# Internalizing Behavioral Externalities: Benefit Integration in Health Insurance

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**Abstract**

We show that profit-maximizing firms alter product design in the market for Medicare prescription drug coverage to account for underutilization by consumers. Using plausibly exogenous variation, 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 $405 million per year.

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# 1 Introduction

Health insurance, while mitigating financial risk, can create a welfare loss by lowering the price of medical services to consumers below marginal cost. Optimal insurance contracts rely on deductibles and coinsurance to mitigate the welfare loss due to moral hazard.[1] However, there is also strong evidence that consumers reduce utilization of cost effective care in the face of 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. Underutilization could be driven by a number of mechanisms, including consumer difficulty in distinguishing between high and low value services, differential cost sharing across treatment type, and biases described in the behavioral economics literature. The latter has been described as "behavioral hazard" by Baicker, Mullainathan and Schwartzstein (2015).[2]

Foregoing cost effective care in the present may lead to additional, more costly health care consumption in the future, creating an externality. The extent and consequences of underutilization critically depend on how health insurers design their products in equilibrium. If insurers must face the fiscal consequences of inefficient under-consumption, they have a clear incentive to mitigate this underutilization through 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.[3]

More broadly, the analysis of firm responses to departures from the neoclassical model is limited and focused on the ability of firms to exploit biases and information frictions (Grubb and Osborne 2012, Grubb 2012, Grubb 2014, Ellison 2006). As summarized by Akerlof and Shiller 2015, competitive firms have incentives to exploit both the psychological biases and informational frictions

[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] Baicker, Mullainathan and Schwartzstein (2015) describe "mistakes due to mistakes or behavior biases," as behavioral hazard. See excellent, additional discussions in Frank (2012) and Brot-Goldberg et al. (2015).

[3] The notion that health insurance can correct for behavioral hazard dates at least to "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.

often inherent in consumer decision making. Less well documented and accordingly less appreciated, competing firms may also play an important role in "de-biasing" consumers or mitigating information frictions through pricing and product design decisions so long as it is profitable to do so. Thus, the welfare consequences of underutilization of high value health care services depend on firm incentives; these incentives, in turn, depend upon the institutional and regulatory setting in which firms compete. In this paper, we empirically examine the incentives of health insurers to internalize the externalities created by under-consumption through product design.

We study supply side reactions to enrollee demand responses to benefit design, which may include moral hazard, information frictions, and behavioral hazard in setting their benefit design. In particular, the presence of cost offsets across categories of care (e.g. increased pharmaceutical adherence can reduce inpatient care) imply that insurers have a cost-side rationale to improve adherence by altering benefit design. In this paper, we build a model of consumer choice and endogenous insurer plan design. We derive the empirical implications of the model and show that a subset of firms increase drug plan generosity beyond what would be implied by consumer demand in order to mitigate underutilization by consumers. This has important health, financial and, ultimately, welfare consequences.

We apply our model to detailed data from the Medicare Part D program. This institutional setting provides an excellent opportunity with important policy consequences to explore the role of under-consumption in affecting plan design and welfare. First, there is mounting evidence that Part D enrollees display behavioral hazard in prescription drug utilization. The typical benefit design in Part D is nonlinear and very complicated leading to myopic behavior and both under- and over-consumption relative to the optimum (Abaluck, Gruber and Swanson (2015); Dalton, Gowrisankaran and Town (2015)). Second, there is variation across types of plans in the incentive to design benefits accounting for underutilization and offsets. Under the Medicare Part D program, there are (broadly) 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 plans differ in their benefit design incentives for insurers. 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 our empirical work by performing detailed, reduced form analysis of the 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 metrics of prescription drug consumption 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 leading to bias if unaddressed. Furthermore, specific benefit design choices may also generate differential selection. In order to identify effects of moral and behavioral hazard, 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 perform many specification tests of the identification assumption which strongly support its validity.

We find that enrollment in MA-PD plan enrollees causally increases total drug expenditure. We find that 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 utilization. Importantly, 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.

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. These

parameters estimates imply that the increased generosity of MA-PD plans is driven by insurer cost side incentives. We then measure the impact of plans internalizing the externalities generated by drug offsets. 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. Given estimates from this flexible model, we estimate benefit externalities by assuming that firms optimally design coinsurance. We find substantial benefit externalitites in MA-PD plans: a $1 increase in prescription drug spending reduces non-drug expenditure by approximately 20 cents. This estimates aligns with previous work by Chandra, Gruber and McKnight (2010), who examine offsets using demand-side utilization.[4]

The model and our structural estimates also allow us to perform several additional policy experiments. If stand-alone PDPs are forced to account for this externality in their premiums and benefit design behavior, PDP plans would increase drug spending by 13%. Based on these estimates, we find that stand-alone Part D plans impose a $405 million externality on traditional Medicare each year. Broad cost-sharing subsidies, including closing the donut hole, are not cost effective from the government's perspective because consumers do not value reductions in out-of-pocket costs (OOPC) as much as reductions in premiums. 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 that insurers internalize the externality associated with under-consumption of high value services when they are incentivized to do so. In doing so, our paper adds to a small but growing literature examining how firms react to the information frictions and behavioral biases of consumers. By contrast to previous studies, we show that firms can increase welfare rather than exploiting deviations from the fully informed, rational model of consumer decision-making. Our reduced form work provides causal evidence of increased utilization by MA-PD plans, and our structural

[4]We cannot employ a similar strategy because we do not observe medical claims for enrollees in MA-PD plans.

model of plan design estimates the incentives that lead MA-PD plans to increase utilization. Our focus on insurer incentives and behavior in the Medicare Part D program complements the large literature exploring plan choice (Abaluck and Gruber (2011); Ketcham et al. (2012); Ho, Hogan and Scott Morton (2015)) and drug utilization (Abaluck, Gruber and Swanson (2015); Dalton, Gowrisankaran and Town (2015); Einav, Finkelstein and Schrimpf (2015)).

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 is the program providing health insurance to the elderly in the United States. Parts A and B, which have existed since 1965, cover hospital costs and outpatient services, respectively. Medicare Advantage (Part C) and Part D are administered by private insurers. Medicare Advantage is an alternative to traditional Medicare under Parts A and B. Medicare Part D coverage 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 incentive to take this offset into account; in this paper, we focus on the behavior of these private plans relative to stand-alone PDPs.

Seniors have obtained health insurance through private insurers, often providing HMO options, 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 has waxed and waned in popularity over time, often coinciding with the level of federal reimbursement; as of 2014, 38% of Part D beneficiaries were enrolled in a Medicare Advantage plan (Gold et al. (2014)). Enrollment rates have continued to grow post-Affordable Care Act (ACA).[5] There is significant heterogeneity in the popularity of MA-PD plans. Across consumers within a market, MA may be more attractive to middle class retirees or consumers with lower risk. There is also a great deal of geographic disparity. For example, MA covers only 10% of consumers in

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

Baltimore but 34% of consumers in Milwaukee.

During our sample period, a senior eligible for Medicare had a number of choices. First, 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)).

By contrast, the Part D program has been popular among both beneficiaries and policymakers since its inception 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 costs lower than projection. The subsidy, which covers 74.5% of the premium, is substantial and it is financially beneficial for most Medicare eligibles to enroll in some form of drug coverage. The program provides a "standard benefit," which implies a very non-linear contract between the insurer and the enrollee. The deductible in 2014 was $310, followed by 25% cost sharing in the initial coverage region (ICR), followed by the infamous donut hole and, finally, catastrophic coverage. Coordination of care and innovation in benefit design could be especially important given the nonlinear, likely sub-optimal, nature of the Part D standard benefit.

However, private insurers may recognize that this design is not necessarily optimal: 47% of plans eliminated the deductible in 2014, and nearly one quarter of MA-PD plans had some form of donut coverage in 2006.[6] 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. Bidding is an important feature of both programs, but is largely outside the scope of this paper, which explores plan design, rather than prices. 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.

### 2.1 Framework and Literature

Since the RAND health insurance experiment (Manning et al. (1987)), the literature has conclusively shown that increased cost sharing causally leads to a reduction in the consumption of medical services. Furthermore, reductions in consumption seem to affect both high- and low-value services. Consumers may not have enough information to accurately assess the value of specific medical services. More recently, the theoretical literature has documented the potential for underutilization "due to mistakes or behavior biases," and referred to this phenomenon 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).

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

[6] 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.

Vogt (2007)) and the Medicare Part D program (McWilliams, Zaslavsky and Huskamp (2011)). 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)). 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)). A naive consumer will not place additional value on contracts that correct for underutilization. This has important implications in our setting: if consumers are sophisticated, differences across PDP and MA-PD plan drug benefit designs will be smaller than in the case of naive consumers, because consumers will demand contracts that internalize the potential for both financial and health offsets. Therefore, if MA-PD plans are meaningfully "more generous" than consumer demand would predict, this is evidence of underutilization by naive consumers.

In addition, there is substantial evidence that consumers are naive about the potential for under-consumption; the literature documents that consumers tend to underweight generosity when choosing Part D plans. 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). While much of the research incorporating information frictions and biases has focused on plan choice, a growing literature has explored the potential for biases to impact utilization within a plan, including consumer myopia. This research indicates that removal of the donut hole from the benefit design can increase drug adherence (Einav, Finkelstein and Schrimpf 2015, Abaluck, Gruber and Swanson 2015, Dalton, Gowrisankaran and Town 2015). Our research builds on this work by considering the role that insurers play in designing plans.

## 2.2 Data

Our main data source is 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 additional data on beneficiary and plan characteristics - also available from Centers for Medicare and Medicaid Services (CMS) - as well as MA reimbursement levels and county and metro population.

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 drop any beneficiaries who receive low-income subsidies and are subject to lower cost sharing. 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 drop 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 information or population information. This leaves us with a total of 3,019,197 observations.

We describe our sample in Table 1. In the full sample, the average beneficiary is 77 years old, 62% are female and 91% are white. Average utilization is $1639, with substantial variation; 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 utilization for this group is $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 are relatively small. Critically, we do not observe non-prescription medical claims for MA enrollees. We will infer the offset from insurer plan design decisions.

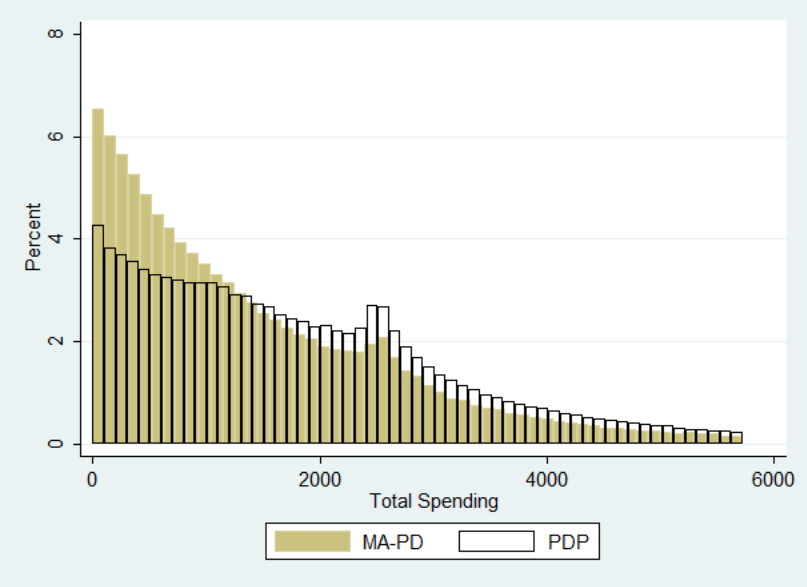
There is substantial heterogeneity in consumers spending. We capture some of this observed heterogeneity by controlling for lagged utilization in our reduced form results and consumer demand system. To do this, we create five consumer types corresponding to the five quintiles of 2006

Table 1: Summary Statistics

| | Metro Population Restrictions | | | |
|---|---|---|---|---|
| | None | 100-400k | 100-250k | 251-400k |
| Drug Utilization | 1636.39 | 1697.33 | 1691.51 | 1704.51 |
| | [1288.74] | [1284.98] | [1284.65] | [1285.36] |
| Insurer Spending | 1026.79 | 1031.08 | 1021.48 | 1042.94 |
| | [826.31] | [782.74] | [775.54] | [791.38] |
| OOPC | 609.60 | 666.25 | 670.04 | 661.57 |
| | [664.60] | [680.57] | [682.11] | [678.64] |
| 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 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.

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.

spending. Total utilization in the first group averages $895 per year for 2007-2009, while yearly spending in the top quintile averages $3503.

This heterogeneity is also 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 into the MA program. Despite this, we will 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.

We also construct a number of variables to describe 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 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

Table 2: Plan Summary Statistics

| | 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: Table presents summary statistics describing plan design. 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. Statistically different means at the 1% level denoted by ***.

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 $q_{dt}$. By weighting $p_{djt}$ by this quantity measure for a nationally representative population, we can 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.

### 2.3 Identification Strategy

We want 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 may unobservably healthier than non-MA enrollees. Specifically, MA-PD plans tend to attract enrollees who are healthier than average or healthier than average conditional on risk adjustment (Brown et al. (2014)). 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. We need an instrument for MA enrollment that is uncorrelated with both individual and market level total drug and medical spending.

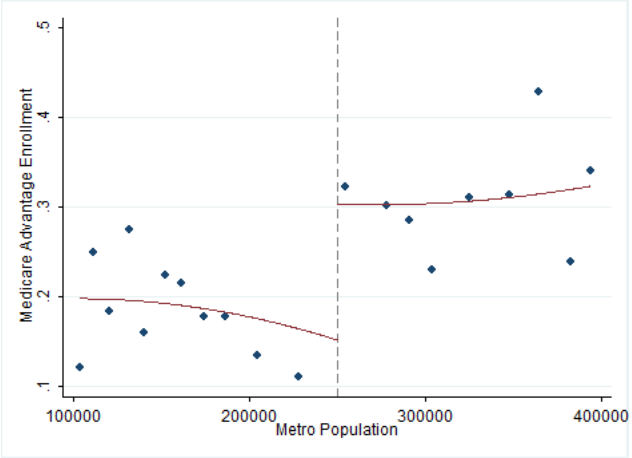
Following a series of papers (Afendulis, Chernew and Kessler (2013); Cabral, Geruso and Mahoney (2014); Duggan, Starc and Vabson (2015)), we use a statutory discontinuity in MA-PD plan reimbursement. For counties with relatively low fee-for-service (FFS) spending, payment is set equal to a payment floor. Beginning in 2003, differential floors were set for urban and rural counties. 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 is plausibly exogenous: it is not correlated with individual health risk, and approximately two-thirds of counties are floor counties. Furthermore, because an urban areas is defined as 250,000 or more in metro population, we can focus on comparable counties close to 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.[7]

The identification strategy hinges on the similarity of urban and rural floor counties near 250,000 in metro population. We provide evidence of balance in Table 12; using data from the Area Resource files, we show that the "treated" and "control" counties are similar in terms of demographic characteristics. In Figures 9, 10, 11, and 12 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)). While none of these previous studies have found evidence of increased 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.

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 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 strategy using an

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

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.

instrument variables framework. Specifically, we estimate:

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

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

where $\beta_3$ 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, $y_{itj}$, 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 utilization 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 quintiles 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 controls for historical use of medical services, including drugs, within a medical market.

In Table 3, we report the results of OLS regressions of total utilization, 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 more comparable to the IV estimates, we focus the analysis on consumers living in counties with associated metro populations between 100,000 and 400,000.[8] In the bottom panel, we examine the impact on total utilization. In the first column, which controls only for year and the quintile of 2006 spending, we see that the average MA enrollee has lower drug utilization: total spending on drugs is $252 less than their counterparts in stand-alone PDP plans. The average total utilization for this subsample is $1697, indicating that MA beneficiaries have 15% lower drug spending than PDP enrollees. This lower utilization 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, which should control for a great deal of the observable variation in health status. However, there may be selection conditional on unobservarbles 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 plausibly exogenous changes in MA reimbursement as an instrument for MA coverage; our IV estimates can be thought of as a fuzzy regression discontinuity, as MA enrollment is more likely in urban counties than rural ones, as shown in Figure 2. In the first panel of Table 3, we present the results of the first stage regressions, which 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

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

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 Costs | | | | | | |
| 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. Spending | | | (0.0189) | | | (0.0226) |
| R-Squared | 0.217 | 0.219 | 0.221 | 0.114 | 0.119 | 0.159 |
| Dependent Variable: OOPC | | | | | | |
| 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. Spending | | | (0.0160) | | | (0.0183) |
| R-Squared | 0.193 | 0.195 | 0.195 | 0.193 | 0.194 | 0.192 |
| Dependent Variable: Total Drug Spending | | | | | | |
| 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. Spending | | | (0.0298) | | | (0.0343) |
| R-Squared | 0.264 | 0.265 | 0.267 | 0.230 | 0.233 | 0.252 |
| Year Fixed Effects | X | X | X | X | X | X |
| Type Fixed Effects | X | X | X | X | X | X |
| Demographic Controls | | X | X | | X | X |
| Observations | 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 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.

eligibles in our dataset are 16-17% more likely to enroll in a MA-PD plan if they live in an urban county. Given an average MA market share of 25% within our sub-sample, this is a large shift.[9] By exploring what happens to consumers who are exogenously shifted into MA-PD plans, we can isolate the impact of plan design on utilization.

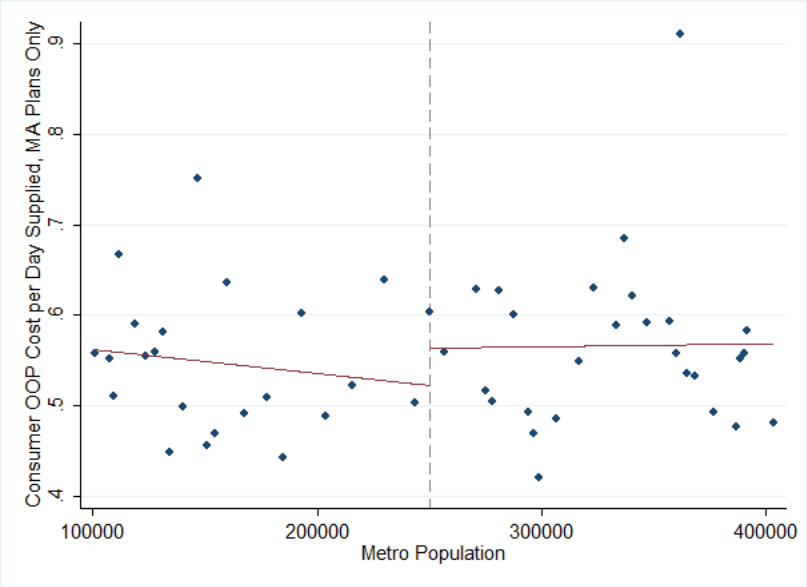
The second panel of Table 3 shows the impact of MA enrollment on insurer drug costs. The estimates imply that MA-PD plans spend much more on drugs than stand-alone PDPs once we account for selection. The estimate of $514 in column 4 is approximately half of average insurer spending ($1031 per enrollee per year). The same enrollee will cost an insurer more under a MA-PD plan. This estimate is more attenuated in the final column, which includes county level FFS costs as an additional control. This is our preferred specification. It indicates that MA-PD plans spend $388 more per year than stand-alone PDPs for an equivalent enrollee. 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.

We believe the effect of MA enrollment on enrollee and insurer spending is due to differences in MA-PD plan design intended to internalize the impact of drug offsets on non-drug medical spending. However, the observed 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. However, we find this interpretation inconsistent with other analyses.[10] We present four pieces of empirical evidence that support our interpretation that cost considerations drive the MA-PD pharmaceutical spending differences.

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

[10] 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.

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.

First, we show direct evidence that there are not differences in MA-PD plan characteristics across the urban threshold. To do this, we restrict attention to MA-PD plans and measure 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.[11] Figure 3 plots patients costs per day supplied as a function of population. In this figure, we see that 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.[12] Therefore, we argue that our local average treatment effect measures the causal impact of moving consumers from traditional FFS to MA plans, rather than reflecting differences in MA plans across the payment discontinuity.

[11] 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.

[12] 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 8, we show that rebates do not discontinuously increase across the discontinuity. In Table 12, 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.

Second, we examine the impact of enrollee retention on the magnitude of the estimated MA effect. If 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.[13] 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 only the differences in out-of-pocket costs are statistically significant and plan retention is certainly 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. Based on the results in 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 that target conditions for this population relative to the population as a whole. In columns 4-6 of Table 4, we present evidence that MA enrollment increases insurer drug spending by $559 in this 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).[14]

Fourth, we show that the effect of 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.

[13] 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.

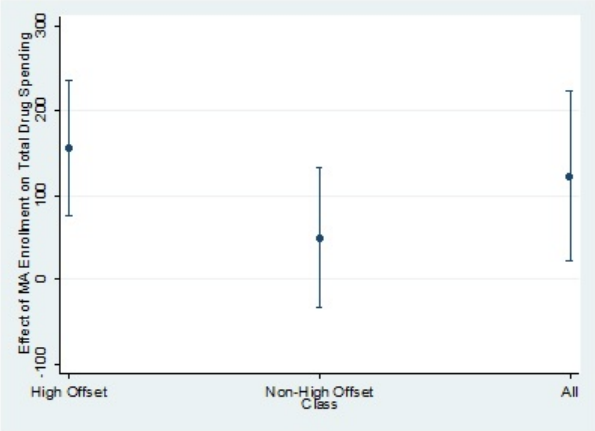
[14] The more pronounced increase in insurer spending also leads to higher overall utilization, though the estimates are noisy. We further explore the effect on consumers in Figure 4.

Table 4: Impact of MA Enrollment on Drug Spending

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Above Median Retention Plans | | | Hyperlipidemics | | |
| Dependent Variable: Insurer Drug Costs | | | | | | |
| 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. Spending | | | (0.0246) | | | (0.0352) |
| R-squared | 0.037 | 0.042 | 0.114 | 0.188 | 0.114 | 0.119 |
| Dependent Variable: OOPC | | | | | | |
| 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. Spending | | | (0.0198) | | | (0.0307) |
| R-Squared | 0.192 | 0.193 | 0.190 | 0.149 | 0.150 | 0.150 |
| Dependent Variable: Total Drug Spending | | | | | | |
| 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. Spending | | | (0.0370) | | | (0.0541) |
| R-Squared | 0.199 | 0.203 | 0.238 | 0.133 | 0.132 | 0.172 |
| Year Fixed Effects | X | X | X | X | X | X |
| Type Fixed Effects | X | X | X | X | X | X |
| Demographic Controls | | X | X | | X | X |
| Observations | 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 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 enrollee level.

Figure 4: Spending by Class




Notes: This figure presents the coefficient 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.

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 in MA-PD plans is concentrated in these large offset drugs.[15] This can also 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.

In our final reduced form analysis, we further explore the relationship between MA-PD enrollment and out-of-pocket drug costs to consumers.[16] These tests do not rely on the exclusion

[15] 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.

[16] 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.

Table 5: Impact of MA Enrollment on Spending, Drugs with Large Offsets

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | OLS | | | IV | | |
| Dependent Variable: Insurer Drug Costs | | | | | | |
| Mean | 401.16 | | | | | |
| Standard Deviation | 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. Spending | | | (0.0150) | | | (0.0170) |
| Mean | 0.046 | 0.047 | 0.047 | 0.005 | 0.005 | 0.018 |
| Dependent Variable: OOPC | | | | | | |
| Mean | 246.96 | | | | | |
| Standard Deviation | 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. Spending | | | (0.0103) | | | (0.0116) |
| R-Squared | 0.064 | 0.065 | 0.065 | 0.063 | 0.064 | 0.065 |
| Dependent Variable: Total Drug Spending | | | | | | |
| Mean | 648.11 | | | | | |
| Standard Deviation | 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. Spending | | | (0.0230) | | | (0.0260) |
| R-Squared | 0.064 | 0.065 | 0.066 | 0.043 | 0.044 | 0.051 |
| Year Fixed Effects | X | X | X | X | X | X |
| Type Fixed Effects | X | X | X | X | X | X |
| Demographic Controls | | X | X | | X | X |
| Observations | 322,066 | 322,066 | 322,066 | 322,066 | 322,066 | 322,066 |

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 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.

restriction from our IV specifications as the level of observation is the drug fill. 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). 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. 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.[17]

In Figure 5, we show that our 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). If these conditions are not properly addressed with medication, they may lead to hospitalizations. The results for hypertension (high blood pressure) are more mixed. However, in Figure 7, we show that this is due to heterogeneity across types of hypertensives. For the most cost-effective, recommended initial therapy (non-beta blockers)[18], the effect is in the expected direction. In summary, MA-PD plans have

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.

[17] 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.

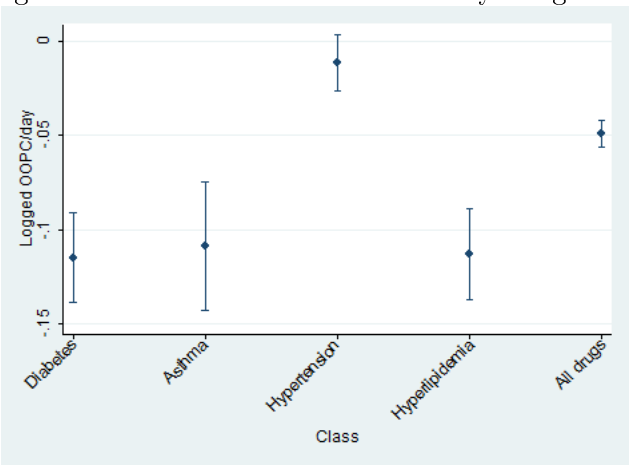
[18] NICE (2011)

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 differences 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.

lower out-of-pocket costs for identical drugs, and this effect is especially large for high value drugs. Furthermore, the plan summary statistics show that, for the average consumer, the typical bundle of drugs consumed will be cheaper under a MA-PD plan than a PDP plan. Finally, we see some limited evidence of "medical management," including the encouragement of ninety day fills.

In the Appendix, we perform a number of robustness checks. First, there is a bias-variance trade-off in bandwidth selection. With that in mind, in Table 13, 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 13, we can 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 outliers. In the final three columns of Table 13, we include enrollees with no fills and expenditure above the catastrophic limit. The results are again similar, though noisy. We also show that our

results are robust to alternative population controls in Table 14. 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 250,000. While the point estimates vary slightly, none of the estimates are statistically different from our preferred estimates as shown in column 3 of Table 4. Finally, in Table 15 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. This is due in large part to lower cost sharing for consumers. We next examine the incentives MA carriers face when designing their plans to internalize offsets using a model of insurer plan design.

# 4 Model of Insurer Premium and Benefit Design Setting

In this Section, we describe our model of equilibrium insurer plan design behavior 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 relatively simply yet rich enough to capture the complexity of equilibrium insurer behavior when setting premiums and benefits. In this framework insurers have three choice variables: premium, $p_{jt}$, and the average out-of-pocket cost per days supply in both the initial coverage phase and in the donut hole, $P_{jt} = \left[P_{jt}^{ICR}, P_{jt}^{Donut}\right]'$. These choice variables are a simplification aimed at making the model more tractable.

Firms do not set premiums directly, but submit a "bid" for both drug and non-drug coverage. If the bid is above a benchmark amount, the consumer pays the difference. If the bid is below the benchmark amount, which happens for MA plans, insurers must devote part of the difference to improving plan benefits. 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.[19] Insurers also design formularies along with coinsurance and copayment rates; as in the reduced form section, we collapse all of this variation into average consumer out-of-pocket costs per days supply. Directly modeling formulary placement of every drug would be computationally infeasible. We focus on these cost-sharing parameters because they represent both the average and marginal prices for most consumers, and there is substantial heterogeneity in both, as documented in Table 2. Consumers choose plans based on the premium and generosity as measured by this out-of-pocket cost.

Firms maximize profits, which depend on their own premiums, subsidies and costs as well as the equilibrium decisions of their competitors. Insurer drug costs are a function of the generosity of the plan. We begin by describing incentives for a stand-alone prescription drug plan and then modify the analysis to take into account differential incentives faced by MA-PD plans. Variable profits for a stand-alone PDP are given by:

$$\Pi_{jmt} = \left(p_{jmt} + r_t^{PDP} - c_{jmt}\right) s_{jmt},$$

where $r_t$ is the federal subsidy, $c_{jmt}$ is the cost to the insurer, and $s_{jmt}$ is the market share. This implies first order conditions for all three choice variables:

$$\left(p_{jmt} + r_t^{PDP} - c_{jmt}\right) \frac{\partial s_{jmt}}{\partial p_{jmt}} + s_{jmt} = 0$$

$$\left(p_{jmt} + r_t^{PDP} - c_{jmt}\right) \frac{\partial s_{jmt}}{\partial P_{jmt}^{Phase}} + \left(1 - \frac{\partial c_{jmt}}{\partial P_{jmt}^{Phase}}\right) s_{jmt} = 0 \, for \, P_{jmt}^{ICR}, P_{jmt}^{Donut}.$$

While premiums, subsidies, drug costs, and market shares are observed in or easily inferred from the data, each of the derivatives needs to be estimated. In order to calculate these objects, we need to estimate a model of consumer demand for plans.

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

[19] We explore the effect of rebates, which are positive for approximately 5-10% of plans (Stockley et al. (2014)) in Figure 8 and Table 12.

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, MA-PD plans will differ from PDPs in their cost sharing arrangements because their first order conditions differ with respect to one key term. In mathematical terms, $\frac{\partial c_{ijt}}{\partial P_{jt}^{Phase}}$ is not equal under MA-PD and PDP plans.

The average total costs for a MA-PD plan can be written as $c_{jmt} = c_{jmt}^{Drug} + c_{jmt}^{Medical}$. We are interested in $\frac{\partial c_{jmt}^{Medical}}{\partial P_{jmt}^{Phase}}$. In the presence of drug offsets, this term will be non-zero. Therefore, the first-order condition for a MA-PD plan can be re-written as:

$$\left(p_{jmt} + r_t^{PDP} + r_{mt}^{MA} - c_{jmt}^{Drug} - c_{jmt}^{Medical}\right) \frac{\partial s_{jmt}}{\partial P_{jmt}^{Phase}} + \left(1 - \left(\frac{\partial c_{jmt}^{Drug}}{\partial P_{jmt}^{Phase}} + \frac{\partial c_{jmt}^{Medical}}{\partial P_{jmt}^{Phase}}\right)\right) s_{jmt} = 0.$$

There are a few things to note in this model. First, we note that 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. Second, the current formulation does not allow for consumer heterogeneity in preferences or costs. In the empirical implementation, we will incorporate consumer heterogeneity by allowing preferences to be fully flexible by quintile of 2006 spending. Furthermore, firms will account for the differences in drug costs across quintiles when designing plans.

### 4.1 Plan Choice

We estimate insurance demand in order to calculate the elasticities necessary to describe firm incentives. This allows us to take account of the fact that both MA-PD and PDP plans may simply be responding to differences in consumer demand, rather than creating incentives for consumers to increase drug consumption due to offsets. The structural model allows us to separately identify the effects of utilization and plan choice.

We estimate a nested logit model and allow the parameters to vary by enrollee expenditure type. The market is defined as a county; while Part D insurers have identical offerings within the large 34 PDP regions, MA-PD plans can choose which counties to enter. Therefore, the consumers'

choice set varies by county. Following a number of papers (Lustig (2010); Nosal (2011)), a product is defined as a unique contract ID for both MA-PD and PDP plans. If there is more than one plan within a contract, we use the product characteristics of the lowest numbered plan. The key product characteristics are the premium attributed to drug coverage, and out-of-pocket costs, as described above.[20] Beyond these product characteristics, which can vary at the market level, we use product fixed effects to capture invariant features of plan quality, including relative non-drug premiums for MA-PD plans.

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 $j$ in market $m$ at time $t$ is given by:

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

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

These specifications reflect a few modeling choices. First, while we allow plan fixed effects, premium and out-of-pocket cost coefficients, and the dissimilarity term to vary by consumer type, there is no unobserved consumer heterogeneity in the model. Our specification allows for consumer heterogeneity in preferences by including flexible plan fixed effects that can vary by consumer type. 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. Still, our formulation allows for selection into plans based on consumer type.[21] This implies that the derivative of shares with respect to any element of the tariff vector is given by $\sum_q \frac{\partial s_{qjtm}}{\partial OOPC_{qjtm}} \frac{\partial OOPC_{qjtm}}{\partial P^{Phase}_{jtm}}$. Second, 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 $P^{ICR}_{jtm}, P^{Donut}_{jtm}$, and $OOPC_{jtm}$ is purely mechanical.

[20] 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.

[21] 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 design (Carey (2015); Lavetti and Simon (2014)).

Finally, we model the problem as a static one. We do not allow for the kind of inertia documented by Handel (2013) in the employer-sponsored setting or Ho, Hogan and Scott Morton (2015) in the Part D setting. While we believe that these behavioral biases are important for plan incentives, we believe that our model accurately estimates the relevant elasticities. We test this assumption in the Table 16; models that restrict analysis to new consumers aged 65 and active choosers (defined as those who change plans) are qualitatively similar to our main results. In no specifications do we see a strong consumer preference for lower OOPC, which is consistent with our hypothesis that cost considerations drive increased MA-PD generosity. Furthermore, our reduced form results indicate that inertia reinforces the effect that we find; therefore, we believe that substantial inertia would be likely to bias our estimates toward zero.

We estimate the parameters of the model separately for each quintile type using the Berry (1994) specification. This allows us to aggregate to the quintile-plan level while still estimating a specification flexible enough to account for substantial heterogeneity in consumer preferences, including differential plan fixed effects by quintile. However, 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, $\xi_{jmt}$, 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, we instrument for the inside share using the urban dummy interacted with an MA dummy. This allows us to capture 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 should capture common cost shocks as well as correcting for any measurement error in our measure of out-of-pocket (drug) costs.

The results of the IV specifications for each of the five consumer groups are in Table 7. We notice a couple of patterns across the models. First, 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 smaller in magnitude than the premium coefficient, consistent with Abaluck and Gruber (2011), and attenuated among sicker consumers. We note that the premium variable is

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) |
| $\sigma$ | 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 |

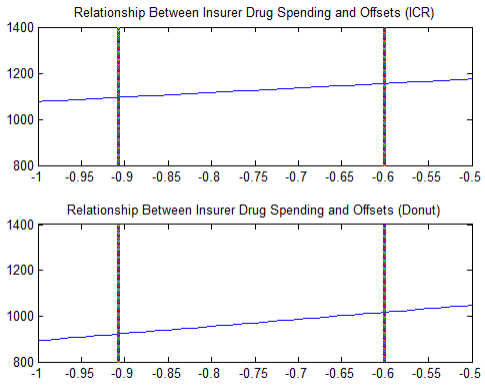
Notes: Table presents instrumental variable regression models, where outcome variables is the log of the plan share less the log of the outside share. The outside share is constructed as all Medicare eligibles not enrolled in a stand-alone Medicare Part D plan or MA-PD plan. In all specifications, we 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.

observed, while the OOPC is observed with error and may be attenuated. Furthermore, while differences across consumer groups may reflect differential preferences, it may also reflect larger measurement error among higher spending enrollees. This indicates 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. Finally, own-price elasticities 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). These results are consistent with MA-PD plans serving a healthier population and providing more generous benefits. Finally, across all groups, the dissimilarity parameter indicates that MA-PD plans are much better substitutes for MA-PD plans than PDP plans.

### 4.2 Supply Side Estimation

Premiums, drug costs, and shares are all observed in the data. The derivatives of shares with respect to premiums and out-of-pocket costs are calculated using estimates from the demand system. Conditional on our demand estimates, the derivative of insurer costs with respect to patient cost sharing is the only parameter to be identified. 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

Figure 6: Supply Side Identification




Notes: This figure plots the optimal level of insurer spending under alternative levels of $\theta$ 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.

willing the firm is to increase generosity. From our reduced form estimates, we also know that for the same set of consumers, a MA-PD plan will spend more. Figure 6 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. On the x-axis, we plot different values of the derivative of interest, denoted by $\theta$, 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 $\theta$ is, the more the plan spends on drugs.

We calculate subsidies using the formula provided by CMS, averaging 74.5% of bids. Given premium elasticities, premiums, subsidies, and observed market shares, we impute $c_{jmt}^{Medical}$ using the first-order condition with respect to premiums. Formally, for MA-PD plans,

$$c_{jmt}^{Medical} = \left(p_{jmt}^{MA} + r_{mt}^{MA}\right) + \sum_{q} \frac{s_{qjmt}/Q}{\frac{\partial s_{qjmt}}{\partial p_{jt}}},$$

where $Q$ is the number of quintiles.[22] 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). We utilize the fact that we observe separate bids (and, therefore premiums) and subsidies for the medical and drug spending components of

[22]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.

MA plans to separately identify medical costs. This allows us to infer these medical costs "offline" separately for each plan and 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 $c_{jmt}^{Drug}$,. 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 $c_{jmt}^{Medical}$ . Table 8 describes how all of the critical quantities are calculated or estimated.

Critically, we write derivatives with respect to these firm choice variables in terms of changes in out-of-pocket costs. For example, $\frac{\partial s_{qjtm}}{\partial P_{jtm}^{Phase}} = \sum_{Phase} \frac{\partial s_{qjtm}}{\partial OOPC_{qjtm}} \frac{\partial OOPC_{qjtm}}{\partial P_{jtm}^{Phase}}$. This requires a function that relates $P_{jtm}^{Phase}$ to out-of-pocket costs for each phase. Given a vector of $P_{jtm}^{Phase}$, we can create counterfactual out-of-pocket costs given constant consumption (days supply) for consumer $i$ with consumption (days supplied) $q$ as:

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

where $q$ is the days supplied, $\gamma$ represents the average coinsurance in each phase, and $DED$, $ICL$, and $CAT$ represent the deductible, initial coverage limit, and catastrophic cap, respectively. While this piece-wise function appears complicated, calculation of derivatives is quite simple. 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

Table 8: Identification

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

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.

Armed with these estimates, we can estimate the object of interest - $\frac{\partial c_{ijt}}{\partial OOPC_{jt}}$ - using Generalized Method of Moments. Let $\theta = \frac{\partial c_{ijt}}{\partial OOPC_{jt}}$. The first-order conditions imply that:

$$\int_q [\left(p_{jmt}^{Drug} + r_t^{PDP} + 1(MA)\left(p_{jmt}^{Medical} + r_{mt}^{MA}\right) - \left(c_{jmt}^{Drug} + 1(MA)c_{jmt}^{Medical}\right)\right) \frac{\partial s_{qjmt}}{\partial OOPC_{qjmt}} \frac{\partial OOPC_{qjmt}}{\partial P_{jmt}^{Phase}} +$$

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

We parametrize $\theta$ in couple of different ways. All of the models are parametrized such that the constant is 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. Without asymmetric information or offsets, $\theta = 1$. Selection and offsets will both lead to estimates of $\theta$ that differ from 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

Table 9: Supply Results

| $\partial c/\partial OOPC$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Constant | -0.8761 | -0.9069 | -0.9069 | -0.9069 |
| | (0.0102) | (0.0092) | (0.0102) | (0.0094) |
| MA | | 0.3063 | 0.1861 | 0.3124 |
| | | (0.0335) | (0.0351) | (0.1049) |
| MA*Normalized Non-Drug Costs | | | 0.1259 | |
| | | | (0.0203) | |
| MA*Normalized 3-year Retention Rate | | | | 0.0561 |
| | | | | (0.1253) |
| 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.

costs. We then allow $\theta$ to differ across MA-PD and PDP plans: $\theta = \theta_1 + \theta_2 * 1(MA)$. Finally, we allow $\theta$ to vary with the level of medical spending in the MA-PD plan.

The estimates are in Table 9. 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. An estimate statistically different from one implies 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 turn to the second model, which isolates the portion of $\theta$ that is unique to MA-PD plans. In this model, we allow $\theta$ 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, the calculation for a MA-PD plan is very different. The average MA-PD plan would only save \$60 per member by increasing out-of-pocket costs by \$100. We have parametrized MA costs as $c_{jmt} = c_{jmt}^{Drug} + c_{jmt}^{Medical}$; the estimates indicate that the derivative of $c_{jmt}^{Medical}$ with respect to insurer drug spending is positive. As plans spend more on drugs, some of the insurer's cost is offset by reductions in spending in other areas. The difference between the spending implied in Figure 6 is largely consistent with the reduced form estimates for the entire sample.

We explore heterogeneity in the size of the offset effect along two dimensions. The size of this

"offset" effect may depend on the illness severity of the consumers in the plan. In reduced form results, we saw higher insurer spending among consumers with chronic conditions. Higher spending would be implied by a model in which the offset effect is bigger among sicker consumers. In order to test this hypothesis, we interact the Medicare 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 9. The results imply a bigger offset among the sickest consumers. A MA-PD plan with average beneficiaries would save $72 by increasing out-of-pocket costs by $100, while a plan with average non-drug spending one standard deviation larger than average would save only $59 by increasing out-of-pocket costs by $100, due in part to a larger offset of non-drug costs. Finally, 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.

# 5 Counterfactuals

We use our structural estimates in two exercises. First, we quantify the size of the implied prescription drug offsets and (fiscal) externality imposed by stand-alone Part D plans. Second, we examine policies that may address the fiscal externality created by PDP plan.

## 5.1 Firm Behavior, Externalities, and Offsets

The model estimates imply that stand-alone PDP and integrated MA-PD plans design benefits differently in order to capture the extent to which drug expenditures reduce non-drug expenditures. Broadly, consumers do not value plans that explicitly correct for inefficient underutilization. Whether due to signaling the value of drug consumption (value-based insurance design, Chernew, Rosen and Fendrick (2007)) or de-biasing consumers (correcting for behavioral hazard, Baicker, Mullainathan and Schwartzstein (2015)), private firms play an important role in designing insurance products that promote more efficient utilization of health care services.

In order to put these incentive differentials into context, we provide estimates of the size of both the fiscal externality and the offset. In the first, we consider how PDP plans would adjust

their plan offerings if they were forced to internalize 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 an equilibrium in which we allow drug costs to the insurer, $c_{jmt}^{Drug}$, 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 10 describes the results; in the first two columns, we describe baseline summary statistics. The average MA-PD plan has lower premiums (due to generous reimbursement) than the average PDP plan, which have average premiums of $406 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 next two columns, 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.

Therefore, we also 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 slightly (2%) to offset some of the additional drug costs. The subsidy would increase mechanically but not enough to make the PDP plans "whole." Therefore, some plans might exit the market. However, in this exercise, MA-PD plans do not increase their generosity nearly as much as they did in the previous counterfactual. They do not want to raise their premiums in order to provide generosity beyond the previously optimal amount, as consumers value a $1 decrease in premiums more than a $1 decrease in cost sharing.

Our estimates quantify how changes in cost sharing affect firms. By combining our estimates with estimates of the observed behavioral response to cost sharing by consumers, we can estimate 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 model of drug consumption. The elasticity is identified by exploiting the kink in individuals' budget sets created by the donut hole; we reproduce their elasticity estimates in Table 11 and use the elasticity

Table 10: Counterfactuals

| | Baseline | | Internalize Externality | | Internalize Externality | | Sophisticated Consumers | |
|---|---|---|---|---|---|---|---|---|
| | MA | PDP | MA | PDP | MA | PDP | MA | PDP |
| Premium | 207.54 | 405.89 | 207.54 | 405.89 | 206.02 | 414.35 | 207.54 | 405.89 |
| ...% Change | - | - | - | - | -0.0073 | 0.0208 | - | - |
| Drug Spending | 1285.22 | 1211.04 | 1376.07 | 1364.62 | 1345.80 | 1367.32 | 1357.41 | 1337.64 |
| ...% Change | - | - | 0.0707 | 0.1268 | 0.0471 | 0.1291 | 0.0564 | 0.1038 |

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.

for a 1% uniform out-of-pocket cost reduction of -0.54 in our calculation. 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. However, from our supply side estimation, we know 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 $\frac{\partial c^{Medical}}{\partial \mathbf{P}}$.[23]

For a 1% uniform decrease in cost sharing, denoted by $\mathbf{P}$, we calculate the implied 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 $\theta_2$ (0.30) estimated in Table 9 and the mechanical value of $\frac{\partial OOPC}{\partial \mathbf{P}}$, \$10.15.[24]

[23] 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).

[24] For this calculation, we use the average value of consumer out-of-pocket cost per day supplied and the formula

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 42 cents per day supplied, or 19%.

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 $405.3 million per year.[25]

### 5.2 Policy Interventions

Next, we consider budget neutral policies that attempt to internalize the externality generated by the PDP plans.[26] 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 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

described in Section 4.2, evaluated at average consumption.

[25] We would obtain a similar estimate if we used the implied additional spending by PDP plans in Table 10. By contrast, MedPAC (Medpac (2015)) 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.

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

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.[27]

A 1% cost-sharing subsidy would increase utilization by 7.2 days supply based on the behavioral elasticities in column 2. The implied offset, in column 3, is \$3.05.[28] 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 \$7.11 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 \$44.44 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 \$312. Therefore, if the policy is to be budget neutral, premiums will have to rise dramatically.[29]

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.[30] This is for two reasons: consumers are not sophisticated

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

[28] This is calculated as the additional spending multiplied by the 19% figure described above.

[29] 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.

[30] 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 and 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

Table 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 | 3.05 | 10.15 | 7.11 | -0.0009 | 4.30 |
| 2.50% | -0.38 | 5.36 | 25.28 | 19.93 | -0.0027 | 10.70 |
| 5.00% | -0.33 | 9.307 | 50.51 | 41.20 | -0.0057 | 21.38 |
| 10.00% | -0.30 | 16.92 | 100.94 | 84.02 | -0.0118 | 42.74 |
| 25.00% | -0.29 | 40.89 | 252.30 | 211.41 | -0.0313 | 106.82 |
| 50.00% | -0.29 | 81.79 | 504.60 | 422.82 | -0.0638 | 213.64 |
| 75.00% | -0.31 | 131.1 | 757.27 | 626.13 | -0.0947 | 320.61 |
| Eliminate the Donut Hole | | 44.4 | 355.99 | 311.54 | -0.0640 | 150.72 |

Notes: Results are calculated as described in Section 5.

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 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 enrollment by 7.4%.

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 due to behavioral hazard, as described in Baicker, Mullainathan and Schwartzstein (2015). Of course, this is not the only possibility. Underutilization could also be driven by asymmetric information about the value of treatment (Manning et al. (1987)) or misalignment of copays across multiple technologies (Ellis, Jiang and Manning (2015); Goldman and Philipson (2007)). Regardless, 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.[31] 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

payment (and reduces Parts A and B spending by 0.3%) internalizes the externality. 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).

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

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.

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 Table 10; 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 nearly equal to the amount that fully internalized the fiscal externality. Therefore, if consumer decision utility was more closely aligned with value (in the very limited sense of simply valuing OOPC and premiums equally), we believe that plan designs would be closer to fully internalizing the externality generated by under-consumption. Ultimately, public policies that align consumer demand or the structure of subsidies with providing value will incentivize insurers to offer contracts that increase welfare.

# 6 Conclusion

This paper examines how health insurers react to both over-utilization and, particularly, under-utilization by consumers. We build on an empirical literature that quantifies consumer responses to cost-sharing and non-linear benefit design in insurance contracts and a theoretical literature that considers contract design in the face of behavioral biases. While we do not take a strong stand on whether behavioral biases or information frictions lead to underutilization in our setting, we provide an empirical example in which firms mitigate potentially inefficient underutilization by consumers.

We examine these issues in the Medicare Advantage and Part D markets. We 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 stand-alone counterparts; this increased spend-

ing 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. Our calculations show that cost-sharing subsidies are less effective than policies that inform consumers about trade-offs inherent in insurance plans.

Our empirical work also shows that consumers likely under-consume high value health care services. This is consistent with a long literature, and the canonical RAND health insurance experiment (Manning et al. (1987)). Under-consumption by consumers could be due to informational frictions or behavioral hazard, but is conceptually separate from more commonly studied moral hazard. We do not take a stand on whether information frictions or behavioral hazard drives under-consumption by consumers. However, a number of papers (Abaluck, Gruber and Swanson (2015); Dalton, Gowrisankaran and Town (2015)) find evidence of myopia in this market. Myopia is consistent with evidence of "flatter" benefit design, including lower cost sharing in the donut hole, as seen in MA-PD plans. Whether due to information frictions or behavioral hazard, this paper provides new evidence that firms correct for under-consumption by consumers.

Finally, we believe these results could lead to additional research examining the intersection of consumer choice in health care markets and contract design by firms. Profit maximizing insurers may be able to offer plan design features, including value based insurance design and high performance networks, which have the potential to leverage insurance market innovation to reduce health care costs.

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## 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 7.

# Additional Robustness Checks (For Online Publication)

Table 12: 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 12 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. Median age is significant at the 10% level.

Table 13: 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 Fixed Effects | X | X | X | X | X | X | X | X | X |
| Type Fixed Effects | X | X | X | X | X | X | X | X | X |
| Demographic 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.

Table 14: 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 Pop Controls | Linear | Quadratic | Cubic | Quartic | Linear Spline | Cubic Spline |
| Year Fixed Effects | X | X | X | X | X | X |
| Type Fixed Effects | X | X | X | X | X | X |
| Demographic 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. Linear and cubic splines have knots at 250,000.

Table 15: 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 Fixed Effects | X | X | X | X | X | X |
| Type Fixed Effects | X | X | X | X | X | X |
| Demographic 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.

Table 16: IV Nested Logit Results, 65 year olds and Active Choosers

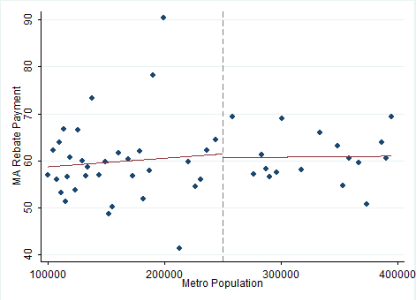
| Quintile of 2006 Spending (IV) | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| New Medicare Beneficiaries (at age 65) | | | | | |
| Premium | -0.216*** | -0.166*** | -0.274*** | -0.185*** | -0.256*** |
| | (0.0458) | (0.0430) | (0.0533) | (0.0478) | (0.0405) |
| OOPC | -0.00562 | -0.0175** | -0.00643 | -0.00696 | -0.00712 |
| | (0.0127) | (0.00884) | (0.00923) | (0.00738) | (0.00448) |
| Log(Inside Share) | 0.421 | 0.340 | 0.439 | 0.359 | 0.0622 |
| | (0.489) | (0.482) | (0.635) | (0.638) | (0.467) |
| Active Choosers | | | | | |
| Premium | -0.250*** | -0.0928* | -0.0810 | -0.0307 | 0.0312 |
| | (0.0682) | (0.0556) | (0.0559) | (0.0449) | (0.0406) |
| OOPC | -0.113*** | -0.127*** | -0.0929*** | -0.0624*** | -0.0509*** |
| | (0.0166) | (0.0137) | (0.0111) | (0.00753) | (0.00498) |
| Log(Inside Share) | 0.815*** | 0.821*** | 0.714*** | 0.845*** | 0.778*** |
| | (0.0585) | (0.0578) | (0.0590) | (0.0479) | (0.0403) |

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. Instrument 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.

Figure 7: Price Effects by Drug Class

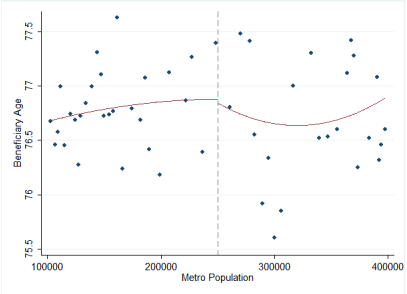

Notes: This figure plots the differences in prices by plan type. Other hypertension drugs include ACE inhibitors, angiotensin II receptor antagonists, renin inhibitors, antiadrenergic agents (centrally & peripherally acting), alpha-adrenergic blockers, aldosterone receptor antagonists, vasodilators and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

Figure 8: Effect of Population on MA Plan Rebates



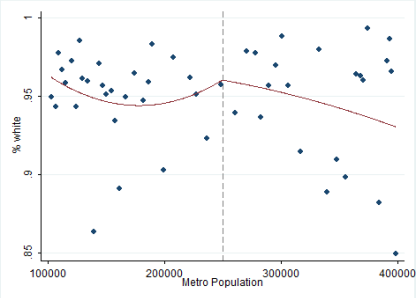

Notes: Plots a binscatter with fifty population bins using data from 2008 using data from Medicare Landscape Files. We drop counties with FFS costs above the urban floor. Lines represent a linear fit.

Figure 9: Effect of Population on Sample Demographics



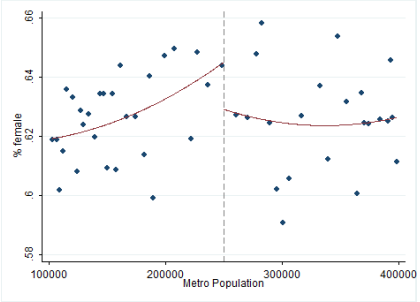

Notes: Plots a binscatter with fifty population bins using 2008 data. We drop counties with FFS costs above the urban floor, and control for beneficiary age, sex, race, 2006 spending type, and county-level FFS costs. Lines represent a quadratic fit.

Figure 10: Effect of Population on Sample Demographics



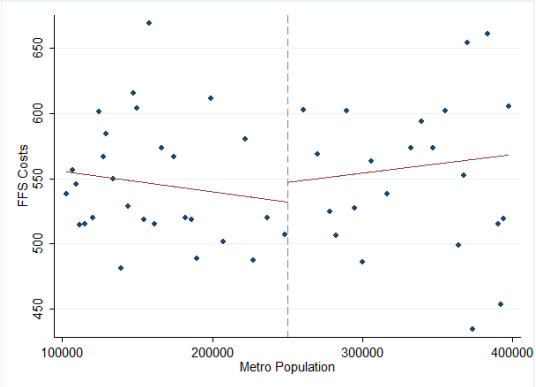

Notes: Plots a binscatter with fifty population bins using 2008 data. We drop counties with FFS costs above the urban floor, and control for beneficiary age, sex, race, 2006 spending type, and county-level FFS costs. Lines represent a quadratic fit.

Figure 11: 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 12: 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.