Externalities and Benefit Design in Health Insurance

Amanda Starc

Kellogg School of Management, Northwestern University and NBER

Robert J. Town*

University of Texas - Austin and NBER

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Abstract

We show that profit-maximizing insurers alter product design in the market for Medicare prescription drug coverage to account for underutilization by consumers. Using policy induced variation in subsidies, we document that plans that cover all medical expenses spend more on drugs than plans that are only responsible for prescription drug spending, consistent with drug spending offsetting some medical costs. The effect is driven by drugs that are likely to generate substantial offsets. Our supply side model confirms that differential incentives across plans can explain this disparity. Counterfactuals show that the externality created by stand-alone drug plans is $475 million per year.

*Kellogg School of Management, 2001 Sheridan Road, Evanston, IL and Department of Economics, The University of Texas at Austin, 2225 Speedway, Austin, TX. They gratefully acknowledge funding from the Leonard Davis Institute. Michael French, Matt Grennan, Ben Handel, Jonathan Ketcham, Kurt Lavetti, Maria Polyakova, Joshua Schwartzstein, Ashley Swanson, and participants at the American Health Economics Conference, FTC Microeconomics Conference, NBER Insurance Meetings, Kellogg Healthcare Markets Conference, Wharton IO lunch, and Yale provided helpful comments. Emma Boswell Dean provided excellent research assistance.

1 Introduction

Health insurance, while mitigating financial risk, can create a welfare loss from moral hazard by lowering the price of medical services to consumers below marginal cost. Optimal insurance contracts rely on cost sharing via deductibles, coinsurance and co-payments to mitigate this welfare loss.[1] However, there is also substantial evidence that consumers reduce the utilization of cost effective care in the face of increased cost sharing (Manning et al. (1987), Brot-Goldberg et al. (2015)). This can lead to inefficient underutilization, which we define as foregoing treatments for which the societal benefit exceeds the treatment cost. Foregoing cost effective care in the present may lead to additional, more costly health care consumption in the future, creating an externality. The extent of underutilization critically depends on how health insurers design their products in equilibrium. If insurers face the financial consequences of inefficient under-consumption, they have a clear incentive to mitigate this underutilization through more generous benefit design and other interventional strategies. To the extent that insurers do not internalize and mitigate (and perhaps even exploit) this underutilization, there are likely large societal and welfare consequences. Unlike the large literature devoted to insurers' responses to moral hazard, little empirical analysis examines insurers' incentives and equilibrium responses to inefficient underutilization.[2]

In this paper, we empirically examine insurers' cost-side incentives to improve adherence by altering plan characteristics such as coinsurance and copayments. We build a model of consumer choice and endogenous insurer product design, and then leverage policy induced variation in firm incentives to estimate the cost of providing product "quality" in the form of drug plan generosity. The model is used to calculate equilibrium product quality under alternative policies and incentives. In our setting, the extent of underutilization of high value health care services depends on insurer incentives, which, in turn, depend upon the institutional and regulatory setting in

[1] The optimal insurance design across multiple treatments depends on the sustainability or complementarity between different medical treatments (Ellis, Jiang and Manning (2015); Goldman and Philipson (2007)).

[2] The notion that health insurance can correct for behavioral hazard dates at least to the "value-based insurance design" movement (Chernew, Rosen and Fendrick (2007)). There are case studies of the impact of these designs but no analysis of the incentives to implement these types of designs or their impact in the market context. Lavetti and Simon (2014) consider the role of both selection and offsets in driving formulary decisions. Our approach utilizes claims data, allowing us to show a causal effect on utilization in addition to plan design.

which firms compete.

We apply our model to detailed data from the Medicare Part D program. This institutional setting provides an excellent opportunity to examine these issues as there is variation across types of plans in the incentive to design benefits accounting for underutilization and offsets in medical expenditures generated by increased pharmaceutical utilization. Under the Medicare Part D program, there are (roughly) two types of drug plans: stand-alone prescription drug plans (PDPs) and Medicare Advantage (MA-PD) plans. Stand-alone PDPs only cover pharmaceutical expenditures while MA-PD cover both drug and medical expenditures. These differences imply that these two types of plans face different benefit design incentives. Stand-alone PDPs have an incentive to minimize drug expenditures, while MA-PD plans have an incentive to minimize overall medical and drug expenditures taking into account spillovers from drug consumption to medical care utilization.

We begin by performing a detailed, reduced form analysis of the causal relationship between Part D plan enrollment and measures of drug adherence, costs and utilization. Specifically, we examine the impact of PDP versus MA-PD enrollment on a number of prescription drug consumption metrics using a large, detailed, representative sample of Part D claims. These data capture every drug purchase occasion for a 10% random sample of Medicare beneficiaries. We also observe the beneficiary demographics, their previous purchase occasions, the specific drug(s) they purchased, the out-of-pocket cost of the drug(s) to the consumer, the location of the purchase in the benefit design (e.g. donut hole) and the point-of-sale pharmacy price of each drug.

Causal inference is an obvious challenge in our setting. Medicare beneficiaries may differentially select into MA-PD and PDP plans and plans may operate in markets with different demand and cost structures, leading to biased estimates if unaddressed. In order to identify effects of MA-PD enrollment, we exploit institutional discontinuities in the subsidies for Medicare Advantage plans across counties. Specifically, we use a discontinuity in payment rates that increases payments for plans in Metropolitan Statistical Areas with more than 250,000 people. In the subset of counties to the right of the discontinuity, the MA-PD subsidy is exogenously more generous and the MA-PD enrollment rates are correspondingly significantly higher, allowing us to identify the causal effect of MA-PD enrollment.

We find that enrollment in MA-PD plan causally increases total enrollee drug expenditure. MA-PD plans reduce consumer out-of-pocket costs and increase their

own spending relative to stand-alone PDP plans. The net effect is to increase overall drug consumption. Importantly and consistent with our underlying explanation, the increase in utilization is concentrated among drugs previously identified by Chandra, Gruber and McKnight (2010) to have large health consequences in the short-run. Furthermore, the effect is larger in plans with higher enrollee retention, as would be predicted by Fang and Gavazza (2011), and among enrollees with chronic conditions, as would be predicted by Chandra, Gruber and McKnight (2010). Despite statistically similar drug prices across plans, MA-PD plans have lower cost-sharing for consumers for identical products; this effect is especially large for drugs used to treat chronic conditions, like asthma, diabetes, and high cholesterol. Our results are robust to alternative specifications, controls for levels of FFS spending, and distortions due to other institutional features of the market, including the low-income subsidy.

We then turn to specifying and estimating the structural parameters of an oligopoly model of premium and benefit design choice. The model recovers cost and demand side parameters, allowing us to understand the economic rationale behind increased prescription drug benefit generosity in MA-PD plans. The model parameters imply that the increased generosity of MA-PD plans is driven by insurer cost side incentives and cannot be rationalized by demand-side considerations. In order to capture insurer incentives, we model both consumer choice and insurer plan design. Importantly, our 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. Consistent with other work (Abaluck and Gruber (2011)), the demand side estimates imply that consumers undervalue plan generosity when choosing plans. Because we find the demand responses to benefit design are so modest, MA-PD plans therefore increase drug plan generosity to reduce medical costs rather than attract consumers.

We then use the model to measure the impact of plans internalizing the externalities generated by drug offsets. We find substantial benefit externalities in MA-PD plans: a $1 increase in prescription drug spending reduces non-drug expenditure by approximately 20 cents.[3] Our estimates directly account for or are robust to many institutional features of the MA and Part D markets, including the bidding mechanism

[3]This estimate aligns with previous work by Chandra, Gruber and McKnight (2010), who examine offsets using demand-side utilization. We cannot employ a similar strategy because we do not observe medical claims for enrollees in MA-PD plans.

and distortions from the low-income subsidy. Our model implies that if stand-alone PDPs are forced to account for this externality in their premiums and benefit design behavior, they would increase drug spending by 13%. Based on these estimates, we find that stand-alone Part D plans impose a $475 million externality on traditional Medicare each year. Therefore, the plan design and medical management applied by MA-PD plans may increase welfare beyond what can be obtained by traditional social insurance alone. In contrast to a large literature focused on the dead-weight loss due to moral hazard, our paper shows when an externality is present the optimal benefit structure is more generous and insurers will internalize offsets if incented to do so.

Our paper contributes to several strains of the health insurance and industrial organization literature. Our work expands on the recent literature examining insurer competition in private Medicare markets (e.g. Decarolis, Polyakova and Ryan (2015); Curto et al. (2015)); more broadly, this paper contributes to a recent and growing literature on endogenous product design (see Fan (2013) as well as Crawford (2012) for a review).[4]

The paper is organized as follows. Section 2 describes the market and 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 Medicare Part D and Medicare Advantage

Medicare provides health insurance to the elderly in the United States.[5] Medicare Parts A and B, enacted in 1965, cover inpatient, outpatient and limited nursing home 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. Medicare Part D represented a large expansion of the program in 2006, as Medicare did not originally cover prescription drugs. Prescription drugs not only represented a growing part of uninsured expenditure, but increased drug spending may reduce other medical spending. Private insurers in Medicare Advantage have an

[4]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 (2016). The paper also contributes to the empirical industrial organization literature examining firm behavior when consumers are imperfectly informed or have non-standard preferences (Grubb and Osborne (2012); Grubb (2012, 2014); Handel (2013); Ellison (2006)).

[5]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.

incentive to take this offset into account; in this paper, we focus on the behavior of these private plans relative to stand-alone PDPs.

Private insurance options have been available to Medicare enrollees since the 1970s. This program has gone by a variety of names over time (see McGuire, Newhouse and Sinaiko (2011) for a comprehensive history), but is currently known as Medicare Advantage. The program's popularity has waxed and waned over time generally coinciding with the level of federal reimbursement. As of 2009, the last year of our sample, 23% of Part D beneficiaries were enrolled in a Medicare Advantage plan. Enrollment rates have continued to grow post-Affordable Care Act (ACA).[6] There is also significant geographic heterogeneity in the popularity of MA-PD plans. Across consumers within a market, MA may be more attractive to middle and lower income as well as healthier beneficiaries.

During our sample period, a senior eligible for Medicare had a number of private insurance choices. They could opt out of traditional Medicare and into a Medicare Advantage plan. In this scenario, the private Medicare Advantage insurer would be responsible for all medical spending. By contrast, the senior could remain in traditional fee-for-service (FFS) Medicare and then choose to augment Medicare Parts A and B with a Part D plan. In this scenario, the private Part D insurer would cover drug expenditure, while the Medicare program would directly cover non-drug medical spending, including hospitalizations and physician services.

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

[6]During our time period, from 2007-2009, approximately 1 in 4 beneficiaries was enrolled in a MA-PD plan.

The Part D program has been popular among both beneficiaries and policymakers since its introduction in 2006. Researchers have argued that Part D has lowered the price of drugs by increasing insurer market power relative to drug manufacturers (Duggan and Scott Morton (2010)); these potential efficiencies, along with a shift toward generic drugs, have led to program costs lower than forecasted when this benefit was passed into law. The subsidy, which covers 74.5% of the premium, is substantial and it is financially beneficial for most Medicare beneficiaries to enroll in some form of drug coverage. The program requires insurers to provide coverage at least as generous as the "standard benefit." The standard benefit has a very nonlinear structure. The deductible in 2009 was $295, followed by 25% cost sharing in the initial coverage region (ICR) up to $2700 of expenditure, followed by the infamous donut hole where the enrollee incurs the entire cost of drug expenditures and, finally, catastrophic coverage where the enrollee faces a 5% coinsurance rate. Coordination of care and innovation in benefit design could be especially important given the nonlinear and idiosyncratic structure of the Part D standard benefit.

However, the majority of plans in our sample eliminate the deductible, and nearly one quarter of MA-PD plans had some form of donut coverage in 2006.[7] The strict regulation of Part D plans, covering both the financial details of plans and formularies, creates a minimum standard for plans. In addition to providing coverage that is actuarially equivalent to the standard benefit, plans must cover all or substantially all drugs within six protected drugs classes and two or more drugs in another 150 categories. However, firms can design their plans within these limits and, potentially, increase the generosity of their plans. Part D benefits are administered in both stand-alone PDP plans and Medicare Advantage MA-PD plans. The set of PDP plans available depends on which of the thirty-four regions an enrollee lives in, while the set of MA-PD plans available depends on the county of residence. Our paper explores these two programs in tandem, noting that insurers have differential incentives across plans: While Medicare Part D plans are simply minimizing drug expenditures, MA-PD plans have an incentive to take total medical costs into account.

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 medical services. Furthermore, reductions in consumption due to

[7] 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.

higher cost sharing seem to affect both high- and low-value services. Underutilization is especially important if there are drug offsets; that is, if spending on drugs reduces spending on other medical services. Numerous studies have documented the presence of drug offsets in employer-sponsored plans (Chandra, Gruber and McKnight (2010); Gaynor, Li and Vogt (2007)) and the Medicare Part D program (McWilliams, Zaslavsky and Huskamp (2011)). These offsets of medical care costs are viewed as important enough to be included in government budget forecasts of health care expenditures. The Congressional Budget Office, surveying the literature, assumes that a 1% increase in drug consumption reduces non-drug medical consumption by 0.2% (CBO (2012)). Cost sharing may lead to sub-optimal consumption due to 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)), misalignment of copays across multiple technologies (Ellis, Jiang and Manning (2015); Goldman and Philipson (2007)), or underutilization may be "due to mistakes or behavior biases," referred to in the literature as behavioral hazard (Baicker, Mullainathan and Schwartzstein (2015)). Within the context of the Part D program, the behavioral bias most frequently explored is myopia (Abaluck, Gruber and Swanson 2015, Dalton, Gowrisankaran and Town 2015).[8]

2.1 Data

Our primary data source is the rich Medicare Part D prescription drug 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 this data to the enrollee-year level. We supplement this data with information on beneficiary and plan characteristics and merge in MA reimbursement levels and county and metropolitan

[8]Ex ante, consumers may be naive or sophisticated about the potential for underutilization due to information issues, behavioral biases, or both. A sophisticated consumer will demand an insurance contract that corrects for this underutilization of high-value services to the extent that they value reduced spending or improved health, creating a market for value-based insurance designs (Ellison (2006); Chernew, Rosen and Fendrick (2007)).

In addition, there is substantial evidence that consumers have difficulty assessing the impact of differential benefit design on their drug consumption when selecting a plan. The average consumer has 18 MA-PD plans and 35 PDP plans from which to choose. This can potentially lead to substantial consumer confusion, as enrollees must compare potential out-of-pocket costs and premiums across a wide range of plans. Abaluck and Gruber (2011) document deviations from the predictions of a rational choice model and over-weighing of plan premiums, while Ketcham et al. (2012) argue that consumers have learned over time. Potentially counteracting consumer learning is consumer inertia, which has been documented by Ho, Hogan and Scott Morton (2015).

demographic information.

We begin with 14,407,011 beneficiary years for the period 2007 to 2009. Of those beneficiary-year combinations, we observe fills for 7,597,476 enrollees and drop enrollees with no claims. We also exclude any beneficiaries who receive low-income subsidies and are subject to lower cost sharing.[9] This leaves us with 4,802,000 beneficiary-year observations. We then drop any enrollees for whom we do not have claims in 2006 so that we can control for previous utilization, leaving us with 3,534,965 observations. We exclude those consumers who spend over the catastrophic cap, as insurers are only responsible for their small fraction spending on the margin. Finally, we have to drop a number of observations for which we do not have complete plan or population information. This leaves us with a total of 3,019,197 observations.

Summary statistics of our sample are presented in Table 1. In the full sample, the average beneficiary is 77 years old, 62% are female and 91% are white. Average total annual expenditure is $1639, and the variance is nearly as large as the mean despite the lack of high spenders in the analysis sample. In many specifications, we restrict attention to consumers who live in counties with metro populations between 100,000 and 400,000. In column 2, we present summary statistics for this sub-sample. Average total expenditure for this group is very similar for the population as a whole at $1697 per enrollee per year. Finally, in the last two columns, we compare the characteristics of enrollees above and below the 250,000 cutoff that defines an urban county and translates into higher reimbursements. Due to our large sample size, there are statistically significant differences in the observable demographics and utilization across these two groups, however, the magnitudes of the differences are economically insignificant. We do not observe non-prescription medical claims for MA enrollees and an important goal of the structural analysis is to infer the level medical expenditures and importantly the drug offset from insurer plan design decisions.

There is substantial heterogeneity in consumer spending, as highlighted in Figure 1. This figure plots a histogram of total spending in both MA-PD and standalone PDP plans in 2008. There are a couple observations to highlight: first, as expected, there is excess mass at the initial coverage limit, as highlighted by Einav, Finkelstein and Schrimpf (2015). Second, consumers in MA-PD plans spend substantially less than PDP consumers, consistent with advantageous selection of healthy consumers

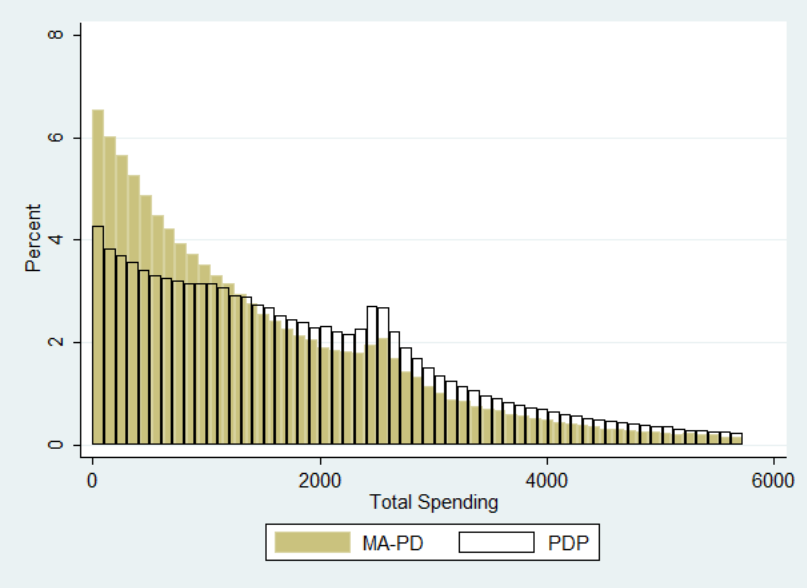
[9] While we drop LIS enrollees for our main analysis, we run numerous robustness analyses to test the sensitivity of our findings to supply-side responses to the presence of the LIS population.

Table 1: Summary Statistics (Means and Standard Deviations)

	Metro Population Restrictions			
	None	100-400k	100-250k	251-400k
Total Drug Expenditure	1636.39	1697.33	1691.51	1704.51
	[1288.74]	[1284.98]	[1284.65]	[1285.36]
Total Insurer Drug Expenditure	1026.79	1031.08	1021.48	1042.94
	[826.31]	[782.74]	[775.54]	[791.38]
Enrollee Out-of-Pocket Costs	609.60	666.25	670.04	661.57
	[664.60]	[680.57]	[682.11]	[678.64]
Total Rx Days Supply	1230.18	1262.58	1268.12	1255.75
	[796.30]	[785.66]	[788.69]	[781.86]
% in MA	0.4048	0.2492	0.1962	0.3147
	[0.4908]	[0.4326]	[.3971]	[.4644]
Age	76.9181	76.4850	76.5246	76.4361
	[7.2325]	[7.1025]	[.0155]	[.0171]
% Female	.6167	.6268	.6279	.6255
	[.4862]	[.4836]	[.4834]	[.4840]
% White	.9053	.9475	.9502	.9441
	[.2929]	[.2230]	[.2175]	[.2295]
Observations	3,019,197	381,921	210,947	170,974

Notes: Table presents summary statistics describing mean consumer demographics, coverage, and utilization. The unit of observation is the enrollee-year. Sample is restricted to consumers living in counties with populations in the range described in the top row of the table. Standard deviations are in brackets.

Figure 1: Histogram of Total Drug Spending by Plan Type, 2008



Notes: Plots a histogram of total spending by plan type. For visual simplicity, we drop consumers 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.

into the MA program. Despite MA-PD plans' mean cost advantage over PDPs, we show that MA-PD plans offer more generous drug coverage. This histogram highlights the need for a credible identification strategy to capture the causal effect of MA-PD enrollment on prescription drug spend.[10]

We also construct a number of variables to characterize plans. In our model, plans are characterized by a premium p_{jt} and a tariff schedule $P_{jt} = \left[\begin{array}{cccc} P_{jt}^{Ded} & P_{jt}^{ICR} & P_{jt}^{Donut} & P_{jt}^{Cat} \end{array} \right]'$. Each element of this matrix is defined as a weighted average of beneficiary out-of-pocket costs (OOPC) per days supply, where the copayments or coinsurance rates are plan-specific, but national consumption weights are applied. To create this variable, we construct an average price per days supply for each product d in each phase-plan j specific combination in year t. These out-of-pocket costs, p_{djt}, do not reflect consumer utilization within that plan. To capture average, national levels of utilization, we simply average the days supply by drug-year combination to create q_{dt}. This

[10]We control for this observed heterogeneity by controlling for lagged utilization in both our reduced form results and consumer demand system. To do this, we create five consumer types corresponding to the five quintiles of their 2006 spending. Total utilization in the first group averages $895 per year for 2007-2009, while yearly spending in the top quintile averages $3503.

Table 2: Mean Plan Characteristics

	PDP	MA
1(Deductible)	.1912	.1655
P^{ICR}	.5026	.4608***
P^{Donut}	1.93	1.71***
Premium	23.16	12.77***
Observations	381	1926

Notes: The unit of observation is the year-contract. P^{ICR} and P^{Donut} are calculated for a standardized population using claims data. 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 ***.

weighting allows us to construct a measure of consumer out-of-pocket costs that does not depend on the utilization of consumers within the plan as:

$$P_{jt}^{Phase} = \sum_d p_{djt} q_{dt}.$$

Table 2 describes summary statistics for each of these variables. Cost sharing is lower in MA-PD plans, especially in the donut hole, where the average out-of-pocket cost per day supplied is 11% lower ($1.71 versus $1.93 for PDP plans). MA-PD plans also have lower cost sharing in the initial coverage phase (46 cents versus 50 cents) and lower premiums, due in part to generous reimbursement. These summary statistics indicate that MA-PD plans are likely to be more generous and have flatter cost sharing schedules than their PDP counterparts.

2.2 Identification Strategy

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

Following a series of papers (Afendulis, Chernew and Kessler (2013); Cabral, Geruso and Mahoney (2014); Duggan, Starc and Vabson (2015)), we rely on a statutory discontinuity in MA-PD plan reimbursement to identify the causal impact of MA-PD enrollment. For counties with relatively low fee-for-service (FFS) spending,

payment is set equal to a payment floor. Beginning in 2003, differential floors were set for urban and rural counties – approximately two-thirds of counties are floor counties. Higher reimbursement in urban counties led to more plan entry and higher MA penetration rates (Duggan, Starc and Vabson (2015)). This variation in MA penetration rates appears driven by the differential MA subsidies and is not correlated with individual health risk. Furthermore, because an urban county is somewhat arbitrarily defined as one with 250,000 or more in metro population, it is natural to focus the analysis on comparable counties near each side of the threshold. Consumers in urban floor counties close to the threshold are more likely to be enrolled in MA-PD plans than consumers in observationally similar rural floor counties just to the right of the urban threshold.[11] In our reduced form analysis, we use the county urban/rural status as an instrument in a linear instrumental variable specification; our empirical strategy is a fuzzy regression discontinuity approach.

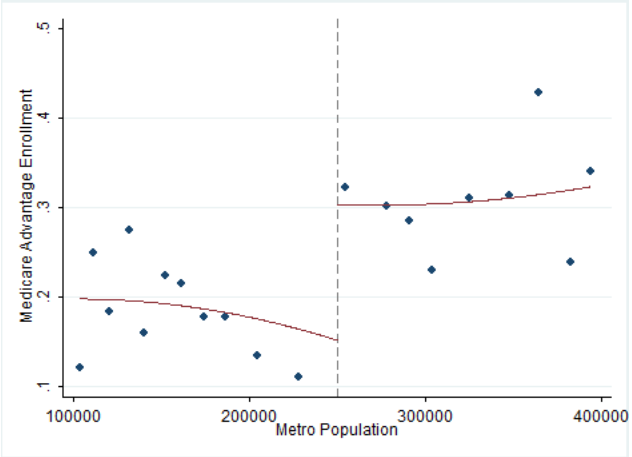
The identification strategy hinges on the similarity of urban and rural floor counties near 250,000 in metro population. We provide a battery of evidence of this balance in Table A.1; using data from the Area Resource files, we show that the "treated" and "control" counties are similar in terms of demographic characteristics. In Figures A.3, A.4, A.5, and A.6, we show binscatter plots confirming that the covariates are not discontinuous across the threshold. Previous research has shown that increased generosity may reduce premiums and increases the amount of advertising (Cabral, Geruso and Mahoney (2014); Duggan, Starc and Vabson (2015)).[12]

The variation we use in our IV specifications is highlighted in Figure 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 type, as well 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 our identification

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

[12] While none of these previous studies have found evidence of a substantial increase in generosity, we will explore this possibility. Finally, unlike studies examining the impact on providers (Afendulis et al. (2011)), we do not need to worry about spillovers or general equilibrium effects, as we study insurer responses to the behavior of individuals.

Figure 2: Effect of Population on MA 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 type, and county-level FFS spending. Lines represent a quadratic fit.

strategy using an instrument variables framework. Specifically, we estimate:

$$y_{itjm} = X^1_{mt}\beta_1 + X^2_{it}\beta_2 + \beta_3 1(MA) + g(pop_{mt}) + \mu_{itj},$$

$$1(MA) = X^1_{mt}\gamma_1 + X^2_{it}\gamma_2 + \gamma_3 1(urban_{mt}) + g(pop_{mt}) + \nu_{itj},$$

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 out-of-pocket costs, and insured costs. We hypothesize that insured spending is causally higher in MA-PD plans, and consumer out-of-pocket costs lower. These relationships are directly due to plan 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.

3 Reduced Form Analysis

To explore the impact of MA enrollment on utilization, 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 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, preferred set of specifications, we also control for historical county-level FFS spending, which proxies for county level variation in of 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 3 reports the results of OLS regressions of total expenditure, OOPC, and insurer spending. These results are likely biased because of adverse selection into PDP plans – we report them in order to provide a benchmark to the IV estimates. To make these results directly comparable to the IV estimates, we focus the analysis on consumers living in counties with associated metro populations between 100,000 and 400,000.[13] 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 enrollee has lower drug expenditures: total spending on drugs is $252 less than their counterparts in stand-alone PDP plans. The average total expenditure for this sub-sample is $1697, indicating that MA beneficiaries have 15% lower drug spending than PDP enrollees. This lower expenditure is associated with savings in the form of out-of-pocket costs 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.

In all of these specifications, we control for a rich set of observable characteristics. Clearly, there may be selection conditional on unobserverbles as well as conditional on risk adjustment (see Brown et al. (2014)). If there is advantageous selection of consumers into MA-PD plans, our OLS estimates will conflate the impact of plan design and the selection of consumers across plans. In order to isolate the impact of plan design, we turn to our IV estimates.

3.1 Causal Estimates of the Impact of MA-PD Enrollment

We use changes in MA reimbursement as an instrument for MA coverage. In the first panel of Table 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 our dataset are 16-17% more likely to enroll in a MA-PD plan if they live in an urban county. Given

[13] Specifications with alternative bandwidths are available in Table A.4.

Table 3: Impact of MA Enrollment on Drug Spending

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			IV		
First Stage, Dependent Variable: MA 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)	-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 Out-of-Pocket Costs						
1(MA)	-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)	-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
Type 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 beneficiary costs and total expenditure levels. The unit of observation is at the enrollee-year level, for the 2007-2009 period. The original data is 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-yr 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.

an average MA market share of 25% within our sub-sample, this is a very large shift.[14] By exploring what happens to consumers who are exogenously shifted into MA-PD plans, we can isolate the impact of plan design on utilization.

The second panel of Table 3 shows the estimated impact of MA enrollment on insurer drug costs. Once we account for differential selection, MA-PD plans spend much more on drugs than stand-alone PDPs. The MA enrollment 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. As noted above, this is our preferred specification. 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 MA 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; this implies that the reduction in average out-of-pocket costs for consumers increases utilization, as confirmed in the final panel. In our preferred estimates, the causal impact of MA enrollment is noisy, but implies a $122 increase in drug utilization. On a base of $1697 of drug spending per year, this represents a 7% increase in spending. Total utilization increases *despite* a drop in consumer spending.

3.2 Mechanisms

We hypothesize that the underlying mechanism driving an increase in drug consumption from MA enrollment is differences in MA-PD plan design intended to internalize the impact of drug offsets on non-drug medical spending. However, it is plausible that the differences could be driven by differences in MA-PD plans themselves across the discontinuity. For example, higher reimbursement may lead to more generous plans in urban floor counties, leading to higher utilization. We test this proposition in four additional sets of analyses and find that the evidence does not

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

support this interpretation, but is instead consistent with insurer cost considerations driving the MA-PD pharmaceutical spending differences.[15]

First, there are no differences in average MA-PD plan characteristics across the urban threshold. In this analysis, we restrict attention to only MA-PD plans and measure benefit generosity in terms of patient costs per day supplied. This measure, which captures copays and coinsurance rates, can be thought of as the average cost of a pill to the consumer under a given insurance plan.[16] Figure 3 plots enrollee costs per day supplied as a function of population. Consumers in MA-PD plans to the left of the 250,000 discontinuity face similar drug costs as those consumers to the right of the discontinuity; the difference (two cents per day or less than three percent) is not statistically significant. MA-PD plans do not offer discontinuously more generous drug coverage in urban counties.[17] Therefore, our local average treatment effect measures the causal impact of moving beneficiaries from traditional FFS to MA plans, rather than reflecting differences in MA plans across the payment discontinuity. We also note the other factors, including upcoding or differential plan networks, could affect utilization across the threshold. Table A.2 presents the reduced form of our main IV specifications separately for the full sample and MA-PD plans. These results confirm that differences in MA-PD plans across the threshold do not drive our main results.[18]

[15]The reduction in OOPC to consumers of $265 per year represents 30% of the increased benchmark, which is greater than the upper bound of pass-though estimates, as described in Cabral, Geruso and Mahoney (2014), and much higher than the estimates in Duggan, Starc and Vabson (2015) that cover the same time period. In addition, while our structural model will incorporate increased subsidies, our model of plan choice will show that increased generosity is not particularly salient to consumers, making changes in plan design unlikely unless they are driven by cost side offsets.

[16]We note that this is a summary measure and abstracts from specific formulary and gap coverage decisions. While this measure abstracts from specific features of Part D plans, it captures a single dimensional measure of plan generosity.

[17]One could also be concerned that non-drug features of MA plans change discontinuously. In particular, if firms bid below the higher benchmark, rebates may be higher in urban counties, leading to more generous medical benefits. To the extent that drug and non-drug consumption are complements, this could bias our results. However, in Figure A.2, we show that rebates do not discontinuously increase across the discontinuity. In Table A.1, we also show balance in plan characteristics across counties above and below the threshold, with the exception of out-of-pocket medical costs, which are slightly lower in urban counties.

[18]Columns 1-3 of Table A.2 present OLS specifications where the coefficient of interest is on the dummy for being above the 250,000 population threshold (our excluded instrument). As predicted, the coefficient is positive and significant in the first panel (where the dependent variable is insurer costs) and negative and significant in the second panel (where the dependent variable is consumer out-of-pocket costs). The net effect is positive. In columns 4-6, we restrict attention to consumers

Second, we examine the impact of enrollee retention on the magnitude of the estimated MA enrollment effect. If insurer cost considerations drive our results, plans with longer average enrollee retention over our sample period should have larger MA effects than plans with below average retention. If consumers are likely to remain with the same plans, insurers have a greater incentive to invest in health benefits that will accrue over time (Fang and Gavazza (2011)). We perform the analysis by splitting our sample by plan level retention and restrict attention to above median retention plans.[19] The results are in columns 1 - 3 of Table 4. MA enrollment increases insurer drug spending by $531 (versus $388 in the full sample) and reduces enrollee OOPC costs by $274 (versus $265 in the full sample) in this sub-sample. Although plan retention is possibly endogenous, they are broadly consistent with the cost consideration hypothesis.

Third, we consider the impact of MA enrollment for enrollees taking medication for a common, chronic health condition: hyperlipidemia. Hyperlipidemia (or high cholesterol) is the elevation of lipid and lipid protein levels in the blood and is a risk factor for heart disease, stroke and other vascular diseases. Adherence to hyperlipidemic medications meaningfully reduces the likelihood of heart attack and stroke. Consistent with Chandra, Gruber and McKnight (2010), which find that offsets are larger among patients with chronic conditions, we expect MA-PD plans to spend more on drugs like hyperlipidemics that target chronic conditions. In columns 4-6 of Table 4, MA enrollment increases insurer drug spending by $559 in the hyperlipidemic sub-sample. Even with a higher level of spending for this group ($2058 per enrollee per year), this represents a larger percentage increase in spending in MA by insurers (27% versus 18% for the entire sample).[20]

Fourth, expanding on our results for hyperlipidemics, we show that the effect of

enrolled in MA-PD plans only and estimated the same reduced form specification. If our results were driven by greater generosity of MA plans across the 250,000 threshold, we would expect a pattern similar to the full sample. However, that is not what we see in the data; if anything, insurers in MA plans are spending less on drugs as you cross the population threshold, though the difference is not statistically significant. Furthermore, we can reject the hypothesis that overall drug spending is higher in urban counties. Therefore, we believe we are capturing the effect of moving consumers from stand-alone PDPs to MA-PD plans rather than increased generosity of MA plans in urban counties.

[19]Because these plans are larger, a substantial percentage of consumers are concentrated in these high retention plans, defined as having the highest percentage of consumers enrolled in 2006 continuously enrolled through 2009.

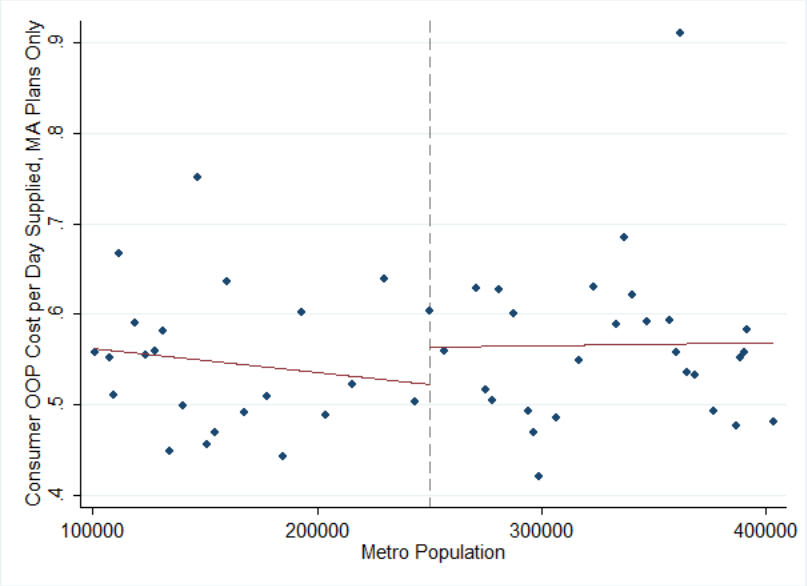
[20]The more pronounced increase in insurer spending also leads to higher overall utilization, though the estimates are noisy. We further explore the effect on consumers in Figure 4.

Table 4: Impact of MA Enrollment on Drug Spending

	(1)	(2)	(3)	(4)	(5)	(6)
	Above Median Retention Plans			Hyperlipidemics		
Dependent Variable: Insurer Drug Expenditures						
1(MA)	710.0***	706.2***	531.2***	718.6***	729.2***	559.1***
	(92.85)	(92.30)	(83.47)	(122.1)	(122.6)	(111.5)
FFS 5 Year			0.522***			0.621***
Avg. Spend			(0.0246)			(0.0352)
R-squared	0.037	0.042	0.114	0.188	0.114	0.119
Dependent Variable: Enrollee Out-of-Pocket Costs						
1(MA)	-192.5***	-202.0***	-273.9***	-203.4***	-193.6***	-259.7***
	(68.43)	(68.06)	(64.29)	(95.46)	(95.51)	(90.78)
FFS 5 Year			0.214***			0.241***
Avg. Spend			(0.0198)			(0.0307)
R-Squared	0.192	0.193	0.190	0.149	0.150	0.150
Dependent Variable: Total Drug Expenditures						
1(MA)	517.5***	504.2***	257.3**	515.2***	535.6***	299.4*
	(133.5)	(132.6)	(121.7)	(177.1)	(177.7)	(163.9)
FFS 5 Year			0.736***			0.862***
Avg. Spend			(0.0370)			(0.0541)
R-Squared	0.199	0.203	0.238	0.133	0.132	0.172
Year FE	X	X	X	X	X	X
Type FE	X	X	X	X	X	X
Demo.		X	X		X	X
Controls						
N	358,108	358,108	358,108	163,435	163,435	163,435
Sample	100-400K	100-400K	100-400K	100-400K	100-400K	100-400K

Notes: Table presents parameter estimates and standard errors of the instrumental variable regression models, where outcome variables are insurer and beneficiary costs and total utilization levels. First-stage regressions are reported in the first panel. The unit of observation is at the enrollee-year level, for the 2007-2009 period. The original data is 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-yr 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.

Figure 3: Effect of Population on MA-PD Plan Drug Generosity

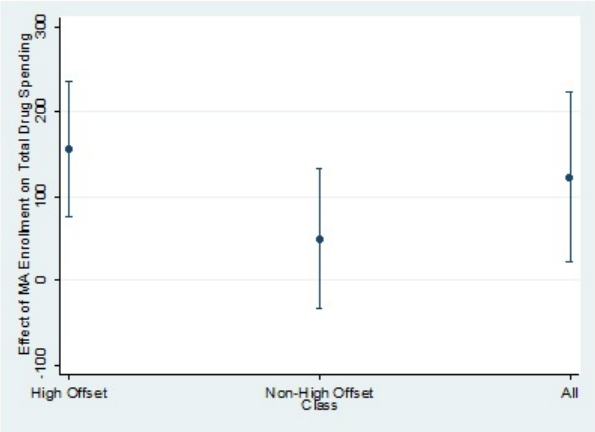


Notes: Plots a binscatter with fifty population bins using data from 2007. We drop counties with FFS spending above the urban floor, and control for beneficiary age, sex, race, 2006 spending type, and county-level FFS spending. Lines represent a linear fit.

MA enrollment on utilization is driven entirely by drugs believed to have large offsets *a priori*. We explore the total beneficiary level of utilization of "Category 1" drugs, as classified by Chandra, Gruber and McKnight (2010) and detailed in the appendix. If these drugs are not taken, a serious event, such as a hospitalization, is likely to occur within the next six months. By contrast to our previous results for those with hyperlipidemia, these specifications explore the effect on a subset of consumption, rather than a subset of consumers.

Table 5 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 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 total spending on these drugs; on a base of $648, this amounts to a 24% increase, versus 7% for total drug utilization. Put differently, all of the increased total expenditure

Figure 4: Spending by Class



Notes: This figure presents the coefficients and 95th percent confidence interval bands on MA-PD enrollment from three separate regressions. In the first, spending on "Category 1" drugs, defined in the appendix, is the dependent variable. In the second, spending in the complement of this set is the dependent variable. In the final, overall drug spending is the dependent variable. All regressions control for year fixed effects, consumer demographics, and county FFS spending. Standard errors are clustered at the enrollee level.

in MA-PD plans is concentrated in these large offset drugs.[21] This can be seen in Figure 4, which plots the results overall, among the high offset drugs, and outside of the high offset drugs. MA-PD plans do not spend more on drugs that are unlikely to have large offsets. We take these results, which describe heterogeneity across plans, patients, and drugs, as additional evidence that our reduced form results capture insurer incentives to mitigate inefficient underutilization by consumers.

Finally, we explore the relationship between MA-PD enrollment and out-of-pocket drug costs to consumers.[22] These tests do not rely on the exclusion restriction from our IV specifications as the level of observation is the drug fill. Furthermore, they are robust to other threats to our identification strategy, including increased non-drug generosity among MA-PD plans in non-urban counties and upcoding by MA-PD

[21] Total expenditure in this category increases by $156, while overall total expenditure increases by $122. This also indicates a drop in consumption of drugs without large offsets.

[22] In unreported regressions, we confirm two additional pieces of information. First, total cost per day supplied for a given drug is equal across plans; negotiated prices are not systematically higher or lower for MA-PD plans. Second, individual contracts do not offer more generous benefits in urban counties. If anything, the average consumer out-of-pocket cost per days supply is slightly higher to the right of the 250,000 threshold.

Table 5: Impact of MA 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)	-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 Out-of-Pocket Costs						
Mean	246.96					
SD	379.18					
1(MA)	-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)	-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
Type 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 beneficiary costs and total utilization 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.

plans.[23] We control for national drug code (NDC) fixed effects, which capture all of the variation related to the detailed product and package (ie 20mg of Lipitor). Therefore, this analysis is complementary to the results in Table 3 as it relies on a different source of variation to identify the MA-PD effect. Table 6 presents the results of this exercise. In the first specification for each dependent variable, we include year fixed effects. In the second, we control for the year and the phase of the prescription drug benefit, as insurers can alter consumer cost sharing given the benefit structure or the benefit structure itself. We examine the impact of MA-PD plans on the log consumer out-of-pocket costs and the likelihood of 90-day fills, noting that there are not statistical differences in point-of-sale prices across plan type. The results show a pattern consistent with the main enrollee-year results. For MA-PD plans, consumers face a cost that is 5-7.5% lower per day supplied, holding the drug (NDC) constant. For identical drugs, consumers in MA-PD plans pay less at the point-of-sale, and this effect is meaningful.[24]

In Figure 5, we show that the cost-sharing results are larger for specific drug classes targeted by value-based insurance designs in the commercial insurance market (Chernew, Rosen and Fendrick (2007); Gowrisankaran et al. (2013)). Specifically, we find statistically larger effects among drugs used to treat diabetes, asthma, and hyperlipidemia (high cholesterol). The results for hypertension (high blood pressure) are more mixed. However, in Figure A.1, we show that this is due to heterogeneity across types of hypertensives. For the most cost-effective, recommended initial therapy (non-beta blockers)[25], the effect is in the expected direction. Furthermore, in Table A.3, we provide a falsification exercise, showing that we do not get the same

[23]Furthermore, we note that drug consumption is not included in the risk adjustment scheme, and both upcoding and risk selection are less likely to be problematic in our setting (Carey (2015)).

[24]Finally, in the second panel, we see some evidence that consumers in MA-PD plans are more likely to fill 90-day prescriptions, which likely 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 unreported regressions, we find that the OOPC cost for hyperlipidemia drugs in MA-PD plans is 12-15% lower than in PDP plans, consistent with lower out-of-pocket costs for drugs for chronic conditions. Finally, in Figure 4, we restrict to drugs labeled as "Category 1" by Chandra, Gruber and McKnight (2010) and estimate the causal effect of MA-PD enrollment separately by class. If these drugs are not taken, a serious event, such as a hospitalization, is likely to occur within the next six months. On average, these drugs are cheaper in MA-PD plans, consistent with an incentive to minimize overall drug costs. This is not true for all categories; as pointed out by Lavetti and Simon (2014), selection may affect plan design as well. In the structural model, we will allow for differential incentives that incorporate both offsets and selection.

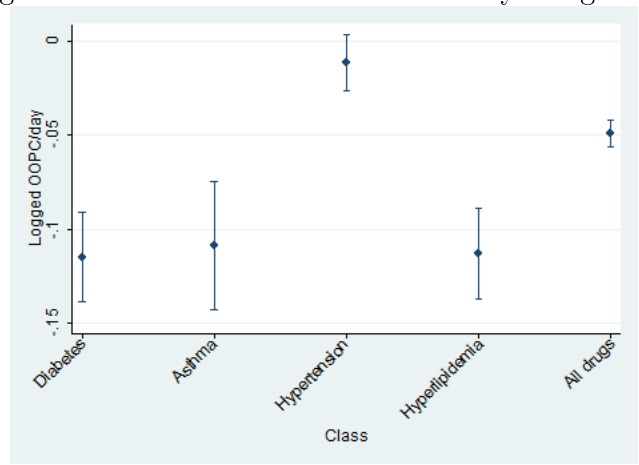
[25]NICE (2011)

Table 6: Mechanisms

	(1)	(2)
	Outcome: Logged OOPC/Day	
1(MA)	-0.075***	-0.049***
	(0.0033)	(0.0035)
Constant	-1.028***	-2.219***
	(0.0024)	(0.0058)
Observations	124,801,603	124,801,603
Adjusted R-Squared	0.607	0.673
	Outcome: 1(90 Day)	
1(MA)	0.001***	0.001***
	(0.0009)	(0.0009)
Constant	0.108***	0.103***
	(0.0007)	(0.0006)
Observations	157,091,471	157,091,471
Adjusted R-Squared	0.096	0.096
Product Fixed Effects	X	X
Phase Fixed Effects		X

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 is 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.

Figure 5: Out-of-Pocket Cost Effects by Drug Class



Notes: This figure plots the mean differences and standard error bands in out-of-pocket costs by plan type for each of four drug classes. Diabetes drugs include glucose monitoring agents, insulins, alpha-glucosidase inhibitors, meglitinides, amylin analogs, sulfonylureas, incretin mimetics, SGLT-2 inhibitors, dipeptidyl peptidase 4 inhibitors, non-sulfonylureas (metformin), thiazolidinediones and antidiabetic combination therapies. Asthma medications include inhaled corticosteroids, anticholinergic bronchodilators, leukotriene modifiers, methylxanthines, and antiasthmatic combination therapies. Hypertension drugs include beta blockers, ACE inhibitors, angiotensin II receptor antagonists, renin inhibitors, antiadrenergic agents (centrally & peripherally acting), alpha-adrenergic blockers, aldosterone receptor antagonists, vasodilators, calcium channel blockers and anti-hypertensive combination therapies. Hyperlipidemia drugs include statins, cholesterol absorption inhibitors, bile acid sequestrants, fibric acid derivatives, and antihyperlipidemic combination therapies. Standard errors are clustered at the plan-product level.

result if we restrict attention to protected drug classes, in which stringent regulation requires generous coverage by stand-alone plans. In summary, MA-PD plans have lower out-of-pocket costs for identical drugs, and this effect is especially large for high value drugs.

In the Appendix, we perform a number of robustness checks. In Table A.4, we restrict our sample to just consumers living in counties with metro populations of 200,000-300,000. Here, our results are larger in magnitude. Also in Table A.4, we restrict our sample to only low FFS counties, where the floor is more likely to bind. Again, the estimates are larger in magnitude, though also noisier. The results are qualitatively similar in logs and levels; this makes sense, as our results exclude out-

liers. In the final three columns of Table A.4, we include enrollees with no fills and expenditure above the catastrophic limit. The results are again similar, though noisy. We show that our results are robust to alternative population controls in Table A.5. We control for linear, quadratic, cubic, and quartic functions of metro population, in addition to linear and cubic splines with knots at the discontinuity of 250,00; none of the estimates are statistically different from our preferred estimates as shown in column 3 of Table 4. Table A.6 shows that our results are not sensitive to the exclusion of beneficiaries enrolled in plans that may be distorted due to the low-income subsidy discussed below. Finally, in Table A.7 we show that our qualitative results are not sensitive to the inclusion of beneficiaries exceed the catastrophic cap, though including these beneficiaries greatly increases the variance and skew of our estimates.

Taken together, our reduced form results show a consistent pattern. MA-PD plans are designed in ways that reduce consumer cost sharing and, to a lesser extent, increase drug utilization. The effect is concentrated in drugs likely to generate large offsets. An identical consumer will pay less for a higher quantity of drugs in a MA-PD plan than in a standalone PDP plan. We next examine the incentives MA carriers face to internalize offsets using a model of insurer plan design.

4 Model of Premium Setting and Benefit Design

4.1 Overview

In this Section, we describe our model of equilibrium insurer plan design and outline our estimation strategy. We estimate the structural parameters of this model in order 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 drug offset; and 3) perform policy counterfactuals. Our model is simple enough to be tractable yet rich enough to capture the complexity of equilibrium insurer behavior when setting premiums and benefits. In this framework, insurers have three choice variables for each contract j: premium, p_j, and the average out-of-pocket cost per days supply in both the initial coverage phase and in the donut hole, $P_j = \left[P_j^{ICR}, P_j^{Donut}\right]'$.

Firms maximize profits, which depend on their own premiums, subsidies and costs (which endogenously depend on the enrollee risk pool) as well as the equilibrium decisions of their competitors. Insurer drug costs, as well as market shares, are a

function of the generosity of the plan. We begin by describing endogenous plan design for a stand-alone prescription drug plan and then expand the analysis to take into account differential incentives faced by MA-PD plans. Consider the following simple model, in which variable profits for a stand-alone PDP are given by (omitting sub- and superscripts):

$$\Pi = \left(p + z^D - c(P)\right) sB,$$

where p is the premium, z is the federal subsidy, c is the cost to the insurer, s is the market share and B is the size of the Medicare population. This implies the standard first order condition with respect to premiums and the following first order conditions product characteristics:

$$(p + z - c)\frac{\partial s}{\partial P^{Phase}} + \left(1 - \frac{\partial c}{\partial P^{Phase}}\right) s = 0 \; for \; P^{ICR}, P^{Donut}.$$

Medicare Advantage plans face a different set of incentives than stand-alone PDP plans. Consider the choice to increase the generosity of a prescription drug plan. The PDP knows that this will directly increase costs, as they bear a higher percentage of a fixed drug expenditure. In addition, higher generosity plans may attract sicker patients and induce consumers to spend more – the adverse selection and moral hazard effects, respectively. MA-PD plans will also take these factors into account. In addition, a MA-PD plan must consider the impact that drug expenditure has on overall medical expenditure. If there are drug offsets, increased drug expenditures lead to reduced (non-drug) medical expenditures. The average total costs for a MA-PD are the sum of drug and (non-drug) medical costs: $c = c^D + c^M$. MA-PD plans will differ from PDPs in their cost sharing arrangements because their first order conditions differ with respect to one key term: $\frac{\partial c^M}{\partial P^{Phase}}$.[26] This is the object we want to estimate: in the presence of drug offsets, this term will be non-zero.

4.2 Empirical Implementation

There are a number of institutional complexities of the Part D and Medicare Advantage programs that affect the mapping from insurer strategies to profits and thus require modification the above illustrative model for estimation. Specifically, we account for the CMS bidding mechanism, the presence of the low-income subsidy

[26] That is, $\frac{\partial c}{\partial P^{Phase}} = \frac{\partial c^D}{\partial P^{Phase}}$ for standalone PDPs and $\frac{\partial c}{\partial P^{Phase}} = \frac{\partial c^D}{\partial P^{Phase}} + \frac{\partial c^M}{\partial P^{Phase}}$ for MA-PD plans.

population, risk corridors, risk adjustment and selection conditional on risk adjustment.

Insurers do not set premiums directly but rather submit a "bid" for both drug and non-drug coverage. If the bid is above a benchmark amount, the consumer pays the difference between the bid and the benchmark. If the bid is below the benchmark amount, which is common for MA-PD plans, insurers must devote part of the difference between the bid and the benchmark to providing more generous benefits.[27] Following Decarolis, Polyakova and Ryan (2015), we write ex-post profits for stand-alone PDPs as a function of the bids, $\mathbf{b}$, of the firm and other firms in the market:

$$\pi_j^{PDP}(b_j; b_{-j}) = \Gamma^{PDP}\left[\sum_{i \in A_j}\left(p_j(\bar{b}; r_i) + z_i^D(\bar{b}; b_j) - c_{ij}^D\left(p_j, r_i, P_j\right)\right)\right],$$

where Γ is a function that adjusts for ex-post risk corridor transfers and p_j is the premium of policy j, which depends on the entire vector of bids. In addition, z^D is the (individual specific, risk adjusted) subsidy, and c_{ij}^D represents individual specific costs, which are a function of the individual's risk score r_i and plan characteristics, P_{jt}. A_j represents the set of consumers who purchase good j which yields share s_j. We separate out the individual component of costs and risk adjusted payments η_{ij}, letting $H_j^D\left(P_j, p_j\right) = \sum_{i \in A_j} \eta_{ij}\left(P_j, p_j\right)$ and summing over markets m:

$$\pi_j^{PDP}(b_j; b_{-j}) = \sum_m \Gamma^{PDP}\left[p_j(\bar{b}; b_j) + z^D(\bar{b}) - c_j^D\left(p_j, \bar{r}, P_j\right) + H_j^D\left(P_j, p_j\right)\right] s_{jm} B_m.$$

The plan chooses their bid and cost sharing parameters P_j to maximize profit subject to an actuarial equivalence (minimum generosity) requirement $\underline{P}$:

$$\max_{b_j, P_j} \pi_j^{PDP}(b_j; b_{-j})$$

$$s.t.\, P_j \geq \underline{P}.$$

[27] Previous research (Stockley et al. (2014)) indicates that consumers primarily respond to premiums, so we model the effect of the premium implied by an insurer's bid and account for subsidies in the profit equation. We explore the effect of rebates, which are positive for approximately 5-10% of plans (Stockley et al. (2014)) in Figure A.2 and Table A.1.

The profit function for Medicare Advantage plans is similar, though there is an additional (risk adjusted) payment for medical costs, z^M.[28] We write:

$$\pi_j^{MA}(b_j; b_{-j}) = \sum_m \Gamma^{MA} \left[p + z^D - c_j^D + H_j\left(P_j, p_j\right) + b_j^M + z^M - c_j^M + H_j^M\left(P_j, p_j\right) \right] s_{jm} B_m,$$

where the M superscripts reflect medical ("Part C") bids and costs, respectively, and b_j^M is equal to the premium plus any rebates. Similar to stand-alone PDPs, MA-PD plans must submit bids for medical coverage, incur costs that depend on individual and plan characteristics, and receive risk adjusted subsidies. Because MA subsidies were generous during our time period, some plans have zero premiums; these plans may include "rebates" to consumers, which can be used to provide additional services or reduce Part B premiums, which are required even for consumers in MA plans. We include these net premium reductions directly in the definition of b^M.[29]

This formulation of firm profits captures the bidding mechanism, risk corridors, and risk adjustment. In order to address potential selection conditional on risk adjustment with respect to plan characteristics, including cost sharing and premiums, we allow for preferences and drug costs to vary flexibly by consumer type (defined as quintiles of the 2006 drug spending distribution). Therefore, $H_j\left(P_j, p_j\right) = \sum_{q \in j} \eta_{qj}\left(P_j, p_j\right)$, where q represents quintiles; if a plan becomes more generous or sets a higher premium and that disproportionately attracts higher cost enrollees, this will be reflected (through a greater weighting of higher cost quintiles) in $H_j\left(P_j, p_j\right)$ and $\frac{\partial H_j(P_j, p_j)}{\partial P_j}$.[30] Conditional on consumer type, we assume constant expected marginal costs. Our results are robust to this assumption as allowing for more heterogeneity by defining finer consumer types (for example, deciles of 2006 spending, or conditioning on demographics) yield similar results.

We do not need to impose an assumption of optimal pricing for PDP plans; we will never use the first-order condition with respect to drug premiums in our esti-

[28] There are separate subsidies for the non-drug component of MA-PD plans that vary at the market level; we incorporate these explicitly. Therefore, higher generosity due to more generous subsidies will not imply offsets. We abstract from MA rebates, which should increase the value of plans.

[29] Finally, we can allow the value of the rebate to be reduced by 25% in accordance with CMS bidding rules. Table A.10 shows that this will not affect our estimates of the key parameters of interest.

[30] We also allow changes in premiums to alter the risk pool the firm attracts through $\frac{\partial H_j(P_j, p_j)}{\partial p_j}$.

mation routine. This is especially important as previous research has highlighted that the presence of the LIS subsidy can distort plan bidding incentives (Decarolis (2015); Decarolis, Polyakova and Ryan (2015)). We explore the robustness of our results to the inclusion of plans that may be distorted by the LIS subsidy in Section 4.5. In addition, while we collapse the variation in formulary design into average consumer out-of-pocket costs per days supply, insurers also design formularies along with coinsurance and copayment rates; we focus on this measure of consumer costs in each phase of the standard benefit, as directly modeling formulary placement of every drug is computationally unfeasible. We assume that plans do not take account of their impact on the benchmark when submitting bids. Given the large number of plans, we believe this is a reasonable assumption. Because of data limitations (CMS prevents the identification of specific plans beyond an encrypted ID in the PDE files), insurers are assumed to set optimal strategies ignoring cross-elasticities between plans in different sectors (for example, the increasing the bid of Humana's PDP plan decreases the enrollment of Humana's MA plan). Below, we show that this elasticity is small and thus any bias from this restriction is also small. Following a number of papers (Lustig (2010); Nosal (2011)), we model firm decisions at the contract level averaging across plan characteristics within a contract.[31] In Section 4.5, we test the robustness of our estimates to these assumptions.

4.3 Plan Choice

We flexibly model insurance demand using a nested logit model that allows for enrollee heterogeneity in preference parameters by estimating the parameters by enrollee expenditure type. A consumer's choice sets defined at the county-level.[32] Beyond these product characteristics, which can vary at the market level, we use product

[31] We do this for two reasons: first, we want to be conservative rather than introducing additional (potentially correlated) observations when computing standard errors. Second, drug prices are likely to be negotiated nationally rather than by plan ID within a contract, and this will affect the within contract price index we estimate.

[32] While Part D insurers have identical offerings within the large 34 PDP regions, MA-PD plans can choose which counties to enter within a given region. Following a number of papers, symmetric with the plan decision assumption discussed above, a MA-PD product is defined as a unique contract ID. The key product characteristics from the consumer's perspective are the premium attributed to drug coverage, and out-of-pocket costs, as described above. If there is more than one plan within a contract, we use the product characteristics of the lowest numbered plan among MA-PD plans and average characteristics across stand-alone PDP plans. We do not directly model the impact of non-drug premiums in MA-PD plans. Many plans have zero premiums, and some rebate a portion of the Part B premium, reducing salience to consumers and making measurement difficult.

fixed effects (which differ by enrollee type) to capture invariant features of plan quality, including relative non-drug premiums for MA-PD plans.

Consumers have preferences over plans, premiums, and out-of-pocket costs. This requires constructing a function that relates P_{jt}^{Phase}(an insurer choice variable) to out-of-pocket costs (the variable enrollee care about) for each phase. Given a vector of P_{jt}^{Phase}, we can create counterfactual out-of-pocket costs given constant consumption (days supply) for consumer i with consumption (days supplied) d as:

$$OOPC_{ijt} = \left\{ \begin{array}{c} P_{jt}^{Ded}(d) \\ if\ R_{jt}d < DED \\ P_{jt}^{ICR}\left(d - \frac{DED}{R}\right) + DED \\ if\ R_{jt}d \geq DED\ and\ R_{jt}d < ICL \\ P_{jt}^{Donut}\left(d - \frac{ICL}{R_{jt}}\right) + DED + \gamma_{ICR}(ICL - DED) \\ if\ R_{jt}d \geq ICL\ and\ R_{jt}d < CAT \\ P_{jt}^{Cat}\left(d - \frac{CAT}{R_{jt}}\right) + DED + \gamma_{ICR}(ICL - DED) + \gamma_{Donut}(CAT - ICL) \\ if\ R_{jt}d \geq CAT, \end{array} \right\},$$

where d is the days supplied, γ represents the average coinsurance in each phase, and DED, ICL, and CAT represent the deductible, initial coverage limit, and catastrophic cap, respectively.

Following the reduced form analysis, we divide the sample into five "types" of consumers based on quintiles of 2006 spending. In each 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:

$$u_{qjtm} = X_j\beta_q - \alpha_{p,qjt}p_{jtm} - \alpha_{P,qjt}OOPC_{ijt} + \xi_{qjmt} + (1-\sigma)\epsilon_{ijtm},$$

where X_j is a matrix of plan fixed effects, such that plan utility is allowed to vary with consumer type, p_{jtm} is the premium, $OOPC_{qjt} = f(P_{jt}^{ICR}, P_{jt}^{Donut})$ is a function of the average prices per days supply, and ξ_{qjtm} is the unobserved product characteristics.

Our specification allows for consumer heterogeneity in preferences by including flexible plan fixed effects that can vary by consumer type, which implicitly allows for differential selection into plans based on consumer type.[33] These specifications reflect

[33] We assume perfect risk adjustment conditional on type, but the cost to the insurer is allowed to vary across quintiles. Our model does not explicitly accommodate selection with respect to formulary

a few additional modeling choices. First, while we allow plan unobserved quality, premium and out-of-pocket cost coefficients, and the dissimilarity term to vary by consumer type, there is no other source of unobserved consumer heterogeneity in the model. In addition, we do not allow for behavioral responses to average costs per days supply to factor into the out-of-pocket cost calculation. Put differently, there is no selection on moral hazard and the relationship between P_{jt}^{ICR}, P_{jt}^{Donut}, and $OOPC_{jt}$ is purely mechanical. The derivative of shares with respect to any element of the tariff vector is given by $\sum_q \frac{\partial s_{qjtm}}{\partial OOPC_{qjtm}} \frac{\partial OOPC_{qjtm}}{\partial P_{jtm}^{Phase}}$.

We estimate the parameters of the model separately for each quintile type using the Berry (1994) specification. We aggregate to the quintile-plan level while still estimating a specification flexible enough to account for substantial heterogeneity in consumer preferences. In order to capture firm incentives, we need to identify the causal impact of premiums and out-of-pocket costs. The presence of unobserved quality, ξ_{qjmt}, makes this challenging. We take a two-pronged approach. First, we include product fixed effects, so this unobserved product characteristic is the deviation from the plan mean for the quintile in question. Second, we instrument for the premium, out-of-pocket cost, and inside share. Following the logic of the reduced form identification strategy, the instrument for the inside share is the urban dummy interacted with an MA dummy, which captures the fact that MA-PD plans are more popular in urban counties. For both the premium and out-of-pocket costs, we use Hausman style instruments: the average premiums and out-of-pocket costs in all other markets. These instruments are commonly used in this setting (e.g. Decarolis, Polyakova and Ryan (2015)) and capture common cost shocks as well as correcting for any measurement error in our measure of out-of-pocket (drug) costs.

4.3.1 Demand Parameter Estimates

The results of the IV specifications for each of the five consumer groups are in Table 7. Interestingly, once we allow consumer preferences for individual plans to vary across drug spending quintiles, we do not find much heterogeneity in the premium or OOPC coefficients. While the premium coefficient is negative and significant in all specifications, sicker consumers are slightly less price sensitive than healthier consumers, consistent with adverse selection with respect to generosity. Second, the out-of-pocket cost coefficient is meaningfully smaller in magnitude than the premium

design (Carey (2015); Lavetti and Simon (2014)).

coefficient, consistent with the results in Abaluck and Gruber (2011), and attenuated among sicker consumers.[34] Own-price elasticities are quite sensible and range from -4.6 to -5.7, depending on (observed) consumer types. This is consistent with the results in Decarolis, Polyakova and Ryan (2015) (our estimates for standalone plans range from -5 to -6.3). Finally, across all groups, the nested logit dissimilarity parameter indicates that MA-PD plans are much better substitutes for other MA-PD plans than PDP plans and vice-a-versa.

4.4 Supply Side Estimation

To understand the role of cost offsets in insurer behavior and to perform counterfactuals, we model and estimate insurer supply side behavior. Specifically, while premiums, subsidies, drug costs, and market shares are observed in or easily inferred from the data, relevant derivatives of these variables are not observable (to us) and thus and need to be estimated. Given premium elasticities, premiums, subsidies, and observed market shares, we impute c^M_{jmt} using the first-order condition with respect to premiums. Formally, for MA-PD plans,

$$c^M_{jmt} = \left(b^M_{jmt} + z^M\right) + \sum_q \frac{s_{qjmt}/Q}{\frac{\partial s_{qjmt}}{\partial p_{jt}}},$$

where Q is the number of quintiles.[35] This calculation is standard under the assumption of premium setting differentiated, Bertrand-in-prices model, and is used in other studies, including Decarolis, Polyakova and Ryan (2015) and Curto et al. (2015). For this calculation (and only this calculation), we assume that the expectation of the deviations of medical costs from the average is zero: $E\left(\eta^M_{qj}\left(P_j, p_j\right)\right) = 0$.[36] We cal-

[34] We note that the premium variable is observed directly, while the OOPC is observed with error and may be attenuated; while differences across consumer groups may reflect differential preferences, it may also reflect larger measurement error among higher spending enrollees. Under the standard neoclassical model of consumer choice, the coefficients on premiums and OOPC should be equal. The estimated difference in the parameters suggests that consumers are naive about underutilization that may lead to future adverse medical events or financial costs. They do not demand more generous plans as a commitment device.

[35] For the supply side model, we assume that firms optimize each plan's characteristics, rather than optimizing over their entire portfolio. This is a simplification due to data availability. However, given high correlation within nests in the demand system, we believe it is unlikely that a consumer will substitute between the MA-PD and PDP plans within a single firm; therefore, this assumption seems fairly reasonable.

[36] We utilize the fact that we observe separate bids (and, therefore premiums) and subsidies for the medical and drug spending components of MA plans to separately identify medical costs, and

Table 7: IV Nested Logit Results

Quintile of 2006 Spending	(1)	(2)	(3)	(4)	(5)
Premium	-0.241***	-0.240***	-0.252***	-0.234***	-0.193***
	(0.0148)	(0.0134)	(0.0121)	(0.0111)	(0.0100)
OOPC	-0.0910***	-0.0623***	-0.0432***	-0.0281***	-0.0144***
	(0.00843)	(0.00602)	(0.00438)	(0.00308)	(0.00187)
σ	0.512***	0.525***	0.552***	0.563***	0.559***
	(0.00965)	(0.00984)	(0.00958)	(0.00952)	(0.00907)
Observations	81,553	82,423	83,958	84,767	85,812
Adjusted R-Squared	0.426	0.417	0.410	0.394	0.376

Notes: Table presents instrumental variable regression models, where outcome variables 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. In all specifications, we include plan fixed effects. Instruments are the urban dummy, as well premiums and out-of-pocket costs 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.

culate subsidies using the formula provided by CMS, averaging 74.5% of bids. We define derivatives with respect to these firm choice variables in terms of changes in out-of-pocket costs. For example, $\frac{\partial s_{qjtm}}{\partial P^{Phase}_{jtm}} = \frac{\partial s_{qjtm}}{\partial OOPC_{qjtm}} \frac{\partial OOPC_{qjtm}}{\partial P^{Phase}_{jtm}}$.[37]

We now estimate the object of interest - $\frac{\partial c_{qjtm}}{\partial OOPC_{jt}}$ - using Generalized Method of Moments. Let θ denote the expectation of this derivative. The first-order conditions imply that:

$$\sum_q [\left(p^D_{jmt} + z^D_t + 1(MA)\left(b^M_{jmt} + z^M_{mt}\right) - \left(c^D_{qjmt} + 1(MA)c^M_{qjmt}\right)\right) \frac{\partial s_{qjmt}}{\partial OOPC_{qjmt}} \frac{\partial OOPC_{qjmt}}{\partial P^{Phase}_{jmt}} +$$

$$\left(1 - \theta \frac{\partial OOPC_{qjmt}}{\partial P^{Phase}_{jmt}}\right) s_{qjmt}] = 0.$$

There is a straightforward mapping from different values of this parameter to levels of drug spending by firms. Intuitively, the more "expensive" it is to make plans more generous, due to asymmetric information or the absence of offsets, the less willing the firm is to increase generosity. Figure A.7 illustrates the basic logic of our identification argument using average values of the derivatives of shares with respect to premiums and out-of-pocket costs, and Table A.9 describes how all of the critical quantities are calculated or estimated.[38]

calculate these medical costs "offline" separately for each plan. We then assume that they are known to the firm in the rest of the supply side estimation. In addition, we allow the realization of drug costs to differ from firm expectations. In order to construct expected drug costs, we estimate the regression described in Table 3 on the entire sample; the predicted drug costs are then used to calculate c^D_{jmt}. This allows us to abstract from plan selection and allow for "medical management" on the part of MA-PD plans. Table 2 shows that drug premiums are lower in MA-PD plans. If this is due to cross-subsidization between non-drug premium and drug premiums, we will capture it by first estimating c^M_{jmt} .

[37] The calculation of the derivatives of OOPC with respect to phase specific tariffs is straightforward. For example, consider a $1 increase in the ICR cost. For a consumer with total spending below the deductible, the derivative is zero. For a consumer above the initial coverage limit, the derivative is also zero (though this consumer will reach the limit earlier in the year). In the ICR, the derivative is equal to the days supply less the days 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 the phase-specific costs per day supplied would push a consumer into the next phase of the benefit design as this effect complicates the analysis substantially and is of second order relevance to the analysis. Furthermore, we do not allow the consumer to forecast a behavior response to changes in the phase-level average beneficiary costs per days supply.

[38] On the x-axis, we plot different values of the derivative of interest, denoted by θ, while on the y-axis, we plot insurer spending. The results are slightly different across different phases, but illustrate that the smaller in absolute value θ is, the more the plan spends on drugs.

4.4.1 Supply Side Parameter Estimates

We parametrize θ using four different specifications; in each, the constant term represents the percentage of an out-of-pocket cost increase (reduction) that is passed on to the insurer in the form of savings (costs). First, we simply estimate one parameter for all plans, noting that without asymmetric information or offsets, $\theta = -1$. The presence of selection and offsets will both lead to estimates of θ that differ from (negative) one. If more generous plans attract sicker consumers, increasing out-of-pocket costs will attract healthier consumers, lowering insurer costs more than one-for-one. If there are offsets and drug demand slopes down, higher out-of-pocket costs will increase non-drug medical costs. The estimates are in Table 8. The constant in the first specification implies that a \$100 increase in out-of-pocket costs saves the average insurer \$88 in drug (and, potentially, medical) costs, consistent with selection (less generous plans attract different types consumers), moral hazard (less generous plans have lower utilization), offsets, or some combination of the three.

In order to estimate the impact of offsets directly, we isolate the portion of θ that is unique to MA-PD plans by allowing θ to differ across MA-PD and PDP plans: $\theta = \theta_1 + \theta_2 \times 1(MA)$. In this parameterization, we allow θ to vary with the type of plan; the impact of increasing generosity in a MA-PD plan is simply the sum of the two coefficients. The results show that the relationship between plan generosity and insurer costs is statistically different across different types of plans. The constant term indicates that the average stand-alone PDP would save \$91 per member by increasing out-of-pocket costs by \$100, while the second term indicates that the average MA-PD plan would only save \$56 per member by increasing out-of-pocket costs by \$100. Because MA costs are given as $c_{jmt} = c^D_{jmt} + c^M_{jmt}$, the derivative of MA-PD costs with respect to phase specific prices can be written as $\frac{\partial c_{jmt}}{\partial P^{Phase}_{jmt}} = \frac{\partial c^D_{jmt}}{\partial P^{Phase}_{jmt}} + \frac{\partial c^M_{jmt}}{\partial P^{Phase}_{jmt}}$.[39] Our results indicate that as MA-PD plans spend more on drugs, some of the insurer's cost is offset by reductions in spending in other areas.[40]

We explore heterogeneity in the size of the offset effect along two dimensions. The size of the offset effect may depend on the illness severity of the consumers in the plan; the reduced form results implied higher potential offsets among consumers with chronic conditions. In order to test this hypothesis, we interact the Medicare

[39] We note that c_{jmt} at the plan level is just the enrollment-weighted average over quintiles.

[40] The difference between the spending implied in Figure A.7 is largely consistent with the reduced form estimates for the entire sample.

Table 8: Supply Results

$\partial c/\partial OOPC$	(1)	(2)	(3)	(4)
Constant	-0.8716	-0.9069	-0.9069	-0.9069
	(0.0110)	(0.0108)	(0.0109)	(0.0108)
MA		0.3512	0.2161	0.3546
		(0.0319)	(0.0384)	(0.1075)
MA*Normalized Non-Drug Costs			0.1407	
			(0.0218)	
MA*Normalized 3-year Retention Rate				0.0317
				(0.1206)
Plan-Market-Year Obs.	34,431	34,431	34,431	34,431

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.

Advantage dummy with the implied medical, non-drug spending in that plan (which avoids a mechanical relationship between spending and the magnitude of the offset term), normalized to have a mean of zero and a standard deviation of one. The results are in the third column of Table 8 and imply a bigger offset among the sickest consumers. A MA-PD plan with average non-drug spending two standard deviations larger than average would save only $41 by increasing out-of-pocket costs by $100, due in part to a larger offset of non-drug costs. In addition, 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. While the results in the final column are not statistically significant, they are consistent with this hypothesis.

4.5 Robustness

In this section, we test the robustness of the model to assumptions along three dimensions. First, we explore the extent to which selection in combination imperfect risk selection may influence our results. We then examine the impact of regulatory constraints and, finally, we examine the impact of behavioral biases of consumers at the plan choice stage.

In order to address the role of selection in the determination of contract characteristics more directly, we model plan choice as a function of contract characteristics.[41]

[41] This is in contrast to our current approach, which relies on plan fixed effects and identifies

In these specifications, we include premiums, OOPC, and dummies for deductible and donut hole coverage as the observable characteristics. Following Decarolis, Polyakova and Ryan (2015), we use plan vintage as a proxy for switching costs. Consistent with previous results, we find evidence of selection with respect to donut hole coverage in Table A.8: consumers with higher 2006 drug consumption (our measure of severity) have a higher preference for donut hole coverage. In contrast, the results in Table 7 imply that sicker consumers are slightly less sensitive to both premiums and OOPC. One concern is that this last result could be driven by increased OOPC measurement error among sicker consumers and that could have broader implications for our base estimates. In order to address this, we examine the sensitivity of our supply side estimates to to differences in preferences over plan generosity of sicker consumers. In unreported specifications, we find that increasing the plan generosity elasticity of sicker consumers affects our mean estimate of θ_1, but not the principle parameter of interest, the interaction with the MA plan dummy (θ_2).[42]

By allowing heterogeneity across severity types in preferences and unobserved plan quality (through different fixed effects for severity type), we can allow implied plan marginal costs (net of risk adjustment) and the changes in these marginal costs to differ across severity classes. Because of the flexibility of our demand system, we believe our baseline approach removes the confounding unobservables that would bias parameter estimates and thus we accurately capture plan incentives for choosing plan characteristics in our setting.[43]

In Section 4.2, we highlighted a number of regulatory features of this market that may affect firm incentives. In particular, distortions created by the LIS subsidy could affect our main results. Insurers may alter product characteristics in response to the LIS program. Decarolis, Polyakova and Ryan (2015) account for this possibility in

sensitivity to price and OOPC using cross market variation.

[42]This finding is consistent with a greater degree of adverse selection but no difference in offsets across severity levels. These results are available from the authors upon request. Furthermore, as stated above, increased measurement error among sicker enrollees could drive this pattern in our preferred estimates.

[43]Table A.10 shows that the results are similar if we use variation from only the ICR price, which eliminates any concerns about selection with respect to donut hole coverage. The main estimate is now greater than one in absolute value, consistent with adverse selection along this margin. However, the differential effect for MA-PD plans (θ_2) is quite similar to our main specifications. In unreported regressions, we also estimate our model with the two tariffs directly. While the results are qualitatively similar, we note that the tariffs are highly correlated, leading to noisier coefficients. Finally, while differential reinsurance and risk corridors may have a small effect on our results, we believe their impact is directionally ambiguous (Medpac (2015*b*)).

their analysis. Following their approach, we restrict attention to those contracts that bid above the LIS benchmark amount in the majority of regions in which they operate and 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.10) are qualitatively similar to our main specification indicating that our basic results hold even allowing for the LIS distortion. Similarly, in the bottom panel of Table A.10, we restrict attention to "enhanced" plans that are unlikely to be constrained by minimum plan generosity requirements; the results are quantitatively similar.[44]

Our reduced form results show that differences in plan generosity are most pronounced among drugs believed a priori to have large offsets. We can reconstruct our plan characteristics to focus on cost sharing for this subset of drugs and re-estimate θ; in this exercise, we are assuming that the level of coverage for these drugs alone is set optimally. The results are in the second panel of Table A.10; because differences among these drugs drive much of the variation in plan characteristics by plan type, the results are qualitatively similar.

Finally, our demand model is in the neoclassical, static tradition and does not capture the possibility that consumers may meaningfully deviate from that framework in selecting plans. These deviations could affect both the measurement and the interpretation of our results. Handel (2013) documents plan choice inertia in the employer-sponsored setting and Ho, Hogan and Scott Morton (2015) document inertia in the Part D setting. To examine the robustness of our results to our static demand assumption, we repeat our entire analysis focusing on active choosers who are more likely to behave like neoclassical consumers. We define active choosers as consumers either aging into the Medicare program or switching plans.[45] Table A.8 shows that these active consumers are more sensitive to both premiums and OOPC, but the relative magnitudes of the coefficients is consistent. We recompute our supply side model using these demand estimates; Table A.10 shows that the results are, again,

[44] 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.

[45] This is, of course, is endogenous; this issue is addressed directly in Ho et al. (2015).

quite similar to the main specification.[46]

5 Counterfactuals

To quantify the importance of the offset, we first consider how PDP plans would adjust plan generosity if they were forced to account for non-drug medical costs in the same way as their counterparts in the MA program. Mechanically, we set $\theta_{PDP} = \theta_{MA}$ and then resolve for a new equilibrium.[47] The first column of Table 9 presents the baseline results. The average MA-PD plan has lower premiums (due to generous reimbursement) than the average PDP plan, which have average premiums of $407 per year. By contrast, the average MA-PD plan spends almost $75 dollars more per year on drugs ($1285 versus $1211) once we account for selection, similar to our reduced form results. In the lower panel of Table 9, we report the results of a simulation in which premiums are not allowed to adjust, but PDP plans internalize the offset. In this counterfactual, we see that the average PDP plan would spend 13% more on prescription drugs if they took the entire medical offset into account. In addition, we note that MA-PD plans increase their spending as well – 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. Here, PDP plans increase their spending by roughly the same amount, but also increase their premiums (13%) to offset some of the additional drug costs. However, in this exercise, MA-PD plans do not increase their generosity nearly as much as they did in the previous counterfactual, as generosity was previously optimal and consumers value a $1 decrease in premiums more than a $1 decrease in cost sharing.

Our estimates quantify how changes in cost sharing arrangements affect insurers' cost structure. By combining our estimates with estimates of the observed behavioral response to cost sharing by consumers, we can calculate the implied offsets and the impact of counterfactual policies. We take estimates of the behavioral response to cost sharing from Einav, Finkelstein and Schrimpf (2015), who estimate a dynamic

[46] We can also estimate our results using a balanced panel of plans (those available since 2006). As shown in Table 7, the results are again similar.

[47] We allow drug costs to the insurer, c_{jmt}^{Drug}, to adjust to account for the new incentives. We solve for drug costs, rather than phase-specific average out-of-pocket costs, for two reasons. First, drug costs enter into the plan's first order condition directly. Second, from a policy perspective, we are primarily interested in impact of different incentives on drug spending.

Table 9: Counterfactuals

	Baseline		"Sophisticates": $\alpha_p = \alpha_P$	
	MA	PDP	MA	PDP
Premium	206.00	407.93	206.00	407.93
% Change	-	-	-	-
Insurer Rx Spend	1285.25	1211.62	1357.41	1337.64
% Change	-	-	0.0564	0.1038
Internalize Externality: $\theta_{PDP} = \theta_{MA}$				
Premium	206.00	407.93	219.38	462.05
% Change	-	-	0.0650	0.1327
Insurer Rx Spend	1371.61	1373.90	1331.31	1413.26
% Change	0.0509	0.1339	0.0358	0.1664
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.

model of drug consumption.[48] Consider a small out-of-pocket cost decrease from P_0 to P_1. This price decrease will increase insurer drug costs by an amount equal to the drug point-of-sale price less out-of-pocket cost for the marginal units, plus the price difference times all of the infra-marginal units. We know from the supply side estimation that the increase in insurer costs associated with lowering OOPC to consumers is smaller for MA-PD plans than stand-alone PDP plans. This implies there must be a shadow drug cost, $c' < c$ that applies to MA-PD plans. From the *observed* behavioral elasticity we can infer the increase in quantity. Therefore, we can compute the distance between c' and c such that the magnitude of implied offsets rationalizes firm behavior; the magnitude of this difference is equal to $\frac{\partial c^{Medical}}{\partial \mathbf{P}}$.[49]

For a 1% uniform decrease in cost sharing, denoted by $\mathbf{P}$, we calculate the implied

[48] The elasticity is identified by exploiting the kink in individuals' budget sets created by the donut hole; we reproduce their elasticity estimates in Table A.11 and use the elasticity for a 1% uniform out-of-pocket cost reduction of -0.54 in our calculation.

[49] Does c' represent the drug cost less the total savings in medical expenditure? No; the shadow drug cost only takes insurer medical costs $c_{jmt}^{Medical}$ into account and is therefore strictly higher than the "true" shadow cost. This has important implications for welfare, as discussed in Glazer and McGuire (2013).

difference in insurer costs for MA-PD plans as (omitting subscripts for simplicity):

$$\frac{\partial c^{Medical}}{\partial \mathbf{P}} = \theta_2 \frac{\partial OOPC}{\partial \mathbf{P}},$$

which gives the difference in the change in insurer costs between MA-PD plans and stand-alone PDP plans. The shadow drug costs is simply the point-of-sale cost less implied offsets. This quantity must be equal to the change in quantity times the difference in the drug cost and the shadow drug cost:

$$\frac{\partial q}{\partial \mathbf{P}}(c - c').$$

We use the value of θ_2 (0.35) estimated in Table 8 and the mechanical value of $\frac{\partial OOPC}{\partial \mathbf{P}}$, \$10.15.[50] We take $\frac{\partial q}{\partial \mathbf{P}}$ directly from Einav, Finkelstein and Schrimpf (2015), and use the average empirical value of c (\$2.20). Solving for c', we get \$1.78. Put differently, the "discount" implied by offsets is 49 cents per day supplied, or 22%.

The offset we calculate is very close to previous estimates and obtained using supply side variation. The reduced form estimates show that MA-PD plans spend \$122 more per year, implying an offset of \$23.18 per enrollee per year. Multiplying this by 17.5 million, the number of stand-alone PDP enrollees in 2008, we find that PDP plans impose an externality of \$475.3 million per year.[51] 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. Our results illustrate the value of insurer incentive alignment in the Medicare Advantage program and the potential of more efficient benefit design by private insurers, who may align benefit design more efficiently than the federal government (see also Finkelstein, Einav and Polyakova (2016)).

Furthermore, Table A.11 shows that it would be costly for the government to

[50] For this calculation, we use the average value of consumer out-of-pocket cost per day supplied and the formula described in Section 4.2, evaluated at average consumption.

[51] We would obtain a similar estimate if we used the implied additional spending by PDP plans in Table 9. By contrast, MedPAC (Medpac (2015*a*)) estimates that spending on an equivalent enrollee in a MA-PD plans is approximately 2% higher than traditional Medicare. The average total Medicare spending was approximately \$10,000 per enrollee in 2008 (an \$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.

achieve 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). To see why such a policy could improve market outcomes, note that our estimates imply two potential sources of behavioral biases. First, higher spending in MA-PD plans is consistent with underutilization; the insurer has an incentive to address this friction and appears to do so, at least in part, by reducing the out-of-pocket drug costs to its enrollees. Second, consumers appear to undervalue reductions in out-of-pocket costs at the plan choice stage.[52] This behavior has two consequences. Consumers enroll in "sub-optimal" plans in the sense that they would be in better financial and physical health (via increased the drug consumption) if they placed more weight on the expected out-of-pocket costs of the plan. In addition, and perhaps more importantly, there would be a supply response by insurers if enrollees placed more weight on the expected out-of-pocket costs. We quantify the size of this supply response.

In our final counterfactual, we consider the impact of better aligning consumer preferences with neoclassical views on optimal decision making. One way to align consumer decision utility with value is to provide targeted consumer search tools that better highlight the trade-offs between plan premiums and generosity (Handel and Kolstad (2015)). In this setting, we believe that would lead consumers to place greater weight on out-of-pocket costs (Ericson and Starc (2013)) and lead to reduced naivete about potential under-consumption. 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 9. If consumers were "sophisticated," plans would increase their generosity. MA-PD plans would spend 5.6% more on prescription drugs, while PDP plans would spend 10.4% more. This increased spending by standalone PDP plans is less than the amount that fully internalizes the fiscal externality, yet shows that public policies that align consumer

[52]This is clear because a $1 reduction in OOPC is valued at less than a $1 reduction in premiums by consumers.

demand or the structure of subsidies with providing value will incentivize insurers to offer contracts that reduce costs or increase health.

6 Conclusion

This paper examines how health insurers react to both over-utilization and, particularly, underutilization by consumers. 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 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 benefits.

We find causal evidence that MA-PD plans spend more on drugs than their standalone counterparts; this increased spending is concentrated in those drug categories with large offsets and among consumers with chronic conditions. Our model of firm behavior highlights the mechanisms that drive this differential: MA-PD plans have an incentive to internalize the effect of drug offsets. By measuring firm incentives, we are able to calculate the size of the implied offset. Our estimate of an approximately 20% offset is similar in magnitude to demand-side estimates. This implies that firms take offsets into account when designing plans and may be able to mitigate inefficient underutilization by consumers. Finally, the counterfactuals show how policy changes can increase plan incentives to help consumers internalize offsets.

These results highlight the importance of the intersection of consumer choice in health care markets and contract design by firms in oligopolistic settings. Our work shows that incentives meaningfully affect plan design features, which in turn impact both health and health care costs. This work also highlights the important role that government policy plays in determining how market forces will work in the private provision of Medicare benefits.

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A Drug Classification (For Online Publication)

We follow Chandra, Gruber and McKnight (2010) in classifying drugs in three categories. 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/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 (2014). 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).

We also note that additional drugs have been introduced since the time period

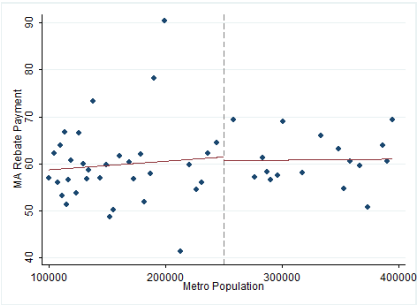
studied in Chandra, Gruber and McKnight (2010) and that clinical guidelines evolve over time. Therefore, we also consider an alternative, more recent set of classes targeted by a value based insurance design program implemented by Blue Cross Blue Shield of North Carolina (BCBSNC) in addition to other examples from the commercial market (Chernew, Rosen and Fendrick (2007); Gowrisankaran et al. (2013)). These plans target chronic conditions including asthma, diabetes, hypertension, and hyperlipidemia. Sample restrictions are described in the notes for Figures 5 and A.1.

B Additional Robustness Checks (For Online Publication)

Figure A.1: Price Effects by Drug Class

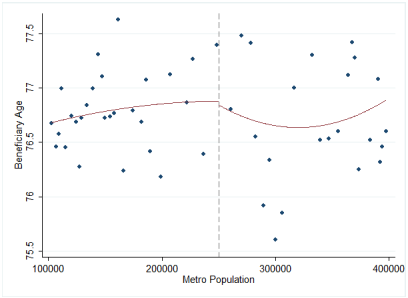
Notes: This figure plots the differences in prices by plan type. Other hypertension drugs include ACE inhibitors, angiotensin II receptor antagonists, renin inhibitors, antiadrenergic agents (centrally & peripherally acting), alpha-adrenergic blockers, aldosterone receptor antagonists, vasodilators and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

Figure A.2: Effect of Population on MA Plan Rebates



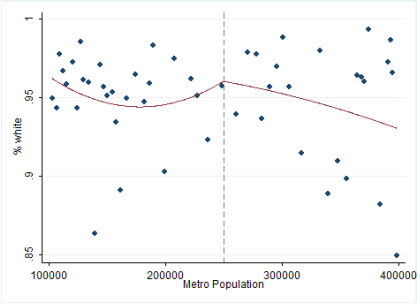
Notes: Plots a binscatter with fifty population bins using data from 2008 using data from Medicare Landscape Files. We drop counties with FFS costs above the urban floor. Lines represent a linear fit.

Figure A.3: Effect of Population on Sample Demographics



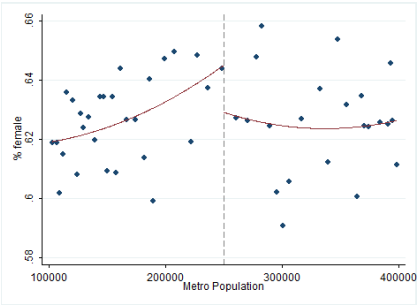
Notes: Plots a binscatter with fifty population bins using 2008 data. We drop counties with FFS costs above the urban floor, and control for beneficiary age, sex, race, 2006 spending type, and county-level FFS costs. Lines represent a quadratic fit.

Figure A.4: Effect of Population on Sample Demographics



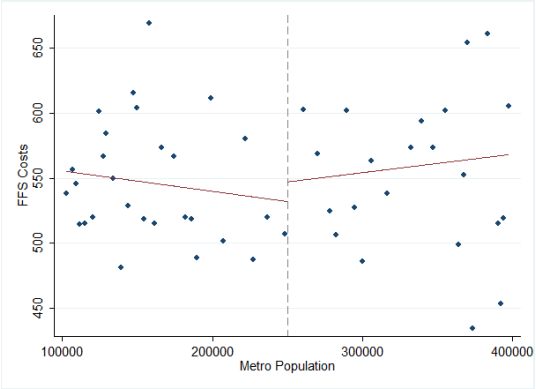
Notes: Plots a binscatter with fifty population bins using 2008 data. We drop counties with FFS costs above the urban floor, and control for beneficiary age, sex, race, 2006 spending type, and county-level FFS costs. Lines represent a quadratic fit.

Figure A.5: Effect of Population on Sample Demographics



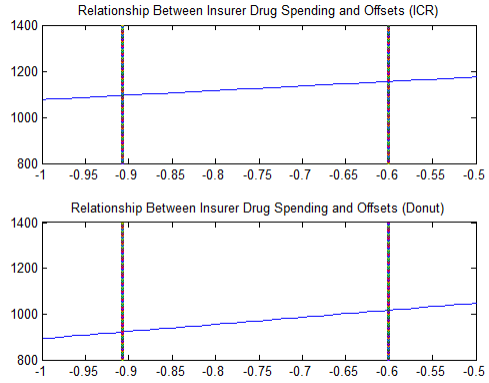
Notes: Plots a binscatter with fifty population bins using 2008 data. We drop counties with FFS costs above the urban floor, and control for beneficiary age, sex, race, 2006 spending type, and county-level FFS costs. Lines represent a quadratic fit.

Figure A.6: Effect of Population on FFS Spending



Notes: Plots a binscatter with fifty population bins using the five year moving average from 2004, when floors were formally (but not practically) discontinued. We drop counties with FFS costs above the urban floor. Lines represent a quadratic fit.

Figure A.7: Supply Side Identification



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

Table A.1: T-test Results

Metro Population	<250K	>250K	t-test value
Primary Care Physicians/Resident (2010)	0.000553	0.000575	-0.666
	(0.000336)	(0.000330)	
Total MDs/Resident (2005)	0.00172	0.00163	0.474
	(0.00198)	(0.00148)	
Inpatient Service Unit Beds/Resident (2012)	0.00107	0.000941	1.307
	(0.00103)	(0.000952)	
Inpatient Days Per Resident (2005)	0.745	0.690	0.565
	(0.974)	(0.928)	
Medicare Enrollment Per Resident (2005)	0.127	0.127	0.1947
	(0.00181)	(0.00240)	
Percentage of Population Male (2005)	0.493	0.494	-0.458
	(0.0322)	(0.0280)	
Number of Observations	**289**	**148**	
Median Age (2010)	38.124	38.941	-1.689*
	(5.126)	(4.171)	
Race (2010):			
White	81.986	81.351	0.419
African American	9.739	11.527	-1.312
	(13.047)	(14.607)	
American Indian/Alaskan	1.220	0.872	0.930
	(4.325)	(2.143)	
Asian	1.449	1.445	0.0162
	(2.560)	(1.436)	
Hispanic/Latino	8.401	6.703	1.409
	(12.972)	(9.870)	
Number of Observations	**296**	**150**	
MA Plan Rebate	61.28	64.11	-2.83
MA Premium	25.97	23.43	2.55
Out-of-Pocket Medical Costs	400.21	392.59	7.63**
Number of Observations	292	150	

Notes: Table A.1 presents t-test results comparing counties with fewer than 250,000 residents to those with greater than 250,000 residents using data from the Area Health Resources File 2014-2015 release. When available, statistics from 2005 are used, otherwise the closest available year to 2005 is used. Race is measured as percentage. Standard deviations are in parentheses. Median age is significant at the 10% level.

Table A.2: Total Sales Utilization Across Urban Threshold

	All Plans			MA Plans Only		
Dependent Variable: Insurer Costs						
Threshold (>250,000)	86.5***	86.2***	68.8***	-29.6	-25.1	-22.2
	(11.5)	(11.5)	(11.5)	(23.3)	(23.3)	(23.3)
FFS 5 Year			0.434***			0.460***
			(0.0189)			(0.0387)
R-Squared	0.216	0.218	0.220	0.204	0.219	0.221
Dependent Variable: OOPC						
Threshold (>250,000)	-36.2***	-37.8***	-47.1***	-66.1***	-67.1***	-69.0***
	(9.43)	(9.43)	(9.41)	(14.8)	(14.8)	(14.8)
FFS 5 Year			0.232***			-0.282***
			(0.0162)			(0.0250)
R-Squared	0.181	0.183	0.184	0.183	0.185	0.187
Dependent Variable: Total Spending						
Threshold (>250,000)	50.3***	48.4***	21.7	-95.8***	-92.3***	-91.2***
	(17.7)	(17.7)	(17.7)	(32.7)	(32.7)	(32.7)
FFS 5 Year			0.666***			0.177***
			(0.0301)			(0.0550)
R-Squared	0.257	0.258	0.260	0.257	0.259	0.259
Year FE	X	X	X	X	X	X
Type FE	X	X	X	X	X	X
Demo. Controls		X	X		X	X
Observations	381,921	381,921	381,921	95,190	95,190	95,190
Sample	100-400K	100-400K	100-400K	100-400K	100-400K	100-400K

Notes: Table presents OLS regression models, where outcome variables are total utilization levels. The unit of observation is at the enrollee-year level, for the 2007-2009 period. The original data is 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 and enrollees with MA plans. We include year-level indicators and indicators for the quintile of 2006 spending in all specifications. In some specifications, we also control for 5-yr average per capita Medicare FFS spending, from 2007 and in others we also include plan contract fixed effects. We also include controls for age categories, race, and gender as demographic controls. In addition, we include a spline of metro population. Standard errors are clustered at the enrollee level and are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.3: Mechanisms - Medicare Protected Class Products Only

	(1)	(2)
	Outcome: Logged OOPC/Day	
1(MA)	-0.117***	-0.0974
	(0.0073)	(0.0076)
Constant	-0.925***	-2.132***
	(0.0044)	(0.0131)
Observations	9,568,940	9,568,940
Adjusted R-Squared	0.580	0.679
Product Fixed Effects	X	X
Phase Fixed Effects		X
All Products	X	X
Protected Classes Only	X	X

Notes: Table presents linear regression models, where outcome variables are as described in each panel. This table only includes drugs that are considered "Protected Classes" by Medicare. This includes anti-cancer, ant-psychotic, anti-convulsant, anti-depressant, immuno-suppresant and HIV/AIDS drugs. The unit of observation is at the fill level, for the 2007-2009 period. The original data is 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 product level and are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.4: Robustness Checks

Dependent Variable: Insurer Costs									
1(MA)	615.7***	610.4***	402.6***	514.2***	506.7***	387.5***	535.0***	481.2***	376.5***
	(89.99)	(90.69)	(76.60)	(74.25)	(73.34)	(68.38)	(75.45)	(74.03)	(69.62)
FFS 5 Year			0.681***			0.506***			0.413***
			(0.0512)			(0.0226)			(0.0221)
Mean	0.093	0.096	0.163	0.114	0.119	0.159	0.058	0.083	0.114
Dependent Variable: OOPC									
1(MA)	152.4**	157.5**	27.41	-215.2***	-222.2***	-265.2***	-249.1***	-288.6***	-304.4***
	(66.92)	(67.48)	(57.49)	(55.51)	(54.92)	(52.74)	(55.01)	(54.81)	(52.73)
FFS 5 Year			0.426***			0.183***			0.0626***
			(0.0425)			(0.0183)			(0.0174)
R-Squared	0.142	0.144	0.172	0.193	0.194	0.192	0.154	0.154	0.153
Dependent Variable: Total Spending									
1(MA)	768.1***	767.9***	430.0***	299.0***	284.6***	122.3	285.8**	192.6*	72.08
	(135.0)	(136.3)	(113.4)	(108.0)	(106.7)	(100.7)	(112.0)	(110.3)	(105.1)
FFS 5 Year			1.107***			0.688***			0.476***
			(0.0803)			(0.0343)			(0.0344)
R-Squared	0.155	0.156	0.219	0.230	0.233	0.252	0.168	0.183	0.193
Year FE	X	X	X	X	X	X	X	X	X
Type FE	X	X	X	X	X	X	X	X	X
Demo. Controls		X	X		X	X		X	X
Observations	91,270	91,270	91,270	381,921	381,921	381,921	424,436	424,436	424,436
Sample	200-300K	200-300K	200-300K	100-400K	100-400K	100-400K	100-400K	100-400K	100-400K
					Low FFS Counties		Includes zero utilization beneficiaries		

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

Table A.5: Population Controls

First Stage						
1 (Urban)	0.144***	0.149***	0.216***	0.218***	0.151***	0.177***
	(0.0050)	(0.0049)	(0.0071)	(0.0071)	(0.0049)	(0.0049)
R-squared	0.035	0.036	0.038	0.040	0.037	0.037
Dependent Variable: Insurer Costs						
1(MA)	209.1***	192.1***	343.8***	339.3***	180.9***	387.5***
	(53.16)	(51.42)	(52.10)	(51.61)	(50.46)	(68.38)
R-Squared	0.197	0.200	0.170	0.171	0.202	0.159
Dependent Variable: OOPC						
1(MA)	-95.11**	-97.48**	-112.2**	-114.0***	-98.23***	-265.2***
	(44.73)	(43.53)	(41.83)	(41.51)	(42.87)	(52.74)
R-Squared	0.191	0.191	0.192	0.192	0.192	0.192
Dependent Variable: Total Spending						
1(MA)	114.0	94.58	231.6***	225.4***	82.67	122.3*
	(83.81)	(81.37)	(79.99)	(79.33)	(80.04)	(100.7)
R-Squared	0.230	0.233	0.252	0.133	0.254	0.252
Metro	Linear	Quadratic	Cubic	Quartic	Linear	Cubic
Pop Controls					Spline	Spline
Year FE	X	X	X	X	X	X
Type FE	X	X	X	X	X	X
Demo. Controls	X	X	X	X	X	X
Observations	381,921	381,921	381,921	381,921	381,921	381,921
Sample	100-400K	100-400K	100-400K	100-400K	100-400K	100-400K

Notes: Table presents instrumental variable regression models, where outcome variables are insurer and beneficiary costs and total utilization levels. First-stage regressions are reported in the first panel. The unit of observation is at the enrollee-year level, for the 2007-2009 period. The original data is 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, indicators for the quintile of 2006 spending, and 5-yr average per capita Medicare FFS spending from 2007 in all specifications. We also include controls for age categories, race, and gender as demographic controls. Standard errors are clustered at the enrollee level and are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively. Linear and cubic splines have knots at 250,000.

Table A.6: Impact of MA Enrollment on Spending, Non-LIS Distorted

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			IV		
Dependent Variable: Insurer Drug Costs						
1(MA)	-76.44***	-78.73***	-75.80***	502.0***	495.9***	376.5**
	(3.973)	(3.978)	(3.977)	(74.05)	(73.16)	(68.20)
FFS 5 Year			0.433***			0.507***
Avg. Spend			(0.0189)			(0.0226)
R-Squared	0.217	0.219	0.221	0.116	0.121	0.161
Dependent Variable: OOPC						
1(MA)	-181.3***	-178.5***	-177.1***	-220.2***	-225.9***	-270.1***
	(2.855)	(2.865)	(2.868)	(55.37)	(54.77)	(52.59)
FFS 5 Year			0.203***			0.187***
Avg. Spend			(0.0160)			(0.0184)
R-Squared	0.194	0.196	0.196	0.194	0.195	0.193
Dependent Variable: Total Drug Spending						
1(MA)	-257.7***	-257.3***	-252.9***	281.1***	270.0**	106.5
	(6.857)	(5.878)	(5.880)	(107.7)	(106.4)	(100.3)
FFS 5 Year			0.544***			0.694***
Avg. Spend			(0.0328)			(0.0344)
R-Squared	0.264	0.265	0.267	0.232	0.234	0.253
Year FE	X	X	X	X	X	X
Type FE	X	X	X	X	X	X
Demo.		X	X		X	X
Controls						
N	377,391	377,391	377,391	377,391	377,391	377,391
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 beneficiary costs and total utilization levels. The unit of observation is at the enrollee-year level, for the 2007-2009 period. The original data is 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 and to plans with less than 50% low-income subsidy enrollees nationally. We include year-level indicators and indicators for the quintile of 2006 spending in all specifications. In some specifications, we also control for 5-yr 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 enrollee level and are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.7: Impact of MA Enrollment on Spending Including Patients over Catastrophic Cap

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			IV		
First Stage, Dependent Variable: MA Enrollment						
1 (Urban)				0.163***	0.165***	0.173***
				(0.00767)	(0.00767)	(0.00768)
FFS 5 Year						X
R-squared				0.026	0.036	0.037
Dependent Variable: Insurer Drug Costs						
1(MA)	-83.20***	-89.30***	-84.85***	1,294***	1,277***	1,067***
	(12.20)	(12.19)	(12.18)	(283.0)	(279.8)	(269.0)
FFS 5 Year			0.656***			0.842***
Avg. Spending			(0.0541)			(0.0643)
R-Squared	0.068	0.069	0.070	.	.	0.017
Dependent Variable: OOPC						
1(MA)	-232.4***	-228.8***	-227.2***	-204.9***	-217.8***	-275.2***
	(3.851)	(3.865)	(3.869)	(79.02)	(78.07)	(74.72)
FFS 5 Year			0.238***			0.231***
Avg. Spending			(0.0218)			(0.0252)
R-Squared	0.199	0.200	0.200	0.199	0.200	0.200
Dependent Variable: Total Drug Spending						
1(MA)	-315.6***	-318.1***	-312.0***	1,090***	1,059***	792.2***
	(14.13)	(14.13)	(14.13)	(314.9)	(311.2)	(298.4)
FFS 5 Year			0.894***			1.073***
Avg. Spending			(0.0670)			(0.0784)
R-Squared	0.127	0.127	0.128	0.077	0.080	0.098
Year FE	X	X	X	X	X	X
Type FE	X	X	X	X	X	X
Demo. Controls		X	X		X	X
Observations	398988	398988	398988	398988	398988	398988
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 beneficiary costs and total utilization levels. The unit of observation is at the enrollee-year level, for the 2007-2009 period. The original data is 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-yr 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 enrollee level and are presented in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and *** respectively.

Table A.8: IV Nested Logit Results

Quintile of 2006 Spending	(1)	(2)	(3)	(4)	(5)
Active Choosers					
Premium	-0.312***	-0.370***	-0.352***	-0.333***	-0.286***
	(0.0253)	(0.0222)	(0.0206)	(0.0178)	(0.0159)
OOPC	-0.155***	-0.116***	-0.0868***	-0.0578***	-0.0403***
	(0.0166)	(0.0112)	(0.00756)	(0.00508)	(0.00326)
σ	0.628***	0.596***	0.603***	0.626***	0.578***
	(0.0182)	(0.0181)	(0.0178)	(0.0176)	(0.0169)
Observations	32,457	33,528	35,376	36,674	36,776
Adjusted R-Squared	0.236	0.220	0.216	0.210	0.200
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)
Age	0.394***	0.453***	0.443***	0.469***	0.490***
	(0.0209)	(0.0222)	(0.0237)	(0.0250)	(0.0241)
σ	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: Table presents instrumental variable regression models, where outcome variables 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. In the top panel, we include plan fixed effects, while in the second panel, we include region and year fixed effects. Instruments are the urban dummy, as well premiums and out-of-pocket costs in other markets, where a market is defined as a county-year combination.

Table A.9: Identification

Object	Inference
p_{jtm}	data, observed separately for drug and medical components
r_{qt}^{PDP}, r_{qmt}^{MA}	data
c_{jmt}^{M}	inferred from pricing decision using "Part C" bids and subsidies, MA plans only
c_{qjmt}^{D}	data, expectation formed using specification in Table 3
$\frac{\partial s_{qjmt}}{\partial p_{jtm}}$	calculated from demand estimates
$\frac{\partial s_{qjmt}}{\partial P_{jt}^{Phase}}$	calculated from demand estimates
$\frac{\partial c_{qjmt}^{Drug}}{\partial P_{jt}^{Phase}}$	mechanical function of phase-specific out-of-pocket costs
s_{qjmt}	data
$\frac{\partial c_{qjmt}^{M}}{\partial P_{jt}^{Phase}}$	object of interest

Table A.10: Supply Results

$\partial c/\partial OOPC$	(1)	(2)	(3)	(4)	(5)	(6)
	Non-LIS Distorted		Active Choosers		ICR Price Only	
Constant	-0.8159	-0.8158	-0.9899	-1.0460	-1.0530	-1.0897
	(0.0101)	(0.0101)	(0.0471)	(0.0002)	(0.0117)	(0.3613)
MA		0.4098		0.5591		0.3613
		(0.0154)		(0.0783)		(0.0342)
Plan-Market-Year Obs.	33,884	33,884	34,431	34,431	34,431	34,431
	(7)	(8)	(9)	(10)	(11)	(12)
	Basic Plans		Alt. Rebate		Lg. Offset Drugs Price Only	
Constant	-0.8346	-0.8345	-0.8727	-0.9068	-0.8729	-0.9069
	(0.0105)	(0.0105)	(0.0096)	(0.0109)	(0.0106)	(0.0104)
MA		0.4132		0.3400		0.3379
		(0.0054)		(0.0574)		(0.0267)
Plan-Market-Year Obs.	33,906	33,906	34,431	34,431	34,431	34,431

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.

Table A.11: 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.

C Additional Counterfactuals (For Online Publication)

Next, we consider budget neutral policies that attempt to internalize the externality generated by the PDP plans.[53] Our presumption is that CMS would like to increase drug utilization by PDP enrollees in order 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 plan's cost to increasing cost sharing coverage. In order for this cost sharing 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.

Consider a uniform cost sharing subsidy for PDP plans, as shown in Table A.11. Mechanically, a subsidy alters both p_{jt} and $OOPC_{jt}$ if it is budget neutral and there is full pass-through; we can write the alternative premium and out-of-pocket costs as a function of the change in out-of-pocket cost due to a change in the premium vector $\mathbf{P}$ and the offset, which is given by $\frac{\partial q}{\partial \mathbf{P}}(c - c')$. For a small change in $\mathbf{P}$ (omitting subscripts for simplicity):

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

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

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.[54]

A 1% cost-sharing subsidy would increase utilization by 7.2 days supply based on

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

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

the behavioral elasticities in column 2. The implied offset, in column 3, is \$3.54.[55] However, the cost sharing 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 policy is to be budget neutral, premiums will have to rise dramatically.[56]

Furthermore, these policies reduce the market share of PDP plans. 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.[57] This is for two reasons: consumers are not sophisticated with respect to potential underutilization and most implementable policies fail to target marginal consumption effectively leading to expensive out-of-pocket cost 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 cost-sharing 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 our reduced form results; Figure 5 shows that MA-PD plans

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

[56] 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.

[57] This includes the recent Part D Enhanced Medication Therapy Management (MTM) Model, which incentivizes stand-alone plans to reduce Parts A and B spending among their beneficiaries. 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 be incentivized to internalize the externality created by prescription drug offsets. Furthermore, we note that a PDP plan that fully internalized the externality would only spend an addition \$153 per beneficiary 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 firms' entire profit margins, based on a 15% profit margin and the estimates in Ho, Hogan and Scott Morton (2015).

have lower out-of-pocket costs 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 7, we believe this can be done in a cost-effective way. For example, rather than closing the donut hole, the federal government could increase MA benchmarks by $312 per year, plus the $23 in implied offsets. This would increase MA-PD market share by 7.4%.