurers as single product firms, however the results are robust for accounting for insurers offering multiple products in a market. Table A.17 presents estimates that incorporate multi-product firms; the cost parameters are similar to the preferred estimates. The table also

Table 6: Supply Results

	Baseline		
	(1)	(2)	(3)
Panel A: Baseline			
Average $\frac{\partial \hat{c}_{jmt}}{\partial OOPC_{jmt}}$	-0.997		
	(0.010)		
θ_1		-1.032	-1.032
		(0.011)	(0.011)
θ_2		0.349	0.352
		(0.034)	(0.067)
θ_2*Normalized 3-year Retention Rate			0.031
			(0.093)
Plan-Market-Year Obs.	34,431	34,431	34,431
Panel B: Accounting for Inertia			
Average $\frac{\partial \hat{c}_{jmt}}{\partial OOPC_{jmt}}$	-0.970		
	(0.008)		
θ_1		-1.343	-1.343
		(0.008)	(0.008)
θ_2		0.423	0.372
		(0.032)	(0.038)
θ_2*Normalized 3-year Retention Rate			0.050
			(0.031)
Plan-Market-Year Obs.	33,538	33,538	33,538

Notes: Parameters are estimated using generalized method of moments as described in Section 4. Standard errors are calculated using a bootstrap that re-samples plans with replacement and presented in parentheses. Panel B also includes enrollees with spending in the catastrophic cap.

shows that the inclusion of unobserved heterogeneity in the demand system does not affect cost parameters. Finally, Section 4.1 highlighted many regulatory features that may affect firm incentives. Table A.17 shows that our results do not depend on the sample of plans or the interpretation of bidding rules.[40]

Under the assumption that asymmetric information is constant across plan types, θ_2 measures the cost offset effect.[41] Absent cost offsets, the results would imply substantial intensive margin advantageous selection among MA-PD plans (the marginal enrollee is much healthier than the average). We find this interpretation implausible and argue that our results indicate a fraction of the MA-PD insurer's drug cost is offset by reductions in insurer spending in other areas.

4.3.3 Implied Offsets

The estimates quantify how changes in benefit design affect insurer costs. Given estimates of the behavioral response to enrollee costs, we can calculate the implied prescription drug offset – the change in medical costs in response to an

[40] We allow the value of the rebate to be reduced by 25% in accordance with CMS bidding rules, which require that the government share in the savings of Medicare Advantage plans that bid below the benchmark.

[41] The parameter θ_2 captures differences across plan types in both $\frac{\partial c^D_{jmt}}{\partial x^D_{jmt}}$ and $\frac{\partial c^M_{jmt}}{\partial x^D_{jmt}}$.

additional dollar of drug spending. Given the model estimates, the increase in insurer costs associated with lowering enrollee prescription drug OOPC is smaller for MA-PD plans than stand-alone PDPs; that is, $\frac{\partial c^M_{jmt}}{\partial x^D_{jmt}} > 0$. For a 1% uniform decrease in enrollee costs in all benefit phases, we calculate the implied difference in insurer costs for MA-PD plans as θ_2 multiplied by $\frac{\partial OOPC_{qjmt}}{\partial x^D_{jmt}}$. We use the value of $\theta_2 = 0.42$ as estimated in Table 6 and the mechanical value of $\frac{\partial OOPC_{qjmt}}{\partial x^D_{jmt}}$ associated with a 1% decrease in x^D_{jmt}, \$10.15.

Holding the medical benefit structure fixed, average total costs for a MA-PD plan are the sum of drug and (non-drug) medical costs. The change in insurer medical expenditure can be written as the offset (how a dollar of drug expenditure reduces medical expenditure) multiplied by the demand response (how increased plan generosity changes drug expenditure). We infer the increase in quantity from the behavioral elasticity using estimates from Einav, Finkelstein and Schrimpf (2015), who estimate a dynamic model of drug consumption.[42] Given an elasticity of -0.54 and an average of 1302.61 day supply per consumer, we calculate a net "discount" implied by offsets of 59 cents per day supply.[43] The total cost of the average prescription is \$2.20 per day; therefore, the implied offset is 27%. The estimate is very close to previous estimates (see CBO (2012) for a synthesis of the literature using demand side variation) and obtained using supply-side variation.

4.3.4 Extensions

In this section, we show how our framework can be extended to incorporate additional contractual richness to explore robustness and answer other key questions of economic and policy importance. In the main empirical exercise, we model insurer choice of composite measures of plan generosity. We further show that the estimates of consumer preferences are not sensitive to the exact definition of product characteristics and are in line with previous estimates. Other product characteristics may be important to both consumers and policymakers, and the framework is sufficiently flexible to model additional plan features.

For example, we are interested in directly modeling different generosity among high offset drugs. We proceed in three steps. First, we define x^D_{jmtd}, the vector of plan generosity specific to a given drug class d. Second, we assume that consumption of the drug of interest is evenly timed throughout the year in proportion to overall spending, which implies that $\frac{\partial OOPC_{qjmt}}{\partial x^D_{jmtd}}$ will be proportional to $\frac{\partial OOPC_{qjmt}}{\partial x^D_{jmt}}$, scaled by the difference in phase-specific out-of-pocket prices for the focal drug and all drugs. Finally, we assume that consumer preferences over generosity are not drug class specific, though this assumption could be relaxed by separately estimating demand taking the new product characteristic into account.

Table 7 displays the estimates by drug class. Across drug classes with large predicted offsets, we estimate higher values of θ_2, ranging from 0.36 for hypertension to 0.58 for cholesterol and diabetes drugs. While the estimates are

[42] The elasticity is identified by exploiting the donut hole kink in enrollee budget sets; we reproduce their analysis in Table A.7 and use the elasticity for a 1% uniform OOPC reduction of -0.54 in our calculation.

[43] This can be calculated as ((.42*10.15)/(1302*-.0054)).

Table 7: Supply Results, by Class

	Asthma	Hypertension	Diabetes	Cholesterol
θ_1	-1.170	-1.310	-1.337	-1.343
	(0.013)	(0.014)	(0.013)	(0.013)
θ_2	0.444	0.361	0.576	0.576
	(0.078)	(0.055)	(0.059)	(0.051)
Plan-Market-Year Obs.	33,538	33,538	33,538	33,538

Notes: Parameters are estimated using generalized method of moments as described in Section 4. Standard errors are calculated using a bootstrap that re-samples plans with replacement and presented in parentheses.

somewhat noisy, the estimates for asthma, cholesterol, and diabetes are all larger in magnitude than the main estimate of 0.39, indicating that heterogeneity across drug classes is important in our setting. The estimates are also closely linked to the reduced form estimates in Figure 2, highlighting the variation in the data that allows us to estimate the key parameters of interest.

Using our model, we also explore how asymmetric information affects the interpretation of cost side parameters. First, consistent with the literature, we find evidence of selection with respect to donut hole coverage in Table A.14. This type of selection may drive our cost parameter estimates. To explore the magnitude of this effect, we estimate the cost parameters without using variation from the donut hole (i.e., $x^D_{jmt} = x^{ICR}_{jmt}$), which eliminates selection with respect to donut hole coverage. Table A.17 presents these cost parameter estimates. Not surprisingly, the parameter estimates imply less asymmetric information.[44] Second, screening incentives could vary by plan type. Lavetti and Simon (2018) and Lavetti and Han (2017) note that enrollees taking certain drugs are more profitable in MA-PD plans than PDPs. In contrast to the drug classes in Table 7, the drugs identified in these studies are typically low-volume (e.g., fentanyl). Table A.17 shows that the results are robust to the exclusion of these drugs: θ_2 is not statistically different from our preferred estimates.

5 Counterfactuals

In this section, we answer two questions with our model and parameter estimates. First, how would stand-alone PDPs design drug plans if they took externalities into account? Second, how large is the effect relative to distortions due to asymmetric information? In the counterfactuals, we perturb the key supply-side parameters – θ_1 and θ_2 – but leave all other parameters and features of the model fixed. While θ_1 and θ_2 are equilibrium objects, they have natural interpretations in specific scenarios. In the absence of offsets and asymmetric information, $\theta_1 = -1$ and $\theta_2 = 0$.[45]

[44] The estimate of θ_2 is also slightly attenuated, consistent with smaller differences in cost sharing across plan type in the ICR.

[45] For tractability and clarity, we follow existing studies, including Einav et al. (2013), and do not explicitly model the underlying primitives that give rise to moral hazard. (They state on page 186, "Our model is designed for conceptual clarity and analytical tractability, both of which come at the cost of not explicitly modeling the underlying primitives that give rise to ω," where ω is the parameter that governs moral hazard.) To interpret the counterfactuals and for the counterfactual equilibria we calculate to be consistent with the specified game, we need to assume that changes to θ_1 and θ_2 do not affect plan choice conditional on observables. This assumption encompasses three behavioral restrictions. First, risk adjustment algorithms do not directly affect consumer choice. Second, there cannot be selection on moral hazard. Finally (and relatedly), consumers cannot

5.1 The Effect of Internalizing Externalities

To quantify the importance of prescription drug offsets, we first consider how stand-alone PDPs would adjust plan benefit design if they were forced to account for non-drug medical costs in the same way as their counterparts in the Medicare Advantage program. Given the specification of the supply-side parameters, we can write $\hat{\theta}_{PDP} = \theta_1$ and $\hat{\theta}_{MA} = \theta_1 + \theta_2$. Mechanically, we set $\theta_{PDP} = \hat{\theta}_{MA}$ and then resolve for a new Nash equilibrium by resolving the system of first-order conditions described in equation (9). In the counterfactual equilibrium, we allow drug costs to the insurer, c^D_{jmt}, and premiums to adjust to account for the new incentives.[46] In the baseline scenario, the average MA-PD plan has lower premiums (because of generous subsidies) than the average stand-alone PDP, which has an average premium of $407 per year. By contrast, the average MA-PD plan spends almost $75 dollars more per year on drugs ($1285 versus $1211).

Table 8 first reports the results of a simulation in which premiums are not allowed to adjust, but stand-alone PDPs internalize the offset. In the counterfactual, we see that the average stand-alone PDP would spend 7% more on prescription drugs if they took the entire medical offset into account. In addition, we note that MA-PD plans increase drug spending: plan generosity is a strategic complement, and there is no implicit trade-off between higher generosity and higher premiums.

Next we report the results of a counterfactual exercise in which insurers are allowed to adjust both drug spending and premiums. In contrast to estimation of the empirical model, we now impose optimal bidding. Specifically, in addition to the previous counterfactual, we require that the first-order conditions with respect to plan bids be satisfied:

$$p^D_{jmt} = \frac{1}{5}\sum_q (c^D_{qjmt} + z^D_t - s_{qjmt}\frac{\partial s_{qjmt}}{\partial b^D_{jmt}}^{-1}). \tag{14}$$

In this simulation, stand-alone PDPs increase drug spending by roughly the same amount, but also increase their premiums by 10% given the additional drug costs.

The counterfactual benefit design choices have important implications for both enrollees and government budgets. Critically, the increase in spending on prescription drugs leads to a fiscal savings for the Medicare program through lower medical expenditures. Our counterfactuals show that stand-alone PDPs would spend $80 more per year if they took medical expenditure into account, implying an offset of $21.60 per enrollee per year ($22.88 in the counterfactual that allows for premium adjustment). Multiplying $21.60 by 17.5 million, the number of stand-alone PDP enrollees in 2008, we find that stand-alone PDPs impose an externality of $378 million per year; based on our bootstrapped

differentially demand insurance contracts that internalize offsets.

[46] We solve for drug costs, rather than benefit design, for three reasons. First, drug costs enter into the insurer's first-order condition directly. Second, from a policy perspective, we are primarily interested in impact of different incentives on drug spending. Mechanically, costs change to fit the model in which the elasticity is taken as given and consumption increases as the cost-sharing schedule changes. Finally, given the monotonic relationship between the insurer's choice variables and both OOPC and drug spending, it suffices to solve for the equilibrium outcome. The first panel of Table 8 presents the baseline results.

estimates, the confidence interval for our estimate ranges from $325 million per year to $431 million per year. By contrast, McWilliams et al. (2016) find that the much-discussed Medicare Shared Savings Program led to an aggregate $238 million spending reduction in the early years; our larger results indicate the potential power of incentive alignment in equilibrium. To give additional context, the changes in Medicare Advantage over-payments due to risk adjustment policies measured in Brown et al. (2014) are approximately $317, or about twice as large as the increase in drug spending.[47]

We also calculate a measure of consumer spending that includes OOPC and premiums. In the counterfactual in which insurers cannot adjust their premiums, consumers benefit from lower OOPC; the effect is slightly larger than the fiscal savings to the Medicare program. When plans are allowed to adjust their premiums, the effect is partially offset.[48] In both simulations, both consumers and the federal government benefit when PDPs take externalities into account; in part, this is a transfer from insurers.

5.2 The Relative Importance of Strategic Incentives and Asymmetric Information

We find that strategic incentives created by offsets drive benefit design in the prescription drug insurance market. Yet a long literature, dating back to the theoretical contributions of Rothschild and Stiglitz (1976), argues that adverse selection should have a significant impact on benefit design. To better understand the magnitude of strategic incentives and asymmetric information, we estimate a counterfactual in which we set $\theta_1 = -1$ in addition to internalizing the externality as in the previous counterfactual. Absent asymmetric information or offsets, we expect a one-for-one relationship between insurer expenditure and enrollee costs. In the counterfactual, all plans face incentives to internalize offsets, but we have simultaneously eliminated asymmetric information.

Both types of plans become more generous in this counterfactual. In particular, MA-PD plans would become more generous absent asymmetric information. The magnitude of the effect is the same order of magnitude as the effect of strategic incentives in the previous counterfactual, though the effects are smaller if premiums are allowed to adjust.

[47] We would obtain a similar estimate if we used the implied additional spending by stand-alone PDPs in Table 8. By contrast, MedPAC (Medpac (2015)) estimates that spending on an equivalent enrollee in a MA-PD plan is approximately 2% higher than traditional Medicare. The average total Medicare spending was approximately $10,000 per enrollee in 2008 ($200 of additional spending in MA); the externality due to offsets does not, on its own, imply greater efficiency in MA-PD plans. However, the externality provides evidence of a potential channel through which MA-PD plans can obtain efficiency gains.

Furthermore, Table A.7 shows that it would be costly for the government to achieve the increased drug consumption generated by MA-PD plans using a flat cost-sharing subsidy alone; this calculation highlights the advantage of nimbler private insurers. However, there is no reason that the profit maximization incentives of MA-PD plans necessarily align with any social welfare criterion. Therefore, another natural policy intervention would be to better align consumer plan choices with value (from a societal perspective, including any externalities on the traditional Medicare program). Mechanically, we implement this by setting the coefficient on OOPC in the demand system equal to the coefficient on premiums, such that consumers treat a $1 increase in premiums equal to a $1 increase in OOPC. The results are in the final two columns of the top panel of Table A.9. If consumers were more "sophisticated" about the potential for underutilization, plans would increase their generosity. MA-PD plans would spend 5.6% more on prescription drugs, while stand-alone PDPs would spend 10.4% more. This increased spending by stand-alone PDPs is less than the amount that fully internalizes the fiscal externality, yet shows that public policies that align consumer demand or the structure of subsidies with providing value will lead insurers to offer contracts that reduce costs or increase health.

[48] We can also calculate a measure that allows consumption to adjust or, alternatively, a measure of consumer surplus (CS) that assumes the parameters of the plan utility function we estimate represent primitive preferences. Given that consumers dislike premium increases more than they like more generous plans, enrollees are made slightly worse off when premiums are allowed to adjust in the first counterfactual.

Table 8: Counterfactuals

Baseline				
	MA		PDP	
Premium	206.00		407.93	
Insurer Rx Spend	1285.25		1211.62	
	Counterfactual Plan Characteristics		Counterfactual Plan Characteristics	
	MA	PDP	MA	PDP
Internalize Externality: $\theta_{PDP} = \hat{\theta}_{MA} = \theta_1 + \theta_2$				
Premium	206.21	406.58	214.02	439.41
% Change	-	-	2%	10%
Insurer Drug Spend	1332.91	1298.72	1253.89	1295.56
% Change	4%	7%	-2%	7%
Change in Consumer Cost ($/Enrollee)	-49.43	-187.04	-41.24	-154.22
Fiscal Savings ($/Enrollee)		21.60		22.88
Premium Adjustment	no		yes	
No Asymmetric Information, Internalize Externality: $\theta_{PDP} = \theta_{MA} = -1 + \theta_2$				
Premium	206.21	406.58	159.48	392.43
% Change	-	-	14%	8%
Insurer Drug Spend	1373.46	1369.69	1299.33	1390.95
% Change	7%	13%	1%	15%
Change in Consumer Costs ($/Enrollee)	-81.79	-158.01	-136.31	-125.19
Fiscal Savings ($/Enrollee)		37.62		44.32
Premium Adjustment	no		yes	

Notes: Results are calculated as described in Section 5. Means across markets are reported, as well as the % change from baseline.

Stand-alone PDPs also become more generous: stand-alone PDPs would be 7% more generous if they faced the same strategic incentives as MA-PD plans; they would be 13% more generous if they faced the same strategic incentives as MA-PD plans and no asymmetric information. The magnitudes are similar if premiums are allowed to adjust. Given the counterfactual estimates, we conclude that strategic incentives due to benefit integration are as important as asymmetric information in driving market outcomes.[49]

In Appendix C, we perform two sets of additional counterfactuals. First, we explore the impact of policy changes on equilibrium outcomes. Second, we explore the extent to which other features of the economic context – including behavioral biases and imperfect competition – drive benefit design.

6 Conclusion

This paper examines how health insurers set premiums and design benefits in equilibrium. We build on empirical literatures that estimate structural models of insurer decisions and model endogenous product characteristics to show how cost-side incentives affect insurance benefit design. We examine these issues in the Medicare Advantage and Part D markets and show that differences in incentives across plan types drive the generosity of the plan.

MA-PD plans offer more generous prescription drug plans than their stand-alone counterparts; this increased generosity is concentrated in those drug categories with large offsets. Our model of firm behavior highlights the mechanisms that drive this differential: MA-PD plans have an incentive to internalize the effect of medical care offsets. By measuring firm incentives, we are able to calculate the size of the implied offset. Our estimate of an approximately 27% offset is similar in magnitude to demand-side estimates in the literature (Chandra, Gruber and McKnight (2010); Gaynor, Li and Vogt (2007)). The counterfactuals show how policy changes can increase plan incentives to help enrollees internalize offsets and explore the impact of alternative subsidies.

Government policy plays an important and understudied role in determining how market forces will affect health care utilization and consumer welfare in the Medicare program. Our framework can be used to further explore endogenous product design in selection markets and can help researchers model firm behavior and measure welfare in an "endogenous contracts framework" (Geruso and Layton (2018)). Thus, we build on an existing literature that considers premium setting conditional on fixed plan characteristics (Handel (2013); Lustig (2010); Starc (2015); Town and Liu (2003); Tebaldi (2017); Ericson and Starc (2015)). Future work should explore the impact of supply-side regulation, including premium and contract regulation, within the context of a rich model that does not require fixed insurance contracts.

[49] This finding is consistent with Starc (2015), which finds that strategic firm incentives, rather than adverse selection, drive firm behavior (in that instance, premiums) and margins in a similar setting.

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Appendices

A Utilization and Insurer Spending

A.1 Reduced Form Relationship Between Benefit Design and Insurer Costs

We regress insurer costs on our key product characteristics: $x_{jmt} = \left[\begin{array}{cc} x_{jmt}^{ICR}, & x_{jmt}^{Donut} \end{array} \right]'$. The results are in Table A.1. In all specifications, we control for contract fixed effects, and risk quintile to capture underlying contract characteristics and consumer risk.[50] In our second and third specifications, we also control for demographic characteristics (age, race, and gender), which capture part of the observable risk. In our final, most conservative specifications, we also control for historical county-level FFS spending, which proxies for county level variation in medical services, including drugs, that might be driven by differences in patient preferences, medical care infrastructure, and the physician culture (see Finkelstein, Gentzkow and Williams (2016)).

Table A.1: Benefit Design and Insurer Costs

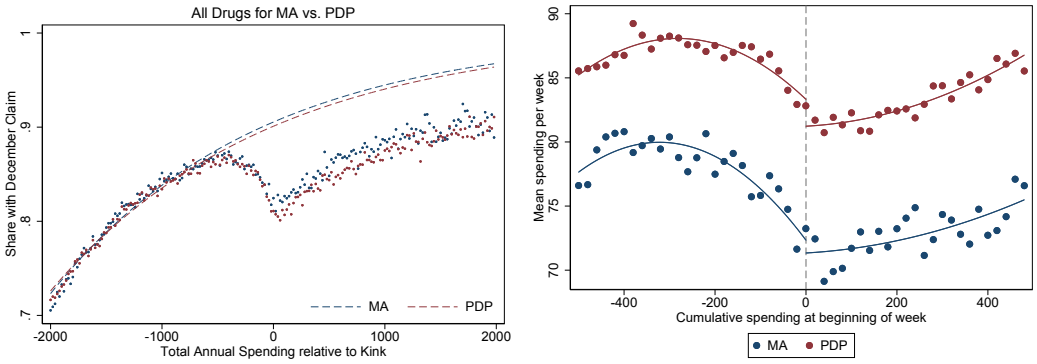
Dependent Variable: Insurer Costs						
	(1)	(2)	(3)	(4)	(5)	(6)
x_{jmt}^{ICR}	-672.9***	-673.4***	-672.4***	-674.2***	-673.6***	-675.6***
	(95.23)	(139.9)	(94.65)	(140.9)	(94.93)	(140.4)
x_{jmt}^{Donut}	-25.39	-66.38**	-25.60	-65.09**	-25.09	-65.62**
	(18.02)	(30.78)	(18.02)	(30.55)	(17.94)	(30.47)
$1(MA) * x_{jmt}^{ICR}$		-1.014		-0.279		1.241
		(158.0)		(158.6)		(158.2)
$1(MA) * x_{jmt}^{Donut}$		54.86*		53.40		54.48*
		(32.68)		(32.49)		(32.47)
FFS Costs					0.388***	0.388***
					(0.0375)	(0.0374)
R-Squared	0.243	0.245	0.245	0.243	0.246	0.246
Observations	569,078	569,078	569,078	569,078	569,078	569,078
Year FE	X	X	X	X	X	X
Risk Quintile FE	X	X	X	X	X	X
Demo. Controls			X	X	X	X
Plan FE	X	X	X	X	X	X

Notes: Table presents OLS regression models, where outcome variable is insurer costs. The unit of observation is an enrollee-year for the 2007-2009 period. The original data are obtained from a 10% sample of CMS prescription drug event files, aggregated to the enrollee-year level. We include year-level indicators and indicators for the quintile of 2006 spending (consumer types) in all specifications. In some specifications, we also control for 5-yr average per capita Medicare FFS spending and demographic controls for age categories, race, and gender. Standard errors are clustered at the contract level and are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

The results show that higher costs for enrollees are associated with lower insurer drug costs: a $1 increase in enrollee cost per day supply in the ICR is associated with $675 less in insurer drug spending. The effect for the donut

[50] Therefore, we are leveraging within contract variation across geographic space and over time.

Figure A.1: Behavioral Response



hole is predictably smaller, as only a small fraction of enrollees enter the donut hole. Critically, we see in columns 2, 4, and 6 that the effect does not vary by plan type: MA-PD and stand-alone PDPs find it equally costly – in terms of prescription drug costs only – to increase plan generosity.[51] That is, on average, MA-PD plans do not have a cost advantage in the provision of their drug benefits and differential costs are not a likely source of the benefit design differential.

A.2 Behavioral Response and Elasticity Estimates

Two plots summarize the behavioral response of consumers. The first describes bunching at the donut hole kink, similar to Einav, Finkelstein and Schrimpf (2015), which focuses on the extensive margin (any fill in the last month of the year). The left panel of Figure A.1 shows a consistent pattern across plans, with a similar quantity response in stand-alone and MA-PD plans; the empirical pattern implies a larger elasticity among MA-PD consumers, who face a smaller increase in OOPC. To examine the differential response to hitting the donut hole, we focus on a sub-sample of enrollees who start a week with total drug spending between $2000 and $2510 following Dalton, Gowrisankaran and Town (2015).[52] We plot weekly spending, which captures both intensive and extensive margin substitution, as a function of total spending relative to the location of the donut hole. The right panel of Figure A.1 shows that consumers reduce overall consumption as they approach the donut hole; furthermore, there is a discontinuous drop in consumption upon entering the donut hole.

To estimate elasticities using the approach described in Dalton, Gowrisankaran and Town (2015), we estimate parameters from the following regression i:

$$Y_{it} = FE_i + \lambda_1 1\{2400 < Spend_{it} \leq Donut_t\} + \lambda_s 1\{Spend_{it} > Donut\} + \upsilon_{it}, \tag{15}$$

[51] Table A.13 shows that these differences translate into lower OOPC for consumers.

[52] We focus on the period starting on the last Sunday of March and ending on the second to last Sunday of July. The logic behind this sample selection criterion is that the shock that results in the enrollee entering the donut hole should not change the enrollee's expectation about the likelihood of entering into the donut hole during the year. That likelihood is very close to one.

Table A.2: Behavioral Response

	(1) ln(1 + Spending)	(2) ln(1 + day supply)	(3) ln(1 + Enrollee Cost)
At Kink	-0.0564***	-0.0439***	0.114***
	(0.00377)	(0.00331)	(0.000999)
At Kink * MA	-0.00761	0.000704	-0.0123***
	(0.00770)	(0.00691)	(0.00227)
Post Kink	-0.103***	-0.0804***	0.151***
	(0.00217)	(0.00190)	(0.000684)
Post Kink * MA	-0.0364***	-0.0227***	-0.0208***
	(0.00459)	(0.00409)	(0.00154)
N	5,220,060	5,220,060	2,452,070

Notes: Standard errors are in parentheses. All regressions include enrollee fixed effects and cluster standard errors at the enrollee level. Each observation is an enrollee-week for enrollees that have beginning-of-week spending in the interval [Kink - $510, Kink) sometime between week 14 and week 30 of the calendar year and enrollee-weeks with beginning-of-week spending in the interval [Kink - $510, Kink + $490]. * p<0.05 ** p<0.01 *** p<0.001

where Y_{it} is the weekly drug spending for individual i in week t, FE_i is an individual fixed effect, $Spend_{it}$ is the total drug spending in that year at the beginning of week t for individual i, *Donut* is the dollar value of the initiation of the coverage gap phase of the benefit package in that year, and υ_{it} is an i.i.d. error term. The individual fixed effects control for individual selection into the donut hole. Identification is driven by variation in the timing of entering the donut hole controlling for mean individual characteristics. Given our sample selection, λ_s coefficient measures the mean impact of transitioning into the donut hole phase. We estimate this equation separately for PDP and MA-PD enrollees.

The parameter estimates are presented in Table A.2. Consistent with the reduced form analysis, enrollee costs increase as consumers enter the donut hole: the average enrollee cost increases by 15% for consumers in stand-alone PDPs and 13% for consumers in MA-PD plans. Consistent with the results presented in Figure A.1, the parameter estimates show that upon entering the donut hole, PDP enrollees drop their spending an average of 10%. In contrast, MA-PD enrollees reduce their spending by 14% upon entering the donut hole; the larger response reflects both a great extensive margin demand elasticity and a shift to lower cost drugs.[53] Comparing these estimates to the estimates of the differences in OOPC between PDP and MA-PD plans implies a donut hole elasticity ranging from -0.53 (stand-alone PDPs) to -0.79 (MA-PD plans).[54]

[53]There are two points to note here. First, we argue below that MA-PD enrollment leads to a causal increase in average consumption. Second, we find no evidence of an increased drop in consumption upon entering the donut hole among high offset drugs. Exploring heterogeneity in this effect is an interesting direction for future work.

[54]Because the elasticity of demand can be written as the percentage change in day supply divided by the percentage change in price post-kink, we divide the coefficient on "Post Kink" in column 2 (where logged day supply is the dependent variable) by the coefficient on "Post Kink" in column 3.

A.3 Total Annual Expenditure

Our goal is to estimate the causal impact of MA-PD enrollment on total drug consumption, insurer, and enrollee drug costs. However, a naive estimate will be contaminated by selection, as MA-PD enrollees are likely healthier than stand-alone PDP enrollees. Therefore, on average, MA-PD enrollees will have lower drug expenditure than their counterparts in stand-alone PDPs for reasons other than benefit design. This is likely to be true even once we control for a rich set of individual characteristics.

As discussed above, consumers in urban floor counties close to the threshold are more likely to be enrolled in MA-PD plans than consumers in similar rural floor counties just to the right of the urban threshold.[55] In our reduced form analysis, we use the county urban/rural status as an instrument in a linear instrumental variable specification; the empirical strategy is a fuzzy regression discontinuity approach.

The variation we use in IV specifications is highlighted in Figure A.2, which plots the probability of MA-PD enrollment as a function of population. This figure depicts a binscatter plot with twenty population bins. We control for consumer demographics, including risk quintile, as well as annual mean county-level FFS spending and plot the average probability of MA-PD enrollment. We fit quadratic curves on either side of the 250,000 population cutoff. We see a dramatic change in the probability of MA-PD enrollment just to the right of the discontinuity. We implement the identification strategy using an instrument variables framework. Specifically, we estimate:

$$y_{ijmt} = X^1_{mt}\beta_1 + X^2_{it}\beta_2 + \beta_3 1(MA\text{-}PD_{jmt}) + g_1(pop_{mt}) + \mu_{ijmt}, \tag{16}$$

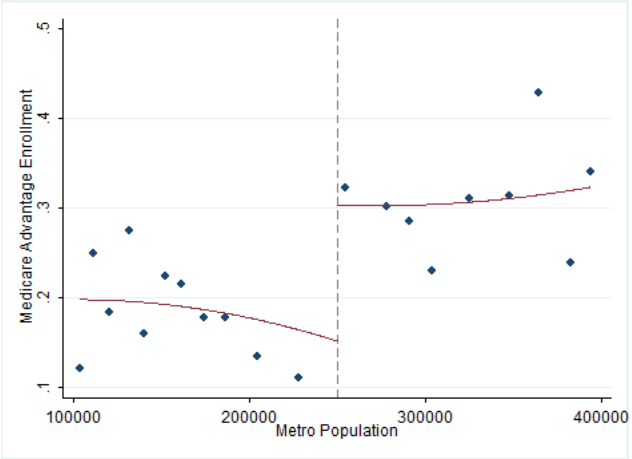
$$1(MA\text{-}PD_{jmt}) = X^1_{mt}\gamma_1 + X^2_{it}\gamma_2 + \gamma_3 1(urban_{mt}) + g_2(pop_{mt}) + \nu_{ijmt}, \tag{17}$$

where β_3 is the coefficient of interest, and X^1_{mt} and X^2_{it} are vectors of market and individual specific covariates, respectively. In all specifications, we control flexibly for metro area population. The dependent variables of interest, y_{itjm}, are total drug spending, consumer OOPC, and insured costs, where j represents a plan. We hypothesize that insured spending is causally higher in MA-PD plans, and enrollee OOPC lower. These relationships are due directly to benefit design on the part of insurers; the overall impact of these changes on total expenditure is more ambiguous, as it depends on the size of the behavioral response, but likely to be positive as well.

To explore the impact of Medicare Advantage enrollment on consumption, we focus on the 2007-2009 time period. In all specifications, we control for the consumer quintile of 2006 drug spending, calculated at the national level. In the second and third specifications, we also control for demographic characteristics (age, race, and gender), which capture part of the observable risk. In the final, most conservative specifications, we also control for historical county-level FFS spending, which proxies for county level variation in medical services, including drugs, that might be driven by

[55] We will also use urban status to predict the inside share of MA-PD plans in the plan choice models.

Figure A.2: Effect of Population on Medicare Advantage Enrollment



Notes: Plots a binscatter with twenty population bins. We drop counties with FFS spending above the urban floor, and control for beneficiary age, sex, race, 2006 spending quintile, and county-level FFS spending. Lines represent a quadratic fit.

differences in patient preferences, medical care infrastructure and the physician culture (see Finkelstein, Gentzkow and Williams (2016)). We focus the analysis on consumers living in counties with associated metro populations between 100,000 and 400,000.

Table A.3 reports the results of OLS regressions of total expenditure, OOPC, and insurer spending. These results are likely biased because of adverse selection into stand-alone PDPs – we report them to provide a benchmark to the IV estimates. In the bottom panel, we examine the impact on total expenditure. The first column, which controls only for year and the quintile of 2006 spending, shows that the average MA-PD enrollee has lower drug expenditures: total annual expenditure on drugs is $252 less than their counterparts in stand-alone plans. The average total expenditure for this sub-sample is $1697, indicating that Medicare Advantage enrollees have 15% lower drug spending than PDP enrollees. This lower expenditure is associated with savings in the form of OOPC to consumers (a reduction of $178) and somewhat smaller reductions for insurers ($74 per enrollee per year). The next two columns, which include demographic characteristics and county-level FFS spending, show that the effect is not attenuated by the inclusion of additional controls.

We use changes in Medicare Advantage reimbursement as an instrument for the MA-PD share. In the first panel of Table A.3, we present the results of the first stage regressions that control for metro population using a cubic spline with knots in increments of 100,000 starting at 150,000. In all specifications, we find that Medicare eligibles in the data set are 16-17% more likely to enroll in a MA-PD plan if they live in an urban county. Given an average Medicare Advantage market share of 25% within our sub-sample, this represents a large shift.[56] By exploring what happens to consumers who are exogenously shifted into MA-PD plans, we can isolate the impact of plan characteristics on

[56]Furthermore, our instrument has a great deal of predictive power. The partial F-stat in the final specification is 509.02.

Table A.3: Impact of MA-PD Enrollment on Drug Spending

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			IV		
First Stage, Dependent Variable: MA-PD Enrollment						
1 (Urban)				0.168***	0.170***	0.177***
				(0.00785)	(0.00785)	(0.00787)
R-squared				0.026	0.036	0.037
Dependent Variable: Insurer Drug Expenditure						
1(MA-PD)	-74.21***	-76.25***	-73.32***	514.2***	506.7***	387.5***
	(3.969)	(3.973)	(3.972)	(74.25)	(73.35)	(68.38)
FFS 5 Year			0.430***			0.506***
Avg. Spend			(0.0189)			(0.0226)
R-Squared	0.217	0.219	0.221	0.114	0.119	0.159
Dependent Variable: Enrollee Drug Expenditure						
1(MA-PD)	-177.5***	-174.6***	-173.3***	-215.2***	-222.2***	-265.2***
	(2.850)	(2.861)	(2.863)	(55.51)	(54.92)	(52.74)
FFS 5 Year			0.198***			0.183***
Avg. Spend			(0.0160)			(0.0183)
R-Squared	0.193	0.195	0.195	0.193	0.194	0.192
Dependent Variable: Total Drug Expenditure						
1(MA-PD)	-251.7***	-250.9***	-246.6***	299.0***	284.6***	122.3
	(5.851)	(5.870)	(5.873)	(108.0)	(106.7)	(100.7)
FFS 5 Year			0.628***			0.688***
Avg. Spend			(0.0298)			(0.0343)
R-Squared	0.264	0.265	0.267	0.230	0.233	0.252
Year FE	X	X	X	X	X	X
Risk Quintile FE	X	X	X	X	X	X
Demo.		X	X		X	X
Controls						
N	381921	381921	381921	381921	381921	381921
Sample	100-400K	100-400K	100-400K	100-400K	100-400K	100-400K

Notes: Table presents linear regression models, where outcome variables are insurer and enrollee costs and total expenditure levels. The unit of observation is at the enrollee-year level, for the 2007-2009 period. The original data are obtained from a 10% sample of CMS prescription drug event files, aggregated to the enrollee-year level. We restrict to those counties in the 100-400k metro population band. We include year-level indicators and indicators for the quintile of 2006 spending in all specifications. In some specifications, we also control for 5-year average per capita Medicare FFS spending, from 2007. We also include controls for age, age squared, race, and gender as demographic controls. In addition, we include a spline of metro population. Standard errors are clustered at the product level and are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

consumption.

The second panel of Table A.3 shows the estimated impact of MA-PD enrollment on insurer drug costs. Once we account for differential selection, MA-PD plans spend much more on drugs than stand-alone PDPs. The estimate of $514 in column 4 is approximately half of average insurer spending across all plans ($1031 per enrollee per year). This estimate is more attenuated in the final column (albeit not statistically different from the estimates in column 4), which includes historical, county-level FFS costs as an additional control. Here the estimates indicate that MA-PD plans spend $388 more per year than stand-alone PDPs for an equivalent enrollee. As expected, historical FFS spending influences drug consumption: Finkelstein, Gentzkow and Williams (2016) find that approximately half of all variation in spending is due to place-specific supply factors. The following panels describe the impact of additional insurer spending on consumers. The third panel shows that a consumer enrolled in Medicare Advantage can expect to spend $265 less per year on drugs, holding health risk constant. Consumer spending does not fall one-for-one with the increase in insurer spending, implying that the reduction in average OOPC for consumers increases consumption, as confirmed in the final panel. In our preferred estimates, the causal impact of MA-PD enrollment is somewhat noisy, but implies a $122 increase in drug consumption. On a base of $1697 of drug spending per year, this represents a 7% increase in spending. Total drug consumption increases *despite* a drop in consumer spending.

We hypothesize that the underlying mechanism driving an increase in drug consumption from Medicare Advantage enrollment is differences in MA-PD benefit design intended to internalize the impact of offsets on non-drug medical spending. In support of this hypothesis, we show that the effect of Medicare Advantage enrollment on drug consumption is driven entirely by drugs believed to have large offsets *a priori.* We explore the total enrollee level of consumption of "Category 1" drugs, as classified by Chandra, Gruber and McKnight (2010). If these drugs are not taken when prescribed, a serious event, such as a hospitalization, is significantly more likely to occur within the next six months.[57]

Table A.4 describes these results. About 40% of average expenditure ($648.11) is concentrated in these "Category 1" drugs. Consistent with previous specifications, the OLS results are biased downward due to advantageous selection

[57] "Category 1" drugs are "acute care drugs are those that, if not taken, will increase the probability of an adverse health event within a month or two." These drugs comprise approximately 40% of total drug spending. Category 2 contains "chronic care medications are designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year (examples include analgesics, antivirals, ACE inhibitors, medications, beta-blockers, hypertension drugs, statins, and glaucoma medications)." Category 3 are "medications that, while necessary to improve patients' quality of life, will not result in an adverse health event if not taken, because they provide symptom relief as opposed to affecting the underlying disease process (examples are acne medications, antihistamines, motion sickness medications, cold remedies, relief of pain drugs)."

The classes included in "Category 1" are Adrenal Corticosteroids, Aminoglycosides, Anaphylaxis Treatment Kits, Anesthesia, Anthelmintics, Antianginals, Antiarrhythmics, Antiasthmatics and broncodilators, Antibacterials, Miscellaneous, Antibiotics, Alkaloids, And Enzymes, Anticoagulants/thrombolytics, Anticonvulsants, Antidotes, Antimalarials, Antimetabolites, Antimycobacterials, Antineoplastics, Antiprotozoals, Antipsychotics/antimanics, Antitoxins/antivenins, Blood Components/substitutes, Blood Glucose Regulators, Cardiac Glycosides, Cardiovascular-renal, Cephalosporins, Chloramphenicol/derivatives, Coronary Vasodilators, Dna Damaging Drugs, Hypotension/shock, Lincosamides and macrolides, Ocular Anti-infective/anti-inflammator, Penicillins, Polymyxins, Quinolones/derivatives, Repl/regs Of Electrolytes/water Balance, Respiratory Tract, Sulfonamides/related Compounds, Tetracyclines, Vascular Disorders, and Cerebral/peripheral. We exclude drugs that are believed to have differential selection effects, as described in Lavetti and Simon (2018). Drug lists for each category were compiled using lists from drugs.com. Respiratory tract drugs include drugs used to treat asthma and COPD. For drugs with multiple uses, the drug was only included under its primary usage (e.g. etanercept is sometimes used to treat Alzheimer's Disease, but is much more commonly used for autoimmune diseases such as rheumatoid arthritis, psoriatic arthritis, plaque psoriasis and ankylosing spondylitis. Thus, it is not included on the list of Alzheimer's drugs).

into MA-PD plans. However, the IV specifications in columns 3-6 show a consistent pattern: MA-PD enrollees consume proportionally more of these "Category 1" drugs, due in large part to greater insurer expenditure. MA-PD enrollment leads to an additional $156 in annual expenditure on these drugs; on a base of $648, this amounts to a 24% increase, versus 7% for total drug consumption. Put differently, all of the increased total expenditure in MA-PD plans is concentrated in these large offset drugs. Total expenditure in this category increases by $156, while overall total expenditure increases by $122, implying that MA-PD plans do not spend more on drugs that are unlikely to have large offsets.

B Risk Stabilization and Regulation

In this appendix, we describe risk stabilization by CMS and its effect on firm incentives. CMS uses a three-pillar system to mitigate adverse selection in Part D; as a result, the impact of adverse selection is muted, though not necessarily eliminated. Most importantly, risk adjustment could affect the relative profitability of different Medicare beneficiaries. The Part D program also affects insurer costs *ex post* in two key ways. First, catastrophic reinsurance mitigates costs for especially sick enrollees. Second, risk corridor transfers limit both upside and downside risk to insurers.

B.1 Risk Adjustment

Risk adjustment attempts to equalize insurer profitability across beneficiaries by increasing subsidies for sicker enrollees. Despite this, there may still be selection conditional on the risk adjustment (Brown et al. (2014); Carey (2017)). We incorporate risk adjustment into the formulation of insurer costs. Drug costs $c^D_{ijmt}(\mathbf{x^D_{mt}}, r_{it}, \eta_{ijmt}) = c^D_{ijmt}(\mathbf{x^D_{mt}}, r_{it}) + \eta_{ijmt}$ are not fully compensated by risk-adjustment and are a function of the entire vector of product characteristics, $\mathbf{x^D_{mt}}$, the individual's risk score, r_{it}, and an idiosyncratic shock, η_{ijmt}. Average plan costs are $\frac{1}{s_{jmt}B_{mt}} \sum_{i \in A_{jmt}} c^D_{ijmt}(\mathbf{x^D_{mt}}, r_{it}) = c^D_{jmt}(\mathbf{x^D_{mt}}, \bar{r}_{jmt})$ where $\bar{r}_{jmt}$ is the average risk score and B_{mt} is the number of Medicare beneficiaries eligible to enroll in a PDP or MA-PD plan. The idiosyncratic error term η_{ijmt} enters linearly and is unknown to the insurer; therefore we omit it.

Mechanically, we operationalize this idea by allowing for five enrollee types (risk quintiles) and allow the net of risk adjustment costs to be constant within risk quintile. As plan characteristics change, the mix of enrollee types and, therefore, insurer costs, changes. If risk adjustment is perfect and there is no moral hazard, $\theta_1 = -1$. If the parameter θ_1 is less than negative one, $1 in additional OOPC saves more than $1 in insurer costs. We can interpret the parameter as a combination of selection conditional on risk adjustment and moral hazard. Several of the key counterfactuals change this parameter.

Additional extensions allow us to incorporate a finer level of risk adjustment into our estimates. One natural

Table A.4: Impact of MA-PD Enrollment on Spending, Drugs with Large Offsets

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			IV		
Dependent Variable: Insurer Drug Expenditures						
Mean	401.16					
SD	512.6					
1(MA-PD)	-18.63***	-18.30***	-17.52***	223.5***	229.6***	190.8***
	(3.118)	(3.122)	(3.124)	(56.20)	(55.66)	(53.20)
FFS 5 Year			0.126***			0.156***
Avg. Spend			(0.0150)			(0.0170)
Mean	0.046	0.047	0.047	0.005	0.005	0.018
Dependent Variable: Enrollee Drug Expenditure						
Mean	246.96					
SD	379.18					
1(MA-PD)	-58.56***	-56.57***	-56.42***	-27.68	-27.73	-34.43
	(1.848)	(1.849)	(1.848)	(37.24)	(37.24)	(35.40)
FFS 5 Year			0.0238**			0.0270**
Avg. Spend			(0.0103)			(0.0116)
R-Squared	0.064	0.065	0.065	0.063	0.064	0.065
Dependent Variable: Total Drug Expenditures						
Mean	648.11					
SD	802.67					
1(MA-PD)	-77.19***	-74.86***	-73.94***	195.8**	201.9**	156.4*
	(4.497)	(4.505)	(4.507)	(84.52)	(83.64)	(80.17)
FFS 5 Year			0.150***			0.183***
Avg. Spend			(0.0230)			(0.0260)
R-Squared	0.064	0.065	0.066	0.043	0.044	0.051
Year FE	X	X	X	X	X	X
Risk Quintile FE	X	X	X	X	X	X
Demo.		X	X		X	X
Controls						
N	322,066	322,066	322,066	322,066	322,066	322,066

Notes: Table presents parameter estimates and standard errors of the instrumental variable regression models, where outcome variables are insurer and enrollee costs and total consumption levels. The unit of observation is at the enrollee-year level, for the 2007-2009 period. We restrict to those counties in the 100-400k metro population band. We include year-level indicators and indicators for the quintile of 2006 spending in all specifications. We include controls for age, age squared, race, and gender as demographic controls. In addition, we include a spline of metro population. Standard errors are clustered at the product level and are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.5: Estimates of the Relationship between Plan Enrollment and Enrollee Expenditure (LIS)

Dependent Variable: Logged Enrollee Expenditure per day		
Panel A: Main Results	(1)	(2)
1(MA-PD)	-0.061***	-0.040***
	(0.007)	(0.007)
1(MA-PD)*High Switcher Surplus	-0.020	-0.024
	(0.015)	(0.016)
Observations	49,652,335	49,652,335
Adjusted R-Squared	0.655	0.716

Notes: Table presents linear regression models with logged enrollee expenditure per day supply as the dependent variable. The unit of observation is at the fill level (weighted by day supply), for the 2007-2009 period. The original data are obtained from a 10% sample of CMS prescription drug event files. We include year-level indicators and product fixed effects in all specifications. In some specifications, we also control the phase of the standard Part D benefit. Standard errors are clustered at the plan-product level. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively. The sample size is smaller because not all NDCs match to a diagnosis code.

concern is that benefit design reflects screening incentives conditional, rather than strategic ones. This concern is exacerbated to the extent that we do not capture the specificity of risk adjustment. Selection conditional on risk adjustment could affect our results along two dimensions. First, there could be selection conditional on risk adjustment across both MA-PD and stand-alone plans. Selection conditional on risk adjustment has been documented in this setting by Carey (2017).[58] Second, screening incentives could vary by plan type. This effect has been documented by Lavetti and Simon (2018); Lavetti and Han (2017). we explore the robustness of our results to the inclusion or exclusion of these drugs. The results are in Table A.5 below, in which we replicate our main specifications but also interact the Medicare Advantage dummy with a dummy that takes on a 1 for drugs treating the 48 conditions with positive and statistically significant "MA Switcher Surplus" that are not in our high offset categories. The coefficient is negative, but not statistically significant. While measurement error (due to linking drugs to diagnoses) may lead to some attenuation of these estimates, the magnitudes are much smaller than the interaction terms in Panel B of Table 2.

We further explore the impact of this selection incentive on our estimate of θ_2 in Table A.17. Consistent with adverse selection (as in Carey (2017)), elimination of these drugs from the model leads to estimates of θ_1 closer to -1. Consistent with small and statistically insignificant differences in Table 2, θ_2 is not statistically different from our preferred estimates. While both (differential) selection and strategic incentives can co-exist, we argue that strategic incentives are empirically larger.

B.2 Individual Reinsurance

Individual reinsurance attempts to counteract the incentive to avoid high spending beneficiaries. During the catastrophic phase of the standard benefit, the government covers 80% of drug expenditure. For example, in 2008, the catastrophic cap was $5726.25. For each additional dollar in spending above this amount, the beneficiary covers 5

[58] In a slightly different setting, Geruso, Layton and Prinz (Forthcoming) show that plans strategically use formularies to cherry-pick consumers.

Table A.6: Counterfactuals

	Counterfactual Plan Characteristics		Counterfactual Plan Characteristics	
Policy Counterfactual: Reduction in Reinsurance Generosity				
Premium	206.21	406.58	159.96	276.37
% Change	-	-	-0.22	-0.32
Insurer Drug Spend	1202.86	1071.14	1166.28	1029.81
% Change	-6%	-12%	-9%	-15%
Change in CS ($/Enrollee)	-16.45	-47.27	-24.71	-58.81
Fiscal Savings ($/Enrollee)*		-36.52		-45.43
Premium Adjustment	no		yes	

Notes: Results are calculated as described above. Means across markets are reported, as well as the % change from baseline.

cents, Medicare covers 80 cents, and the plan covers 15 cents. Our model accounts for reinsurance in two ways. First, we explicitly incorporate individual reinsurance into our calculation of insurer costs. Second, we estimate specifications in which we exclude high cost enrollees with spending above the cap.

The Medicare Payment Advisory Commission has recommended that Medicare significantly lower the amount of reinsurance paid in the catastrophic phase from 80% to 20% while increasing the premium subsidy to maintain the overall generosity level of government subsidies (Medpac (2016)). We use our model to simulate the impact of this policy in equilibrium. This counterfactual policy also illustrates the key mechanisms of selection and strategic incentives. The commission notes that while the change could exacerbate the incentives created by selection, it also creates incentives for insurers to reduce costs. We expect policies that exacerbate adverse selection to lead to less generous insurance plans in equilibrium; mechanically, we re-solve for firm incentives and endogenous insurer costs under the alternative subsidy structure.

The results are in Table A.6. Consistent with selection driving benefit design, plans are much less generous absent reinsurance: stand-alone PDPs spend 12-15% less on prescription drugs under the alternative policy. Consistent with strategic incentives driving benefit design, the effect is muted for MA-PD plans, which spend 6-9% less on prescription drugs. Consistent with previous counterfactual results, selection and strategic incentives are equally important determinants of benefit design. The policy harms consumers and is costly to the federal government, as consumers consume fewer drugs, leading to additional medical expenditure.[59]

B.3 Risk Corridors

Risk corridors attempt to provide down-side protection against plan-level losses and cap plan-level profit margins if overall drug spending is much higher or lower than expected (Medpac (2016)). Following Decarolis, Polyakova and Ryan (Forthcoming), we denote the function which adjusts a plan's ex post profit with Γ. Risk corridor payments are

[59] We hold upstream prices fixed in this simulation; insurers may negotiate additional discounts from manufacturers under the alternative subsidy structure.

applied at the plan level at the end of the year (rather than enrollee by enrollee). Because payments are piece-wise linear and symmetric, they do not affect the optimization of the risk neutral insurer. Therefore, we do not include risk corridor payments in our discussion of firm profits in the main text. If we take risk corridor payments into account, the ex post profit function can be written as:

$$\Pi^{PDP}_{jmt}(\mathbf{b^D_t}, \mathbf{x^D_{mt}}) = \Gamma\left(p^D_{jmt}(\mathbf{b^D_t}) + z^D_t - c^D_{jmt}(\mathbf{x^D_{mt}}, \bar{r}_{jmt})\right) s_{jmt} B_{mt}. \tag{18}$$

Risk corridor payments are an important component of the program. Most plan sponsors returned a portion of over-payments to Medicare because of the risk corridors. Despite being prevalent, industry participants are circumspect about the impact of risk corridor payments on firm behavior (Medpac (2016)). The strongest incentives would be to change bidding behavior; we do not use this information directly in estimation. To confirm that risk corridor payments do not affect the parameter θ_1, we re-estimate our model year by year, noting that the structure of risk corridors changed in 2008. In unreported specifications, we find that the effect is not statistically different from the main specification.

B.4 Rebates and LIS Subsidies

Two additional features of the regulatory environment deserve additional attention: Medicare Advantage rebates and LIS subsidies. Because Medicare Advantage subsidies were generous during our time period, many plans have zero premiums; these plans may include "rebates" to enrollees, which can be used to provide additional services or reduce Part B premiums (which are required even for consumers in Medicare Advantage plans).We include these net premium reductions directly in the definition of b^M_{jmt}; the consumer pays a composite premium equal to $b^M_{jmt} + p^D_{jmt}$. We can allow the value of the rebate to be reduced by 25% in accordance with CMS bidding rules, which require that the government share in the savings of Medicare Advantage plans that bid below the benchmark. Table A.17 shows that this will not affect the estimates of the key parameters of interest.

Second, distortions created by the LIS subsidy may affect firm incentives. Decarolis, Polyakova and Ryan (Forthcoming) account for this possibility in their analysis and we following their approach by restricting attention to those contracts that bid above the LIS benchmark amount in the majority of regions in which they operate. We re-estimate the supply-side parameters, assuming that these remaining contracts will not be distorted by the structure of the LIS subsidy. This restriction leaves fewer contracts available to estimate the parameters. Nevertheless, the results (presented in Table A.17) are qualitatively similar to the main specification, indicating that our basic results hold even allowing for the LIS distortion. Similarly, in the bottom panel of Table A.17, we restrict attention to "enhanced" plans that are unlikely to be constrained by minimum plan generosity requirements; again, the results are quantitatively similar.[60]

[60] We define a plan as "enhanced" if it has a supplemental premium in at least half of all markets in which it operates. This accounts for 7% of all stand-alone plans. The analysis omitting LIS plans serves as an additional robustness check along this dimension as plans not eligible for LIS enrollment are also likely to be more generous than the minimum actuarial standard. These two subsets overlap substantially.

C Additional Counterfactuals

In this section, we consider a number of policy-relevant counterfactuals. In all of these exercises, we assume fixed θ_1 and θ_2. For example, we consider budget neutral policies that attempt to internalize the externality generated by the stand-alone PDPs.[61] Our presumption is that CMS would like to increase drug consumption by PDP enrollees to both improve enrollee well-being and to reduce medical care costs. A natural policy to consider is a plan benefit generosity subsidy where CMS would cover some of the insurer's cost to increase generosity. For this subsidy to be budget neutral, CMS must also decrease the current premium subsidy, which will likely increase premiums faced by consumers. The impact of such a change depends on how consumers evaluate plans with greater generosity but higher premiums. While it is natural to consider the consumer surplus impact of these policies, such a calculation requires interpreting the utility parameters in the neoclassical context, which, given our earlier findings, is probably inappropriate. For this reason, we refrain from making consumer surplus statements here. In addition, we assume fixed θ_1 and θ_2 in all of the policy counterfactuals.

Consider a uniform subsidy for stand-alone PDPs, as shown in Table A.7. Mechanically, a subsidy alters both p_{jmt} and $OOPC_{qjmt}$ if it is budget neutral and there is full pass-through; we can write the alternative premium and OOPC as a function of the change in OOPC due to a change in the benefit generosity and the offset, which is given by $\frac{\partial q}{\partial x}(c-c')$. For a small change in $\mathbf{x}$ (omitting subscripts for simplicity):

$$OOPC' = OOPC + \frac{\partial OOPC}{\partial \mathbf{x}},$$

$$p' = p + \frac{\partial OOPC}{\partial \mathbf{x}} - \frac{\partial q}{\partial \mathbf{x}}(c-c').$$

In this formulation, the offset savings are passed through completely to the consumer in the form of lower premiums, but the reduced premium subsidy is passed through to consumers in the form of higher premiums as well.[62]

A 1% subsidy would increase consumption by 7.2 day supply based on the behavioral elasticities in column 2. The implied offset, in column 3, is \$3.54.[63] However, the subsidy applies to all of the infra-marginal units as well, and the total reduction in OOPC is \$10.15. Subtracting the offsets, this implies that premiums would have to increase by \$6.61 for the policy to be budget neutral. By contrast, the federal government could eliminate cost-sharing in the donut hole, as the ACA does. Using the calculations in Einav, Finkelstein and Schrimpf (2015), this would increase drug consumption by 8%, generating offsets amounting to \$52.54 per consumer. However, this policy is also expensive: while it reduces OOPC by \$356 per consumer, this reduction comes at a cost net of offsets of \$303. Therefore, if the

[61] These calculations do not require knowledge of the "true" demand curve, from which we could derive welfare implications as in Glazer and McGuire (2013).

[62] This gives us an upper bound of the potential welfare gain.

[63] This is calculated as the additional spending multiplied by the 22% figure described above.

Table A.7: Counterfactual Policies

Uniform OOPC Reduction	Elasticity	Offset	Change in OOPC	Effective Cost (to Government)	% Change, PDP Penetration	Consumer Valuation, OOPC Reduction (UB)
1.00%	-0.54	3.54	10.15	6.61	-0.0010	4.30
2.50%	-0.38	6.23	25.28	19.06	-0.0030	10.70
5.00%	-0.33	10.82	50.51	39.69	-0.0064	21.38
10.00%	-0.30	19.67	100.94	81.28	-0.0132	42.74
25.00%	-0.29	47.53	252.30	204.77	-0.0342	106.82
50.00%	-0.29	95.06	504.60	409.54	-0.0744	213.64
75.00%	-0.31	152.43	757.27	604.84	-0.1224	320.61
Eliminate the Donut Hole		52.4	355.99	303.58	-0.0571	152.86

Notes: Results are calculated as described in Section 5.

policy is to be budget neutral, premiums will have to rise dramatically.[64]

Furthermore, these policies reduce the market share of stand-alone PDPs. Consumers do not value the increased generosity at its full cost, as reflected in the measured decision utility; they prefer plans with lower premiums and higher cost-sharing. Therefore, we conclude that it will be difficult for the government to implement broad based changes to the Part D program aimed at reducing externalities that are budget neutral. This includes the recent Part D Enhanced Medication Therapy Management (MTM) Model, which encourages stand-alone plans to reduce Parts A and B spending among their enrollees. The actual financial incentives associated with this program are quite small. If plans reduce Parts A and B spending by 2% (about $200 in 2008), they are eligible for a $2 per member per month increase in their benchmark payment. Because firms only receive approximately one-tenth of the savings, they are unlikely to internalize the externality created by offsets. Furthermore, we note that a stand-alone PDP that fully internalized the externality would only spend an additional $153 per enrollee per year. Given our calculations, this would lead to savings in Parts A and B of about $30. We find that a policy that provides a $12.75 per member per month increase in the benchmark payment (and reduces Parts A and B spending by 0.3%) internalizes the externality, and would increase MA-PD enrollment by 3.4 percentage points. Furthermore, we note that a $153 increase is likely to represent the insurers' entire profit margins, based on a 15% profit margin and the estimates in Ho, Hogan and Scott Morton (2015).

It is costly for the Medicare program to implement a budget neutral policy for two reasons: consumers are not sophisticated with respect to potential under-utilization and most implementable policies fail to target marginal consumption, effectively leading to expensive OOPC reductions on infra-marginal units. These results are consistent with a model in which private insurers can better target and subsidize underutilized, high-value care. For example, while the subsidy we describe is uniform, applying to all drugs, private MA-PD insurers can implement more sophisticated contracts that better target increased utilization. We see evidence of this in the reduced form results; MA-PD plans have lower enrollee expenditure for exactly those drugs likely to generate the largest offsets. While they increase the complexity of insurance contracts and may exacerbate plan choice frictions, targeted subsidies are more likely to be cost-effective. Therefore, it may be more reasonable to encourage MA-PD enrollment; based on our estimates in Table 4, we believe this can be done in a cost-effective way. For example, rather than closing the donut hole, the federal government could increase Medicare Advantage benchmarks by $312 per year, plus the $23 in implied offsets. This would increase MA-PD market share by 7.4%.

By contrast, market outcomes could be very different absent choice frictions. In the main demand specifications, we allow for inertia and do not constrain $\alpha_q^p = \alpha_q^x$. Incorporating deviations from the neoclassical model builds on previous work (Ho, Hogan and Scott Morton (2015); Abaluck and Gruber (2016); Decarolis, Polyakova and Ryan

[64] Exacerbating this is the fact that MA-PD plans become more generous in equilibrium, decreasing OOPC to consumers by $97 per year. We note that the ACA policy is not budget neutral.

Table A.8: IV Nested Logit Parameter Estimates

Risk Quintile (Lowest to Highest)	(1)	(2)	(3)	(4)	(5)
Premium + OOPC	-0.157***	-0.119***	-0.0887***	-0.0581***	-0.0248***
	(0.00610)	(0.00508)	(0.00439)	(0.00355)	(0.00242)
$1-\sigma$	0.439***	0.441***	0.470***	0.463***	0.457***
	(0.0132)	(0.0134)	(0.0130)	(0.0127)	(0.0119)
Plan Vintage	2.148***	1.466**	-2.177	0.437	0.592
	(0.631)	(0.630)	(13,226)	(0.630)	(0.632)
Adjusted R^2	0.308	0.294	0.291	0.285	0.271
Observations	58,189	58,626	59,885	60,463	61,317

Notes: Table presents instrumental variable regression models as described in Berry (1994). The outside share is constructed as all Medicare eligibles not enrolled in a stand-alone Medicare Part D plan or MA-PD plan. In all specifications, we include plan fixed effects. Excluded instruments are an urban county dummy, and premiums and out-of-pocket expenditure in other markets, where a market is defined as a county-year combination. Standard errors are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

(Forthcoming)) and is important for understanding insurer incentives. However, a natural approach would assume that consumers care equally about a dollar reduction in premium and a dollar reduction in OOPC. In Table A.8, we present results that constrain $\alpha_q^p = \alpha_q^x$. Consistent with the patterns in our main specifications, sicker consumers are less sensitive to the combination of premiums and OOPC.

We next consider the impact of consumer decision making in equilibrium. To align consumer choices with value, policymakers could provide targeted consumer search tools (Handel and Kolstad (2015)). In this setting, we believe that would lead consumers to place greater weight on OOPC (Ericson and Starc (2016)) and lead to reduced naivete about potential under-consumption. Mechanically, we resolve for optimal insurer costs assuming the demand specification in Table A.8, such that consumers treat a $1 increase in premiums equal to a $1 increase in OOPC. The results are in the final two columns of the top panel of Table A.9. If consumers were "sophisticated," plans would increase their generosity. MA-PD plans would spend 6% more on prescription drugs, while stand-alone PDPs would spend 4% more. Public policies that align consumer demand or the structure of subsidies with providing value will lead insurers to offer contracts that reduce costs or increase health.

We perform two additional counterfactuals to explore the extent to which other features of the institutional environment affect market outcomes. First, we estimate our main counterfactual using our baseline demand estimates, which do not account for plan vintage and imply substantially less adverse selection. In this counterfactual, stand-alone PDPs are much more generous than in the preferred estimates. This implies that accounting for inertia is critical and that selection – in addition to strategic incentives – plays an important role in benefit design.

Finally, we explore the effect of imperfect competition on benefit design and premium setting. We estimate a counterfactual in which plans are constrained to pay out 80% of the premiums they collect in (drug) claims, known as a (binding) minimum loss ratio regulation. The regulation (enacted as part of the Affordable Care Act) is essentially

Table A.9: Counterfactuals

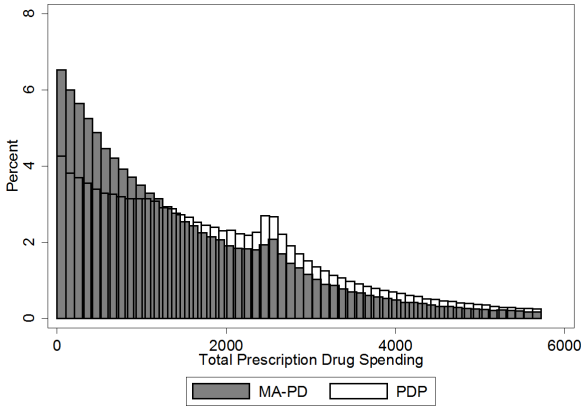
	Baseline		"Sophisticates": $\alpha_q^p = \alpha_q^x$	
	MA	PDP	MA	PDP
Premium	206.00	407.93	206.00	407.93
% Change	-	-	-	-
Insurer Rx Spend	1285.25	1211.62	1354.23	1255.60
% Change	-	-	6%	4%
	No Inertia, Internalize Externality: $\theta_{PDP} = \hat{\theta}_{MA} = \theta_1 + \theta_2$		Fixed Loss Ratio, Internalize Externality:	
Premium	231.42	459.22	194.86	358.55
% Change	4%	15%	-6%	-12%
Insurer Drug Spend	1337.38	1394.30	1121.04	1288.45
% Change	12%	13%	-13%	6%
Premium Adjustment	no		yes	

Notes: Results are calculated as described in Section 5. Means across markets are reported, as well as the % change from baseline. Drug spending represents the insured costs.

a blunt tool that caps insurer profits and reduces incentives to price strategically. If stand-alone PDPs account for medical expenditure under this pricing rule, they become more generous, consistent with previous results. However, MA-PD plans actually become substantially less generous – largely because they cannot cross-subsidize prescription drug expenditure. As a result, enrollees in MA-PD plans are actually made slightly worse off despite lower premiums, whereas enrollees in stand-alone PDPs are made substantially better off.

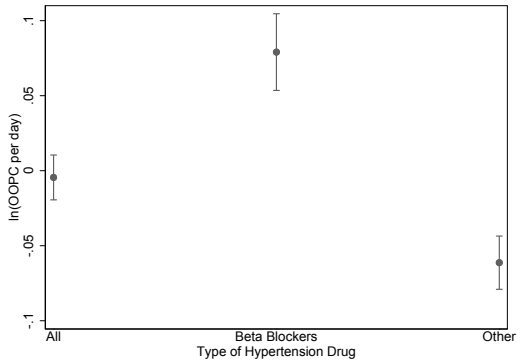
D Robustness Checks

Figure A.3: Histogram of Total Drug Expenditure by Plan Type, 2008



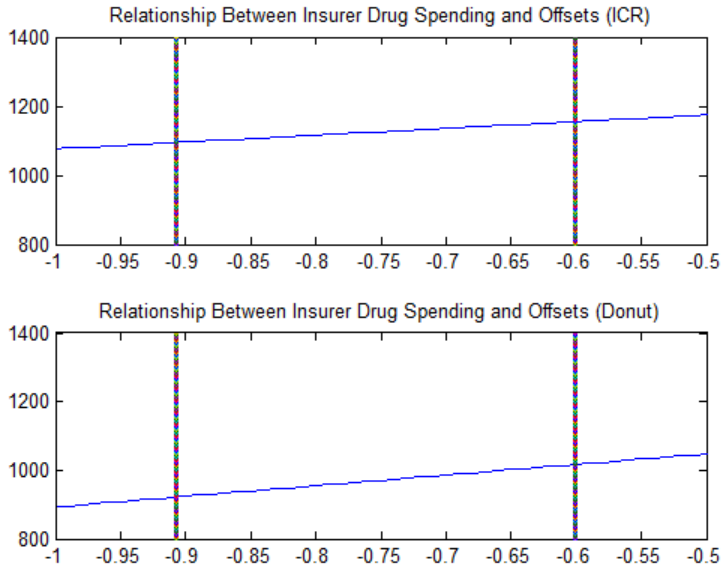
Notes: Plots a histogram of total annual expenditure by plan type. For visual simplicity, we drop enrollees spending more than the catastrophic limit ($5726.25 in 2008). The initial coverage limit in 2008 was $2510. N=981,813; 387,570 in MA-PD plans and 594,243 in stand-alone PDP plans.

Figure A.4: Effects by Drug Class



Notes: This figure plots the differences in prices by plan type. Other hypertension drugs include ACE inhibitors, angiotensin II receptor antagonists, renin inhibitors, antiadrenergic agents (centrally & peripherally acting), alpha-adrenergic blockers, aldosterone receptor antagonists, vasodilators and antihypertensive combination therapies. Standard errors are clustered at the plan-product level.

Figure A.5: Supply-Side Identification



Notes: This figure plots the optimal level of insurer spending under alternative levels of θ from first-order conditions from both x^{ICR} and x^{Donut}, using average values of the derivatives of shares with respect to premiums and out-of-pocket costs.

Table A.10: Estimates of the Relationship between Plan Enrollment and Enrollee Expenditure, No Third Party Payments

Dependent Variable: Logged Enrollee Expenditure per day		
Panel A: Main Results	(1)	(2)
1(MA-PD)	-0.042***	-0.019***
	(0.003)	(0.004)
Observations	119,915,976	119,915,976
Adjusted R-Squared	0.655	0.729
Panel B: By High Offset Class		
1(MA-PD)	-0.036***	-0.015**
	(0.005)	(0.005)
1(MA-PD)*Asthma	-0.088***	-0.102***
	(0.018)	(0.018)
1(MA-PD)*Hypertension	0.033***	0.042***
	(0.009)	(0.009)
1(MA-PD)*Diabetes	-0.035***	-0.034**
	(0.010)	(0.011)
1(MA-PD)*Cholesterol	-0.067***	-0.064***
	(0.009)	(0.010)
Observations	119,915,976	119,915,976
Adjusted R-Squared	0.655	0.729
Product Fixed Effects	X	X
Phase Fixed Effects		X
	ICR or Deductible	
Panel C: By Benefit Phase	(Ded Amt. = 0)	Donut Hole
1(MA-PD)	0.032***	-0.266***
	(0.004)	(0.004)
Observations	94,800,906	16,301,087
Adjusted R-Squared	0.731	0.730

Notes: Table presents linear regression models with logged enrollee expenditure per day supply as the dependent variable. The unit of observation is at the fill level (weighted by day supply), for the 2007-2009 period. The original data are obtained from a 10% sample of CMS prescription drug event files. We include year-level indicators and product fixed effects in all specifications. In some specifications, we also control the phase of the standard Part D benefit. Standard errors are clustered at the plan-product level. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.11: Estimates of the Relationship between Plan Enrollment and Enrollee Expenditure

Dependent Variable: Enrollee Expenditure per day		
	(1)	(2)
1(MA-PD)	-0.050***	-0.029***
	(0.003)	(0.004)
1(day supply < 30)	0.444***	0.434***
	(0.007)	(0.007)
1(day supply 31-90)	-0.181***	-0.177***
	(0.003)	(0.003)
1(day supply > 90	-0.107***	-0.099***
	(0.025)	(0.026)
Observations	123,031,165	123,031,165
Adjusted R-Squared	0.631	0.698
Product Fixed Effects	X	X
Phase Fixed Effects		X

Notes: Table presents linear regression models with logged enrollee expenditure per day supply as the dependent variable. The unit of observation is at the fill level (weighted by day supply), for the 2007-2009 period. The original data are obtained from a 10% sample of CMS prescription drug event files. We include year-level indicators and product fixed effects in all specifications. In some specifications, we also control the phase of the standard Part D benefit. Standard errors are clustered at the plan-product level. Thirty day supply prescriptions (the most common) is the omitted category. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.12: Mechanisms

	(1)	(2)
Panel A: Main Results	Outcome: 1(90 Day)	
1(MA-PD)	0.00272**	0.00212*
	(0.000929)	(0.000939)
Observations	153,964,560	153,964,560
Adjusted R-Squared	0.096	0.097
Panel B: Main Results	Outcome: Total Cost/Day	
1(MA-PD)	-0.00955	-0.00468
	(0.00656)	(0.00657)
Observations	153,962,060	153,962,060
Adjusted R-Squared	0.590	0.590

Notes: Table presents linear regression models, where outcome variables are as described in each panel. The unit of observation is at the fill level, for the 2007-2009 period. The original data are obtained from a 10% sample of CMS prescription drug event files. We include year-level indicators and product fixed effects in all specifications. In some specifications, we also control the phase of the standard Part D benefit. Standard errors are clustered at the plan-product level. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.13: Benefit Design and Out-of-Pocket Costs

Dependent Variable: Out-of-Pocket Costs						
	(1)	(2)	(3)	(4)	(5)	(6)
x_{jmt}^{ICR}	501.5***	638.9***	499.7***	640.6***	498.8***	637.3***
	(49.05)	(56.45)	(48.86)	(56.44)	(48.53)	(55.80)
x_{jmt}^{Donut}	-2.442	5.911	-2.129	5.160	-1.758	6.468
	(9.377)	(18.19)	(9.311)	(18.22)	(9.293)	(18.12)
$1(MA) * x_{jmt}^{ICR}$		-291.4***		-291.2***		-289.8***
		(72.49)		(72.94)		(71.88)
$1(MA) * x_{jmt}^{Donut}$		-6.640		-6.057		-6.916
		(16.54)		(16.53)		(16.52)
FFS Costs					0.281***	0.281***
					(0.0358)	(0.0357)
R-Squared	0.228	0.230	0.230	0.228	0.230	0.231
Observations	569,078	569,078	569,078	569,078	569,078	569,078
Year FE	X	X	X	X	X	X
Risk Type FE	X	X	X	X	X	X
Demo. Controls		X	X		X	X
Plan FE	X	X	X	X	X	X

Notes: Table presents OLS regression models, where outcome variable is consumer out-of-pocket costs. The unit of observation is an enrollee-year for the 2007-2009 period. The original data are obtained from a 10% sample of CMS prescription drug event files, aggregated to the enrollee-year level. We include year-level indicators and indicators for the quintile of 2006 spending (consumer types) in all specifications. In some specifications, we also control for 5-year average per capita Medicare FFS spending and demographic controls for age categories, race, and gender. Standard errors are clustered at the contract level and are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.14: IV Nested Logit Results

Risk Quintile (Lowest to Highest)	(1)	(2)	(3)	(4)	(5)
Product Characteristics Approach					
Premium	-0.0326***	-0.0518***	-0.0633***	-0.0626***	-0.0526***
	(0.00671)	(0.00694)	(0.00732)	(0.00732)	(0.00634)
Donut Hole Coverage	0.997***	1.115***	1.697***	1.957***	1.688***
	(0.0953)	(0.0896)	(0.0985)	(0.0989)	(0.0897)
Has Deductible	-1.036***	-1.050***	-1.174***	-1.213***	-1.054***
	(0.0328)	(0.0332)	(0.0356)	(0.0360)	(0.0325)
Plan Vintage	0.394***	0.453***	0.443***	0.469***	0.490***
	(0.0209)	(0.0222)	(0.0237)	(0.0250)	(0.0241)
$1-\sigma$	0.318***	0.343***	0.374***	0.384***	0.376***
	(0.0110)	(0.0111)	(0.0114)	(0.0116)	(0.0103)
Observations	58,189	58,626	59,885	60,463	61,317
Adjusted R-Squared	0.378	0.356	0.251	0.173	0.242

Notes: Our current approach relies on plan fixed effects and identifies sensitivity to price and OOPC using cross market variation. To address the role of selection in the determination of contract characteristics more directly, we model plan choice as a function of contract characteristics. In these specifications, we include premiums, OOPC, and dummies for deductible and donut hole coverage as the observable characteristics. Table presents instrumental variable regression models, where the outcome variable is the log of the plan share less the log of the outside share. The outside share is constructed as all Medicare eligibles not enrolled in a stand-alone Medicare Part D plan or MA-PD plan. We include plan fixed effects in all specifications. Instruments are the urban dummy, as well as premiums and out-of-pocket costs in other markets, where a market is defined as a county-year combination. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.15: Unobserved Demand Heterogeneity

Risk Quintile (Lowest to Highest)	(1)	(2)	(3)	(4)	(5)
Baseline Model					
Premium, Type 1	-0.1391	-0.1275	-0.0831	-0.0897	-0.0940
	(0.0178)	(0.0053)	(0.0085)	(0.0071)	(0.0303)
OOPC, Type 1	-0.1123	-0.0649	-0.0435	-0.02424	-0.0591
	(0.0167)	(0.0236)	(0.0031)	(0.0030)	(0.0061)
Premium, Type 2	-0.2325	-0.2228	-0.2548	-0.2495	-0.2845
	(0.0167)	(0.0104)	(0.0107)	(0.0084)	(0.0550)
OOPC, Type 2	-0.1263	-0.0826	-0.0486	-0.0303	-0.0159
	(0.0112)	(0.0088)	(0.0044)	(0.0035)	(0.0043)
γ (% of Type 2)	0.6553	0.6617	0.6680	0.6740	0.6108
	(0.0498)	(0.0018)	(0.0330)	(0.0240)	(0.1342)
Allowing for Inertia					
Premium, Type 1	-0.1415	-0.1445	-0.1316	-0.1320	-0.1120
	(0.0261)	(0.0243)	(0.0222)	(0.0206)	(0.0195)
OOPC, Type 1	-0.0965	-0.0516	-0.0298	-0.0139	0.0010
	(0.0134)	(0.0105)	(0.0076)	(0.0005)	(0.0034)
Premium, Type 2	-0.1749	-0.1717	-0.1980	-0.1917	-0.1930
	(0.0516)	(0.0519)	(0.0523)	(0.0532)	(0.0554)
OOPC, Type 2	-0.1199	-0.0774	-0.0435	-0.0267	-0.0007
	(0.0261)	(0.0243)	(0.0222)	(0.0344)	(0.0039)
Plan Vintage	0.7688	0.7456	0.6300	0.6390	0.7779
	(0.0578)	(0.0623)	(0.0654)	(0.0704)	(0.0843)
γ (% of Type 2)	0.6553	0.6617	0.6680	0.6740	0.6799
	(0.2198)	(0.2080)	(0.2288)	(1.7229)	(0.2886)

Notes: Our current approach also models heterogeneity in demand across observable, but not unobservable consumer characteristics. We argue that, given both the empirical literature and reduced form results, we include most of the variation across consumers that is predictable to insurers. However, a more flexible demand system may better capture the patterns of substitution in the data. We report estimates that allow for a mixture of unobserved consumer types, similar to Berry and Jia (2010). The results are qualitatively similar to the main estimates, though they imply slightly less sensitivity among high spenders. For numerical stability, markets with less than 50,000 enrollees were dropped from the analysis. In Table A.17, we show that our supply-side estimates are not sensitive the inclusion of additional consumer heterogeneity. Stars denoting significance omitted.

Table A.16: Supply Side Incentive and Inertia

	(1)	(2)	(3)
Panel A, Dep. Var.: Logged Premiums			
Lagged Market Share	0.855***		0.902***
	(0.00453)		(0.00465)
Enrollment Growth Rate		-0.00281	-0.0846***
		(0.00180)	(0.00187)
N	2,174,111	2,174,111	2,174,111
Panel B, Dep. Var.: Logged Insurer Costs			
Lagged Market Share	0.0103		0.0131
	(0.0142)		(0.0143)
Enrollment Growth Rate		-0.0182**	-0.0186**
		(0.00603)	(0.00615)
N	3,022,704	3,022,704	3,022,704

Notes: The unit of observation is the beneficiary year. All specifications include contract, state, and year fixed effects. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.17: Supply Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Multi-Product Firms		Unobserved Heterogeneity		Non-LIS Distorted		Basic Plans	
θ_1	-0.9729	-1.2798	-0.9714	-1.3427	-1.1871	-1.3376	-0.9761	-1.3427
	(0.0082)	(0.0080)	(0.0081)	(0.0079)	(0.0081)	(0.0082)	(0.0154)	(0.0163)
θ_2		0.3491		0.4211		0.3814		0.2584
		(0.0301)		(0.0304)		(0.0411)		(0.0333)
N	33,538	33,538	33,538	33,538	13,737	13,737	28,975	28,975
	(9)	(10)	(15)	(16)	(11)	(12)	(13)	(14)
	Alt. Rebate		Fixed Markup		x_{jmt}^{ICR} Only		Finer Risk Adj.	
θ_1	-1.0481	-1.3427	-0.9401	-1.3427	-0.5762	-0.8020	-0.8827	-1.1562
	(0.0065)	(0.0378)	(0.0082)	(0.0078)	(0.0046)	(0.0045)	(0.0101)	(0.0093)
θ_2		0.3341		0.4565		0.2559		0.3010
		(0.0397)		(0.0310)		(0.0173)		(0.0469)
N	33,538	33,538	33,538	33,538	33,538	33,538	33,538	33,538

Notes: Parameters are estimated using generalized method of moments as described in Section 4. Standard errors are calculated using a bootstrap that re-samples plans with replacement. Observations are at the plan-market-year level. Models (1) and (2) allow firms to optimize over their full portfolio of plans, while models (3) and (4) incorporate unobserved demand heterogeneity as described in Table A.15. Models (5)-(8) restrict the sample of plans used in the analysis. Models (9)-(16) test robustness to alternative cost assumptions described in the text. Models (11) and (12) set $x_{jmt}^{D} = x_{jmt}^{ICR}$, and Models (13) and (14) exclude drugs identified by Lavetti and Simon (2018) and Lavetti and Han (2017) to lead to differential selection by plan type.