Private provision of social insurance: drug-specific price elasticities and cost sharing in Medicare Part D

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Abstract

Standard theory suggests that optimal consumer cost-sharing in health insurance increases with the price elasticity of demand, yet publicly-provided drug coverage typically involves uniform cost-sharing across drugs. We investigate how private drug plans set cost-sharing in the context of Medicare Part D. We document substantial heterogeneity in the price elasticities of demand across more than 150 drugs and across more than 100 therapeutic classes, as well as substantial heterogeneity in the cost-sharing for different drugs within privately-provided plans. We find that private plans set higher consumer cost-sharing for drugs or classes with more elastic demand. Our findings suggest that benefit design may be more efficient in privately rather than publicly provided insurance.

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1 Introduction

Social insurance is a key function of modern governments. Historically, the public sector directly provided social insurance products, most importantly pensions and health insurance. Increasingly, however, social insurance is privately provided. Public pension systems in many countries now involve publicly-regulated but privately-run investment funds and annuities, and public health insurance is increasingly provided by private companies that are subsidized and regulated by the government.

What are the implications of this move toward privately-provided social insurance? Recently, a sizable academic literature has empirically examined the efficiency tradeoffs inherent in the increased reliance on consumer choice in privately-provided insurance.[1] Other aspects that vary between public provision and private provision of social insurance have received much less empirical attention. In this paper, we attempt to start closing this gap.

We focus on one design aspect of health insurance: the management of moral hazard through the setting of consumer cost-sharing. Optimal consumer cost-sharing involves a classic tradeoff between risk protection and incentives. As we lower the share of the cost that the consumer is required to pay, consumers are less exposed to risk, but at the same time may be more likely to over-utilize healthcare services they do not fully value. The classic theory (Feldstein, 1973; Besley, 1988) emphasizes that the socially optimal consumer cost-sharing mimics standard Ramsey-style optimal commodity taxation results: health events that are more prone to moral hazard, i.e. have a higher price elasticity of demand, should be associated with higher consumer cost-sharing (i.e. share of the cost paid out of pocket by the consumer, also known as co-insurance) and thus less risk protection.

Curiously, however, there is little variation in consumer cost-sharing provisions when health insurance is directly administered by the public sector. For example, a summary of consumer cost-sharing provisions in public prescription drug plans in 34 OECD countries reveals that there is essentially no variation in cost-sharing across drugs in these plans.[2]

[1] For welfare analysis of choice in privately-provided aspects of public pension systems, see for example Einav, Finkelstein, and Schrimpf (2010); Duarte and Hastings (2012); Hastings, Hortacsu, and Syverson (2015). For welfare analysis of choice in privately-provided, publicly-designed health insurance systems, see for example Abaluck and Gruber (2011, 2013); Ketcham et al. (2012, 2015); Kling et al. (2012).

[2] See Barnieh et al. (2014), Table 1, which we reproduce in Appendix Table A1 and which shows uniform cost-sharing across drugs in virtually all countries' publicly-provided prescription drug plans. The table records only a few exceptions. For example, in some public insurance systems cost-sharing terms may be more (less) favorable if patients buy cheaper (more expensive) versions of certain medications. Switzerland differentiates cost-sharing between generic and branded drugs at certain spending levels. Greece and Sweden charge no cost-sharing for insulin; in the Netherlands and Germany, cost-sharing may be related to the difference between the drug's retail and reference prices, which could lead to differential out-of-

In contrast, private insurance plans commonly set complex multi-tiered cost-sharing menus across different health care services.[3] This raises the natural question, which is the focus of this paper: do private plans vary consumer cost sharing across healthcare services in the socially optimal direction?

Our empirical context is Medicare Part D, the large federal insurance program that subsidizes and regulates the private provision of prescription drug insurance to the elderly in the United States. This setting is no exception to the general pattern of uniform public cost-sharing. The government-designed benchmark standard contract in Part D has a uniform, 25 percent consumer co-insurance for any drug in the cost-sharing arm above the deductible and below the famous "donut hole." Part D insurance, however, is in practice offered by private insurers, who have substantial discretion in designing their insurance contracts relative to the benchmark "standard contract", including the ability to vary cost sharing across drugs.

The paper has two main parts. In the first part, we estimate the elasticity of demand with respect to the co-insurance rate for more than 150 common drugs and 100 common therapeutic classes. To do so, we use detailed micro data on prescription drug claims from almost 6 million beneficiary-years from 2007-2011. To estimate the demand response to price we exploit the variation in the out-of-pocket price for a drug created by the famous donut hole or "gap" in Part D coverage. This coverage gap makes insurance discontinuously much less generous at the margin, thus allowing us to observe the utilization response to a sharp increase in the out-of-pocket price. We previously used this research design to study the average behavioral response of drug utilization to cost-sharing and heterogeneity across consumers in this behavioral response (Einav et al., 2015, 2016a, 2016b). Here, we use a similar approach to estimate individual demand elasticities for specific drugs and therapeutic classes with respect to the out-of-pocket price.

We find considerable heterogeneity in the price elasticity of demand across products. Across the approximately 150 common drugs, we estimate an average elasticity of -0.24 with a standard deviation of 0.59. Across the approximately 100 common therapeutic classes, we estimate an average elasticity of -0.14, with a standard deviation of 0.15. The variation appears intuitive. For example, drugs for chronic conditions exhibit a higher elasticity than drugs for acute (and hence likely more symptomatic) conditions. Since these product-specific

pocket costs. While Barnieh et al. (2014) limit their discussion to Medicare in the context of the US, we note that the US Department of Veterans Affairs also sets a uniform $8 co-pay for all drugs (Source: http://www.va.gov/healthbenefits/resources/publications/IB10-430_copay_rates.pdf).

[3]One example (of many) would be the tiered formularies of Blue Cross Blue Shield of California which they use for Medicare, the California Exchange that was established under the ACA, as well as for small and large group coverage. Source: https://www.blueshieldca.com/bsca/pharmacy/formulary/home.sp

elasticities may also be of interest in other contexts, we provide a complete listing of the product-specific estimates in the appendix.

In the second part of the paper we analyze consumer-cost sharing across drugs and classes in thousands of private Part D plans - with hundreds of unique plan designs (known as formularies) - from 2007-2011. We document substantial variation in consumer cost-sharing across drugs within private plans. On average, the co-insurance rate for our common drugs was just over 40 percent, with a within-plan standard deviation of co-insurance across these drugs of 25 percent.[4]

Our key finding is that within a plan, private insurers set higher co-insurance (i.e. the share of the drug's cost that must be paid out of pocket) for drugs with more elastic demand. This empirical pattern is a robust feature of the data. Moreover, in the final section of the paper we also show that, at least within the context of the highly stylized model, this is the socially optimal direction of cost-sharing across drugs, and our empirical finding that private plans vary consumer cost sharing in this socially optimal direction is consistent with the incentives of private, profit-maximizing firms.

Our findings have implications for the textbook public finance treatment of government intervention in insurance markets, which generally concludes that the government may have a comparative advantage at combating adverse selection (Akerlof, 1970; Rothschild and Stiglitz, 1976), but not in combating the moral hazard "costs" associated with insurance. By contrast, our findings suggest a potential comparative *disadvantage* for the public sector in handling moral hazard through optimal cost-sharing; they suggest that benefit design may be more efficient under privately provided than publicly provided insurance.

Our paper relates to several specific research topics in social insurance. Our empirical analysis of how private insurers vary cost-sharing across drugs complements the theoretical literature on optimal health insurance design that trades-off moral hazard and risk protection (Crew, 1969; Feldstein, 1973; Besley, 1988; Ellis and Manning, 2007; Goldman and Philipson, 2007; Ellis et al., 2015). Our analysis of the relative efficiency of private and public benefit design contributes to a small but growing literature analyzing the relative efficiency of private and public health insurance, such as Medicare Advantage compared to Traditional Medicare (Brown et al., 2014; Cabral et al., 2014; Curto et al., 2015; Duggan et al., 2015), or service prices charged to providers by private insurance relative to public Medicare (Clemens et al., 2015). Our analysis of drug-specific consumer cost-sharing intersects with the growing

[4]As we explain in more detail below, Part D plans are highly non-linear in their cost-sharing rules. Throughout the paper, we use "co-insurance rate" to refer to the co-insurance rate in the cost-sharing arm above the deductible and below the donut hole. About three-quarters of purchases occur in this range.

discussion of value-based health insurance design (VBID) (e.g. Chernew et al., 2007).

Naturally, our work also relates to the voluminous empirical literature examining moral hazard in health insurance (e.g. Cutler and Zeckhauser, 2000; Einav et al., 2013; Aron-Dine et al., 2015), and the growing empirical literature on Medicare Part D (e.g. Abaluck and Gruber, 2011, 2013; Ketcham and Simon, 2008; Ketcham et al., 2012, 2015; Kling et al., 2012; Decarolis et al., 2015; Decarolis, 2015; Polyakova, 2016). Our estimation of drug-specific elasticities contributes to the empirical literature that has estimated the price responsiveness of demand for specific drugs (e.g. Fisher Ellison et al. 1997; Goldman et al. 2004; Crawford and Shum 2005; Chandra et al. 2010).

The paper is structured as follows. Section 2 describes the institutional setting of Medicare Part D, and the multiple data sources that we use in the empirical analysis. Section 3 presents our first set of empirical results, estimating product-specific demand elasticities. Section 4 presents our second set of empirical results on consumer cost-sharing in private plans. In Section 5 we develop a simple model which suggests that the empirical patterns we find are a natural prediction of standard economic theory. Section 6 concludes.

2 Setting and data

2.1 Setting

Medicare Part D is a large federal insurance program that provides prescription drug coverage for seniors. Unlike traditional Medicare coverage for physician and hospital services, Medicare Part D, which was launched in 2006, is administered exclusively by private insurers. In 2015 the program covered about 42 million individuals and generated approximately $77 billion in budgetary outlays (Congressional Budget Office, 2015). Part D coverage can be bundled with more comprehensive insurance provided by private plans (via Medicare Advantage), or can be purchased as a "stand-alone" coverage by Medicare beneficiaries who enroll in traditional, fee-for-service Medicare. In this paper we focus exclusively on this "stand-alone" segment of the market.

Enrollment in Part D is voluntary, but premiums are heavily subsidized. Those who choose to enroll can choose from among dozens of plans (about 30 on average) available in their (geographic) market. Part D plan design has two primary components: the overall coverage level and the detailed coverage and cost-sharing rules for specific drugs. Private insurers are required to offer coverage that is actuarially equivalent to or more generous than the standard benefit design, depicted (for 2008) in Figure 1. However, subject to this overall

requirement regarding plan generosity, private insurers are given considerable flexibility as to which drugs to cover and how to assign the out-of-pocket cost to the consumers associated with each purchased drug. This latter aspect of the plan design is our primary focus.

2.2 Data

We use two administrative data sets. The first is a 20 percent random sample of Medicare Part D beneficiaries from 2007-2011, their plan enrollment, and their drug claims. We use these data to compute cost-sharing by plan for different drugs and therapeutic classes, and to estimate drug-specific and class-specific elasticities.

For each beneficiary, we observe the plan they enrolled in and its coverage details, as well as some basic demographics. Crucially, we also observe detailed, claim-level data on each prescription drug claim, including the date of the claim, the drug identifier (NDC code), the quantity purchased, the total amount spent on the claim, the amount paid by the plan, and the amount paid by the consumer out of pocket. We use the NDC code, together with additional data sources, to group claims by drug and by therapeutic class, to classify drugs as branded or generic, and to classify drugs as chronic or acute, and as maintenance or non-maintenance; the online appendix provides more detail on these additional data sources and how we use them. The classification of NDC codes into therapeutic classes allows us to group drugs that have similar chemical structures or mechanism of action and are frequently used to treat the same or related diseases. Thus, drugs within a therapeutic class are more likely to be substitutes than drugs across therapeutic classes.

The second data set consists of publicly-released, monthly files from the Centers for Medicare and Medicaid Services with detailed information about the formularies of all stand-alone Part D plans offered in 2007-2011.[5] As we describe in more detail below, formularies are complete lists of covered drugs, partitioned into distinct sets of cost-sharing "tiers." We use these data to identify on which tier each drug was placed in each formulary. Because there is plan and formulary entry, exit, and re-design year to year, we treat each plan-year as a distinct plan and each formulary-year as a distinct formulary; for convenience we refer to each simply as a "plan" or a "formulary" rather than a plan-year or a formulary-year.

[5]Specifically, we use the "Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information" files.

3 Drug- and class-specific elasticities

3.1 Sample construction

Baseline sample

The 20 percent random sample of Medicare Part D beneficiaries from 2007-2011 consists of about 50 million beneficiary-years. We make a number of key sample restrictions to create our baseline analysis sample in this section. First, we limit to individuals who are enrolled in stand-alone Part D plans (whose design is the focus of the second half of the paper). Second, we exclude individuals who are younger than 65 and those older than 65 that were eligible for Medicare for reasons other than the old age (e.g. due to disability). Third, we exclude individuals who receive third-party assistance with their out-of-pocket spending, such as dual Medicare/Medicaid eligibles or individuals receiving low-income subsidies; such individuals do not face the sharp change in cost-sharing at the donut hole that is key to our empirical strategy. Finally, and more trivially quantitatively, we exclude beneficiary-years who switch plans or die within the year. The final sample covers 6.5 million beneficiary-years, which are based on just over 2 million unique beneficiaries

Table 1 shows some descriptive statistics for our resulting, baseline sample. The unit of observation is a beneficiary-year. The average age is around 76, about two-thirds of the sample are females, and the vast majority (95%) are white.

Beneficiaries in our baseline sample buy on average $1,910 worth of prescription drugs per year. About 5% do not fill any prescription drug claim during the year. The spending level at which beneficiaries enter the donut hole – $2,250 to $2,840 of total annual drug spending (depending on the year) – is around the 75th percentile of the expenditure distribution. The average annual out-of-pocket spending in our sample is $757. Beneficiaries fill, on average, around 31 claims a year, almost evenly split between branded and generic drugs. Our empirical strategy described below is focused on claiming propensity late in the calendar year, and about 75% of individuals fill at least one claim in December. Conditional on having at least one December claim, individuals have approximately 4 claims in December.

"Common" drugs and "common" therapeutic classes

In order to have sufficient power to estimate class-specific and drug-specific elasticities, we limit our analysis to frequently-claimed therapeutic classes and frequently-claimed drugs; we refer to these throughout as "common" therapeutic classes and "common" drugs, respec-

tively.

We define therapeutic classes using the American Hospital Formulary Service® (AHFS) 8-level classification of 256 therapeutic classes. This classification groups drugs that have similar chemical structures or mechanism of action and are frequently used to treat the same or related diseases. We define "common" classes as ones that have at least 100,000 claims in the 2007-2011 data. This results in 108 therapeutic classes, constituting 86% of claims and 85% of expenditures. The first column of Appendix Table A4 provides a complete list.

The most frequently-claimed therapeutic class, representing 8% of total claims and 10% of total expenditures (around $1.2 billion in total) in our baseline sample, is MGH-CoA Reducase Inhibitors; this class includes anti-cholesterol drugs (e.g. Lipitor). The next most common therapeutic class is beta-Adrenergic Blocking agents, which represents 7% of claims and 3% of expenditures; this class includes Beta-blockers, which are used to treat heart attacks, arrhythmias, and high blood pressure.

We define a "drug" by its chemical compound (what the FDA refers to as "non-proprietary names") and whether it is branded or generic. We define a drug as "common" if the sum of its branded and generic versions have at least 100,000 claims in the 2007-2011 data. Specifically, to identify "common drugs," we begin with CMS' 2011 list of the most frequently claimed drugs in stand-alone Prescription Drug Plans.[6] CMS reports the most frequently claimed drugs at a chemical compound level, treating branded drugs and their generic equivalent as separate products; we amend their list to include both the generic and the branded version of each chemical if a generic is available. We apply the 100,000 claims frequency threshold to the number of claims at the chemical level, thus retaining, for example, small branded drugs that would not otherwise meet the frequency threshold.[7]

The result is 160 "common drugs," where a "drug" is a chemical compound sold either as a brand or a generic. For example, "Atorvastatin Calcium" and its branded version (Lipitor) are counted as two different drugs. However, different packaging, dosages and strengths are not counted as separate drugs. There are 85 branded drugs and 75 generic drugs. The first column of Appendix Table A5 provides a complete list.

The 160 common drugs in our analysis account for around 65 percent of total claims and 54 percent of total expenditures in our baseline sample. The top 10 drugs in our sample of common drugs constitute 20 percent of all claims. A generic statin Simvastatin (generic

[6]Centers for Medicare and Medicaid 2011 Medicare Part D Utilization Trends (December 2013), Table "2011 Part D Top 100 Drugs By Total Fills for PDPs."

[7]It is useful to keep track of both brand and generic version of each drug, as we will later distinguish between elasticities for branded and generic drugs.

version of Zocor) has the highest market share, accounting for 3% of total claims (6.9 million claims) and 1% of expenditures. The drug with the highest spending share in our sample is Lipitor, with almost 5.5% expenditure share. The least-frequently-claimed of our "common" drugs represents less than a 0.001% of claims (around 500 claims in total) in our baseline sample; in our empirical analysis in Section 4.2, we explore the sensitivity of our results to the exclusion of infrequently-claimed "common" drugs.

3.2 Empirical strategy

Our goal is to measure the elasticity of demand for the product (a specific drug or therapeutic class) with respect to its out-of-pocket price. Our empirical strategy takes advantage of the sharp increase in the out-of-pocket price individuals face when they hit the "donut hole" associated with essentially every Part D insurance contract. All the plans are based around a government-defined standard benefit design, which includes four separate coverage arms for the calendar year.

Figure 1 illustrates this standard design in 2008; the kink points for the coverage arms change year-to-year but the basic structure has remained constant. In the initial deductible arm, the individual pays for all expenses out of pocket. Once she has spent $275, she enters a cost-sharing arm in which she pays only 25% of subsequent drug expenditures until her total drug spending reaches the kink in the budget set at $2,510. At this point the individual enters the famed "donut hole" (or "gap"), within which she must once again pay for all expenses out of pocket until total drug expenditures reach $5,726, the amount at which catastrophic coverage sets in and the marginal out-of-pocket price of additional spending drops substantially, to about 7%.

Insurers may offer plans that are actuarially equivalent to, or offer more coverage than the standard plan, so that the exact contract design varies across plans and hence across their enrollees. Nonetheless, a common feature of these plans is the existence of a sharp increase in the out-of-pocket price at the kink location. On average, in our baseline sample, out of pocket payments per drug more than triple when an individual enters the donut hole, from $17 in average out-of-pocket payments between the deductible and donut hole for a drug, to $58 in the donut hole. The co-insurance rate approximately doubles going from an average of 48% for pre-gap (but post-deductible) claims to 83% average co-insurance in the gap.

Our basic empirical strategy is to compare the propensity to purchase a specific drug (or therapeutic class) between individuals whose total annual spending is "just below" and

individuals whose total spending is "just above" the kink location. Standard price theory suggests that individuals' annual spending will "bunch" around the convex kink in the budget set at the donut hole. In previous work we documented a behavioral response to the price at the kink. For example, we showed an "excess mass" of individuals with annual drug spending right around the kink (Einav et al. 2015, 2016a). Here, we use the same basic empirical design – with several additional years of data – to examine the behavioral response separately for different drugs and therapeutic classes and to translate this behavioral response into product-specific elasticities.

Our measure of demand is the probability of purchasing that product in the last month of the year (December). We focus on December because at that point forward looking behavior is less important, individuals have less uncertainty about their end-of-year price, and the relevant price associated with purchasing the drug is straightforward to measure (Einav et al., 2015). The strategy would be even cleaner if we focused on purchasing decisions on December 31 of each year, but in order to gain statistical power a month seems a natural unit of time.

Empirical elasticities For each drug (or therapeutic class) d, we define its drug-specific (or class-specific) elasticity of demand by:

$$\sigma_d = \frac{\%\triangle Pr_d(Dec)}{\%\triangle OOP_d} = \frac{(Pr_d^{obs}(Dec) - Pr_d^{pred}(Dec))/Pr_d^{pred}(Dec)}{(OOP_d^{gap} - OOP_d^{pregap})/OOP_d^{pregap}}. \quad (1)$$

The changes are associated with the event of entering the donut hole. The denominator of the elasticity is the percentage change in the average (per claim) out-of-pocket cost of a given drug (or class) that occurs at the kink. OOP_d^{gap} measures the average out-of-pocket payment (in absolute \$) for a given drug (or class) in the donut hole (which comes quite close to the total cost of the drug in the vast majority of plans), and $OOP_d^{pregrap}$ measures the average out-of-pocket payment for that drug between the deductible and the kink.[8]

[8]For our drug-level measure of average out-of-pocket cost we simply average claim-level out of pocket payment across all claims observed for that drug in a given cost sharing arm (i.e. in the donut hole or between the deductible and the donut hole). For the therapeutic class level measure of average out-of-pocket cost, we take the same approach pre-gap, but post-gap we calculate average out-of-pocket cost separately for each drug (at the NDC11 level) in the therapeutic class and then weight each drug (again, at the NDC11 level) by its pre-gap share of claims, so that any substitution across drugs within a therapeutic class in response to the price change does not affect our measure of the price change. We have experimented with a variety of other ways of defining the average out-of-pocket cost, e.g. by averaging first within individuals or plans and then across individuals and plans. The estimates of the percentage change in the out-of-pocket cost turns out to not be particularly sensitive to these variants.

The numerator of the elasticity is the corresponding percentage change in the probability of a December purchase for a given drug (or class). We define this as the difference between the actual probability of a December purchase, $Pr_d^{obs}(Dec)$, and the predicted probability of a December purchase, $Pr_d^{pred}(Dec)$ in the (counterfactual) absence of the donut hole. Both actual and predicted probabilities are measured for individuals whose annual spending is just above the kink; specifically, we focus on individuals who entered the donut hole, but whose annual spending is no more than $400 higher than the kink location. We then define the actual probability of a December purchase as the share of these individuals who have a purchase of drug (or class) d in December.

Estimating the change in demand To construct the counterfactual (in the absence of the kink) December purchase probability for individuals whose annual spending is between $0 and $400 above the kink, we estimate the statistical relationship between claim propensity and annual spending for individuals whose annual spending is below the kink. Specifically, we fit the following statistical relationship, separately for each drug or therapeutic class:

$$log(s_{db}) = \alpha_d - \gamma_d e_b + \epsilon_{db}, \tag{2}$$

where the unit of observation is a total annual spending bin b, s_{db} is the share of individuals within the spending bin b *without* a claim for drug (or class) d in December, and e_b is the mid-point of the spending bin b (we use spending bins of $20 each). This specification is designed to make the probability of a December purchase monotone in the spending bin (as would be expected given that higher total spending is associated with sicker individuals and would mechanically correspond to greater claim propensities) and asymptote to one as the bin amount approaches infinity. Importantly, we fit this regression using only observations from individuals with total expenditures that are sufficiently below the kink location (we use all spending bins that are between $2,000 and $500 below the kink), assuming that late in the year individuals who are $500 or more below the kink are sufficiently certain to not hit the kink by the end of the year. We use the estimates from equation (2) to project it (out of sample) for spending bins that are above the kink, thus constructing the predicted December claim propensity $Pr_d^{pred}(Dec)$ for individuals with total spending of zero to $400 above the kink.

Figures 2 and 3 present our core approach to estimating the change in demand at the kink graphically. For illustrative purposes, Figure 2 shows results for any drug, any common drug, and any common therapeutic class. Since our core estimates are product specific,

Figure 3 shows results for the top three common drugs and the top three therapeutic classes. In all figures, the horizontal axis reflects the annual total drug spending (across all drugs) of each individual, relative to the year-specific kink location. The vertical axis shows the share of beneficiaries in each $20-bin of annual spending who purchased that drug or therapeutic class in December. As would be expected, this purchase probability is increasing in total annual expenditures, reflecting the fact that individuals who spend more on drugs annually are more likely to purchase any given drug. However, for some of the products we see a sharp slowdown in the probability of a December purchase as individuals get close to the donut hole. Once they enter the coverage gap, the pattern reverts to the original monotone pattern (in which the probability of purchasing is rising with total annual spending), albeit at a lower probability of December purchases, presumably reflecting the higher cost-sharing in the gap.

The dotted lines in Figures 2 and 3 record our in- and out-of sample predictions of the probability of filling at least one claim in December for each product. These predictions are based on the predicted values from the estimation of equation (2). The fit appears quite good in sample (i.e. below -$500).

The comparison of predicted and observed probabilities of purchase right around the donut hole allows us to quantify the demand response for each drug (or class) on our list. For example, for those products presented in Figure 3, we see a fairly large demand response for two products (top left and bottom right) and a much smaller one for the rest. To assess the statistical precision of our elasticity estimates, we use 100 bootstrap samples to repeat the same procedure and generate confidence intervals for quantity response. We then combine these estimates of the quantity response with the empirically observed change in out-of-pocket price at the donut hole to obtain elasticity estimates in each case.

3.3 Results

Elasticity estimates

Pooled estimates We start by estimating an elasticity of purchasing any drug (common or not) in December to the change in out-of-pocket cost at the kink. Figure 2 showed the change in the probability of December purchases overall at the kink, relative to the predicted probability; we estimate a 9% decrease in the probability of claiming any drug in December once individuals enter the gap. As described earlier, we separately calculate that the average out-of-pocket price increases by 241 percent (from $17 to $58). These two estimates together

imply that drugs are in general quite inelastic, with an elasticity of -0.037 (s.e. 0.0003); a one percent increase in out-of-pocket cost leads to a 0.037 percent decrease in the probability of filling a claim.

To see how representative our common drugs and common therapeutic classes are to the overall universe of drugs claimed within the Part D program, we calculated a pooled elasticity measures for all 160 common drugs and for all 108 therapeutic classes. The pooled elasticity measures the response of the probability of purchasing *any* common drug (or, respectively therapeutic class) to a one percent increase in the average out-of-pocket cost of all common drugs (or therapeutic classes). We found the pooled elasticity estimates to be very similar for our common drugs, common therapeutic classes, and all drugs samples; the percentage changes in the probability of purchase and in the average out-of-pocket price were also quite similar across these three groups. Specifically, we estimate an elasticity of -0.047 (s.e. 0.0003) for common drugs, and of -0.044 (s.e. 0.0003) for common therapeutic classes.[9]

The price elasticities of demand that we estimate should be interpreted in their specific context. As emphasized by Aron-Dine et al. (2013, 2015), "the" price elasticity of demand is not a clearly defined object when individuals face a non-linear price schedule. Here, the elasticity we measure is the "short-run" elasticity of demand with respect to an end-of-year increase in the spot price of a drug. It does not measure the entire response to the non-linear budget set the individual faces, which may include "anticipatory" behavioral changes in advance of reaching the donut hole, as well as inter-temporal substitution of purchases to the following year once in the donut hole. We explored such dynamic considerations and cross-year substitution in previous work (Einav et al., 2015). Our results there suggest that our focus here on December claim propensities make dynamic considerations relatively unimportant. They also showed that products with a greater behavioral response at the kink also tend to exhibit greater inter-temporal substitution to the following year; this suggests that the ranking of our spot elasticities across drugs or across therapeutic classes, which we now turn to examining, would likely remain similar if estimated net of cross-year substitution.

[9]For common drugs, we estimate that the probability of claiming any common drug at the kink decreases by 11.7 percent, while the average out-of-pocket price increases by 247 percent. For the common therapeutic classes, we estimate that the probability of purchase drops by 10.2 percent at the kink in response to a 233 percent increase in the average out-of-pocket cost. Note that the estimates of the pooled elasticities for common drugs and therapeutic classes are not comparable to the average elasticities we report next, as the pooled measures only reflect the "extensive" margin of whether *any* of the common drugs or classes are claimed.

Drug (or class) specific estimates Figure 4 documents the distribution of the estimated elasticities across the common drugs and common therapeutic classes. The top panel reports the estimated distribution of elasticities across the 108 common therapeutic classes. The average (unweighted) elasticity across therapeutic classes is -0.14. They are all less than 1 in absolute value; we estimate 11 elasticities that are slightly greater than 0, which presumably reflects sampling error. There is substantial heterogeneity in the elasticities, with a standard deviation across therapeutic classes of 0.15. Panel A of Table 2 lists the elasticity estimates – as well as the denominator and numerator separately – for the top 10 most frequently claimed therapeutic classes. The elasticities are estimated quite precisely: Panel A in Appendix Figure A1 plots bootstrapped confidence intervals for the elasticity estimates for the top 10 common therapeutic classes, suggesting that the heterogeneity in the sensitivity of demand to changes in out-of-pocket is not driven by sampling variation. Appendix Table A4 provides a complete list of elasticity estimates for all common therapeutic classes. This "look-up" table also documents that the variation in elasticity estimates comes both from variation in the numerator and the denominator. The average change in the probability of purchase at the kink is -15%, with a standard deviation of 13%. The average increase in out-of-pocket cost is 155%, with a standard deviation of 81%.

It is important to bear in mind that the price of all drugs increase at the donut hole, so that the demand response reflects any impact of own price changes and cross price changes. An attraction of estimating the elasticity of demand for therapeutic classes is that cross-price elasticities are likely close to zero across therapeutic classes; any substitution across drugs should happen within a therapeutic class, either between branded and generic versions of the same chemical compound or between chemical compounds that have a similar therapeutic action. Thus, even though the price of all drugs increases at the donut hole, we are reasonably comfortable interpreting our estimated elasticities of demand for different therapeutic classes as own-price elasticities of demand for drugs in that class.

The interpretation of drug-specific elasticities is less clean, since an overall price increase in all drugs at the donut hole may induce substitution across drugs within a therapeutic class. Thus, the drug-specific elasticity that we estimate likely reflects both own-price and cross-price effects. This is common issue in the existing literature estimating drug-specific elasticities, since pricing variation is usually not drug-specific (see e.g. Goldman et al. 2004; Chandra et al. 2010). Still, pricing decisions are set at the drug level – different drugs within a therapeutic class may well face different consumer cost-sharing in a given insurance plan – making the drug a more natural unit of analysis for the relationship between elasticity and

consumer cost-sharing in the next section.[10]

The bottom panel of Figure 4 reports the drug-specific estimates across our 160 "common" drugs. The bottom panel of Table 2 lists the elasticity estimates for the top 10 most frequently claimed drugs; Appendix Table A5 provides a complete list. Panel B of Appendix Figure A1 plots the confidence intervals for the 10 largest common drugs, again suggesting that the variation in elasticities does not simply reflecting sampling variation.

The average (unweighted) price elasticity of demand for a given drug is about -0.24; the standard deviation of estimated elasticities across drugs is 0.59. The higher (in absolute value) average elasticity for drugs than for therapeutic classes is consistent with the idea that some of the drug-level elasticity estimates may be capturing substitution, while therapeutic class-level elasticities are more likely to only reflect the own-price response. Once again we estimate heterogeneity in elasticities, stemming both from variation in the probability of purchase response as well as variation in the change in out-of-pocket price. For the full set of common drugs the average change in the probability of purchase around the kink is -14% with a standard deviation of 18%. The average increase in out-of-pocket price is 150%, with a standard deviation of 115%.

Elasticity patterns across drug and class types

The above results documented that there is considerable heterogeneity in the price elasticity of demand across drugs and therapeutic classes. We examined some potential systematic sources of this heterogeneity. Table 3 reveals intuitive patterns. Drugs that treat chronic conditions are associated with elasticities that are 0.33 greater (in absolute value) on average relative to drugs that treat acute conditions; the latter presumably treat more symptomatic conditions for which the impact of interrupting treatment is likely more immediate and salient. Maintenance drugs – another way to define drugs associated with ongoing, chronic conditions (see the online appendix for details) – are likewise associated with greater elasticity than non-maintenance drugs, as are therapeutic classes which are predominantly composed of maintenance drugs.

We also find that generic drugs are associated with elasticities that are about 0.2 lower (in absolute value) than branded drugs. This might reflect lower own-price elasticities for generic than branded drugs, but it might also be driven by the substitution effect described

[10]For both the drug- and therapeutic-class specific elasticities, there may of course be income effects from the aggregate price change for all drugs at the donut hole; however, given the relatively small out-of-pocket cost of most drugs, we are reasonably comfortable abstracting from such income effects (i.e., assuming quasi-linear demand for each product).

earlier; for generics, the change in the probability of purchase at the donut hole likely reflects both the (presumably negative) response to an increase in its own price and the (presumably positive) response to an increase in the (more expensive) branded price, which may cause substitution to the generic version. (In principle, there may also be substitution from one branded drug to another drug within a therapeutic class, but it is presumably less common). This highlights the need for caution in interpreting our estimated drug-specific elasticities; they are likely to be more biased downward (in absolute value) as measures of own-price elasticities for cheaper drugs that serve as substitutes for more expensive drugs within the therapeutic class.

As one way of addressing this issue empirically, we constructed a subset of our common drugs for which substitution is less likely, and for which therefore our drug-specific elasticity estimates may more closely approximate own-price elasticities. We refer to this subset of 38 of our 160 common drugs as "lower substitution" drugs. We identified this subset of common drugs using one of two criteria. First, we selected those common drugs that account for more than 90% of all claims in their therapeutic class; seven drugs met this criterion. Second, we selected those pairs of branded and generic drugs for which the differences in out-of-pocket cost between the brand and generic was less than $5 in absolute value both before and after the kink. In other words, in the latter restriction we selected brand-generic pairs that did not really differ in price for consumers before or after the kink, and hence the substitution effect after the kink should be limited. 31 drugs satisfied this criterion.

Appendix Table A5 provides descriptive statistics for the drugs in the "lower substitution" sub-sample. They account for 33 percent of all claims and 35 percent of spending in our common drugs sample. They display a similar skewness to our full sample of "common drugs" in the distribution of claim and spending shares across drugs. The distribution of elasticities for the lower substitution sub-sample of common drugs is similar to the full sample of common drugs. The unweighted average elasticity is -0.28, with a standard deviation of 0.63. This makes the set of lower substitution drugs only slightly more elastic on average than the entire set of common drugs. Overall, this is reassuring that our full set of common drug-specific elasticities may not be greatly affected by substitution.

4 Private plan design: drug-specific cost-sharing

In Section 3 we estimated product-specific elasticities, and provided evidence of substantial heterogeneity in the price elasticity of demand across therapeutic classes and across drugs.

We now use this as an input for examining how private plans set cost-sharing across drugs with different elasticities. We begin by documenting the heterogeneity in cost-sharing across drugs within private part D plans, and then examine the empirical correlation between a product's cost-sharing and its price elasticity of demand.

4.1 Heterogeneity in cost-sharing across drugs

The private insurer makes two distinct decisions in setting coverage rules in a specific plan. First, it creates a formulary.[11] This is a list of covered drugs, partitioned into a distinct set of cost-sharing "tiers." In any plan, all drugs in a given tier within a formulary are assigned the same co-pay or co-insurance rate.[12] While there are no explicit regulatory requirements of cost-sharing levels across tiers (as long as plans satisfy the minimum actuarial requirement described earlier), CMS emphasizes that tier numbers should reflect an increasing level of cost-sharing, with the drugs in Tier 1 having the lowest cost-sharing (CMS, 2011). CMS also requires that private Part D plans include a sufficient number of drugs on their formularies to cover all disease states; moreover, for all therapeutic classes, at least two chemically distinct drugs per class should be included on the formulary, while for six "protected" therapeutic classes all drugs have to be included (CMS, 2011). It is common for a given formulary to be used in multiple plans by the same insurer; overall, we observe 7,996 plans and 429 distinct formularies.

When plans use the same formulary, they have the same set of drugs in each tier but the mapping between tiers and the level of cost-sharing may vary across plans. This creates the second decision the insurer must make: the level of consumer cost-sharing rates associated with the tiers of a plan's chosen formulary. As noted, insurers face little regulatory constraints on how to vary cost-sharing across tiers, provided that their plan meets the minimum actuarial coverage required by the standard benefit design described in Figure 1. Consumer cost-sharing can be either in the form of co-pay (a fixed out-of-pocket dollar amount per prescription) or a co-insurance rate (a fixed percentage of the drug-specific pharmacy price that is paid out of pocket). For example, in 4-tier plans (which enrolled over 80% of beneficiary-years in our sample), tiers 1 through 3 are often associated with co-pays,

[11] In practice, according to CMS requirements, the insurer contracts with an independent scientific committee that makes formulary recommendations (CMS, 2011). Moreover, an insurer may use and alter if necessary a standard formulary from independent organizations, such as US Pharmacopedia.

[12] In practice, there may be additional variation in out-of-pocket prices that stems from the quantity of the drug purchased, and the type of pharmacy it is purchased from. For example, a 30-day supply of Lipitor bought at a "preferred" pharmacy may have a different out-of-pocket price than the same 30-day supply of Lipitor filled through a mail-order, or at a non-preferred pharmacy.

while drugs in tier 4 often have co-insurance.

To operationalize the comparison across plans, drugs, and tiers, we convert all pricing decisions to co-insurance rates at the drug-plan level. Specifically, we calculate claim-level co-insurance as the ratio of out-of-pocket spending to total spending on that claim, using only claims between the deductible and the donut hole. We then average across claims to produce co-insurance estimates for each drug-plan pair.

In contrast to publicly provided drug insurance, we find a high degree of variation in consumer cost sharing across drugs within private plans. The average (pre-gap) co-insurance for common drugs is about 40%, while the average standard deviation of (pre-gap) co-insurance within plans across common drugs is about 25%.

Table 4 provides some summary statistics on plan design and drug pricing. It shows results for 3-tier, 4-tier and 5-tier plans which enroll, respectively, 8%, 81%, and 9% of our baseline sample. A few other plans (not reported) have 1, 2, or 6 tiers. We focus our discussion on 4-tier plans, but the patterns are similar for other types of plans.

About half of drugs are placed in tier 1, with another 20% in tier 2, and another 20% in tier 3 (column 1). This distribution of drugs across tiers is roughly similar for our subsample of common drugs (column 2). Almost two thirds of drugs in tier 1 are generic; generics are fairly uncommon in higher tiers (column 3).

The insurer chooses the out-of-pocket prices associated with different tiers on the formulary for each plan. There is a clear pattern of increasing average out-of-pocket costs paid by consumers in higher tiers. This is shown in column 4, which reports the average out-of-pocket payments per claim in each tier for claims made between the deductible and the donut hole ("pre-gap" claims). The average out-of-pocket cost goes up from $6 per claim for tier 1 drugs to $41 per claim for tier 2 drugs, and $68 per claim for tier 3 drugs. Tier 4, which is sometimes designated as a "specialty" tier, has expensive, rarely claimed drugs for which consumers pay on average $200 per claim out of pocket (but it accounts for less than 1% of claims, so we focus our analysis on tiers 1 through 3).

Some other patterns across tiers are worth noting. Total drug costs per claim are much higher in tier 2 or tier 3 than in tier 1 (column 5); this presumably reflects the disproportionate positioning of the often cheaper generic drugs on tier 1. Not surprisingly, given the differences in out-of-pocket costs for drugs across tiers (column 4), utilization is even more concentrated in the lower tiers than drugs; over 70 percent of claims are for tier 1 drugs, and another quarter are for tier 2 drugs (see columns 7 and 8).

Our main object of interest is variation in consumer cost-sharing. As noted, consumer-

cost sharing can either be in the form of a fixed out-of-pocket dollar amount (co-pay) per claim or a co-insurance rate. Differences in out-of-pocket payments may therefore reflect both cost-sharing rules and (in the case of co-insurance) total drug costs. The theory regarding optimal consumer-cost sharing (i.e. Ramsey-style pricing) is based on co-insurance. In column 6, therefore, we report the average co-insurance for each tier (pre-gap) that we computed empirically from the observations of out-of-pocket payments and total cost of each claim. The result is a somewhat more nuanced pattern. Tiers 1 and 2 have quite similar co-insurance of about 30%, while tier 3 drugs have markedly higher consumer cost-sharing (of 50% percent).

The key empirical pattern in column 6 is that "higher cost-sharing" corresponds to tier 3 drug placement. We investigate this more systematically by analyzing cost-sharing by tier within plans. Table A2 in the Appendix shows that this pattern is even more pronounced when we include plan fixed effects. Co-insurance between tier 1 and tier 2 is substantively and statistically indistinguishable, but is 20 percentage points higher for tier 3 drugs. As a result, in our empirical analysis of the correlation of tier-placement and drug elasticity below, we will focus on the distinction between drugs in tier 3 relative to tier 1 and tier 2.

4.2 Correlations between drug elasticities and cost sharing

Drug Elasticities and Tier Placement

We begin by analyzing the relationship between a drug's elasticity and whether it is placed on tier 3 (versus any other tier), which, as just shown, has systematically higher co-insurance than other tiers. Figure 5 shows an initial look at this pattern. Specifically, for our common drugs, it reports the frequency of tier-3 placement as a function of the elasticity for each drug (we bin drugs into 0.05 elasticity bins in the figure), which was estimated in Section 3. The figure shows a clear pattern: drugs with more elastic demand are more likely to be placed in tier 3, where consumer cost-sharing is the higher.

To analyze more systematically the relationship between a drug's elasticity and its tier in a formulary, we run the following linear regression at the drug-by-formulary-by-tier level:

$$\sigma_d = \alpha_f + \sum_{k=1}^{K} \beta_k \mathbf{1}\{Tier_{df} = k\} + \epsilon_{df}, \tag{3}$$

where σ_d is the estimated elasticity of demand for drug d from equation (1), and α_f denotes fixed effects for each of the 429 formularies. We include a series of indicator variables

$\mathbf{1}\{Tier_{df} = k\}$ for whether drug d is located on tier k in formulary f. We include separate indicators for tiers 3, 4, 5, and 6. The omitted tier category is tiers 1 and 2. The key coefficient of interest is β_3, which measure the within-formulary difference in average elasticity of drugs in tier 3 relative to the reference tiers 1 and 2. By including formulary fixed effects, we are examining the relationship between drug elasticity and (ordinal) tier placement within a formulary.

Table 5 reports the results. Column (1) reports results without formulary fixed effects; it is therefore similar in spirit to the variation presented in Figure 5 although the exact estimates will differ because of differences in the implicit weighting and functional form. Column (2) shows the results with formulary fixed effects, which are quite similar. We estimate that, on average, drugs on tier 3 have 0.12 higher elasticity (in absolute value) relative to drugs on lower tiers.

The remainder of the columns investigate the sensitivity of this main result. As we saw in Table 4, the vast majority of enrollees and claims are in plans that use 4-tier formularies. Therefore, in column 3 we repeat the regression analysis separately for 4-tier formularies only. The results are quite similar. In column 4 we re-estimate the baseline specification from column 2, restricting to a higher frequency sub-sample of our common drugs. Specifically, we limited the sample to the 96 (out of 160) common drugs that have more than 300,000 claims, and hence presumably more precisely estimated elasticities. The magnitude of the estimated β_3 is lower but remains statistically significant.

In column 5, we address a potential confounding variable by repeating the analysis in column 2 with the addition of a control for the average (total) price of the drug.[13] There are two reasons to control for price levels. First, it makes the estimates between drugs with co-pay and co-insurance more compatible, as controlling for price in principle translates co-pays to co-insurance. Second, if price itself is a strong predictor of where insurers place their drugs, then controlling for prices allows us to explore whether conditional on the price of a drug, the insurer is more likely to place higher elasticity drugs on higher tiers. We find that controlling for price levels makes the relationship between drug elasticity and tier placement more pronounced.

Finally, as discussed, a limitation to our drug-specific elasticities is that they reflect a combination of own- and cross-price elasticities. Therefore, in column 6, we repeat the analysis in column 2 limited to the sub-sample of 38 "lower substitution" drugs; as described

[13] We compute the average total price for each drug for each year to be consistent with our treatment of each formulary-year or plan-year as separate observations.

in Section 3, these are drugs for which substitution concerns are less likely, and therefore the estimated elasticities may more closely approximate own-price elasticities. Comparing columns 2 and 6, we find that the magnitude of the relationship between a drug's elasticity and placement on tier 3 is in fact somewhat larger for this sub-sample of drugs.

Drug elasticities and co-insurance

The preceding analysis allows for a relatively straightforward examination of the drug's elasticity and its tier placement. This has the attraction of corresponding closely to the decision the insurer makes (which tier to place a drug on). However, it stops short of the economic object of interest which is the relationship between a product's elasticity and its co-insurance rate; this co-insurance rate depends both on the formulary chosen (which determines the drug's tier) and the insurer's decision regarding the level of consumer cost sharing in each tier of the chosen formulary. Here, therefore, we analyze the relationship between a drug's average co-insurance rate and its elasticity.

One again, we begin with graphical evidence. Panel A in Figure 6 shows the correlation between the elasticity of a drug and the average co-insurance for that drug (for "pre-gap" claims, as described earlier).

The figure shows a clear negative relationship: drugs with higher (in absolute value) elasticities have higher average co-insurance rates.[14] One concern with this analysis is that we have already seen that generic drugs are disproportionately on tier 1 (i.e. lower consumer co-insurance) and, as discussed, our estimated elasticities are likely biased downward (in absolute value) for generic drugs relative to branded drugs due to likely substitution within a therapeutic class from branded to generic drugs at the donut hole. Therefore, in the second and third panel of Figure 6 we plot the same relationship separately for generic or branded drugs. As can be seen, the qualitative relationship remains stable in each case, although it is quantitatively stronger for generics. To more directly tackle this concern about substitution, the final panel of Figure 6 illustrates similar patterns for therapeutic classes which, as discussed, likely have little cross-class substitution. We observe that therapeutic classes for which we estimate higher elasticities (in absolute value) have higher co-insurance.

Since cost-sharing is set separately by plan, we also analyze the within-plan relationship between cost-sharing and drug elasticity. To do so, we run the following linear regression at

[14] Interestingly, while the slope is consistent with the theoretical optimum of higher cost-sharing for more elastic drugs, the intercept (average cost-sharing around 40 percent for drugs with zero elasticity of demand) suggests much lower average coverage than theory would suggest is optimal (full coverage for completely inelastic drugs).

the drug (d) by plan (j) level:

$$p_{dj}^{pregap} = \alpha_j + \beta\sigma_d + \epsilon_{dj}, \tag{4}$$

where p_{dj}^{pregap} denotes the pre-gap co-insurance rate for a drug (or class) in plan j, α_j denotes the plan fixed effects, and σ_d denotes the elasticity of product d estimated in Section 3. The coefficient of interest, β, measures the correlation between pre-gap co-insurance and elasticity.

Table 6 reports the estimates of β. Panel A reports drug-level analysis, and Panel B reports therapeutic-class level analysis. We start in column (1) with a specification that uses all common drugs or therapeutic classes, thus effectively reproducing Figure 6 panel A or D (albeit with differences in implicit weighting and functional form). Column (2) repeats this specification, adding plan fixed effects; the results are quite similar. We estimate that, on average, a drug with a 0.1 higher (in absolute value) elasticity has a 0.02 higher co-insurance rate, and a therapeutic class with a 0.1 higher (in absolute value) elasticity has a 0.03 higher co-insurance rate.

The remainder of the columns investigate the sensitivity of this main result. In column (3) we re-run the baseline specification on the sub-sample of 96 out of 160 "common" drugs with high frequency of claims in our sample, which restricts the sample of common drugs or common therapeutic classes to the set with more than 300,000 claims in the sample that arguably have more precisely estimated elasticities. The coefficient of interest increases in magnitude with this restriction, both for the drugs and for the therapeutic classes, as would be expected with classical measurement error in our estimates of σ_d.

An important limitation to our result is that it is inherently cross-sectional. Therefore any omitted variable correlated with elasticity and co-insurance may be driving the estimated relationship. One natural possibility is the total price of the drug – perhaps lower priced drugs both have lower consumer cost-sharing (to encourage their use) and are less elastic. This is particularly a concern at the drug level where we are concerned that our elasticity estimates are biased toward zero for cheaper drugs that are substitutes for more expensive drugs; it is arguably less of a concern at the therapeutic class level since substitution should primarily occur within, not across classes. In either case, controlling for the total drug price in column (4) slightly attenuates the magnitude of the relationship between elasticity and cost sharing but does not change the sign.

Finally, the last three columns investigate an issue specific to the analysis at the drug level in Panel A, and discussed in the context of the previous analysis as well: the drug-

specific elasticity estimates may reflect cross-drug substitution in response to the overall price increase, as well as the own-price effect. As noted, this issue is less likely to arise at the therapeutic class level in Panel B. As one way of addressing this issue for the drug-level analysis in Panel A, column (5) shows the results of limiting to the "lower substitution" subsample of drugs; the estimated relationship changes very little. A further way of addressing this concern is reported in columns (6) and (7). Here, we separate the results by branded and generic drugs, so that we can test our theoretical prediction on branded drugs only, which we believe are less likely to include a significant degree of cross-price elasticities in their elasticity estimates. The estimated coefficient is much lower for branded relative to generic drugs, and in both cases the estimated magnitudes of the correlation are far from zero, statistically significant, and continue to show more elastic drugs facing higher consumer cost sharing. The results from these alternative drug-level specifications – as well as the results by therapeutic class – leave us relatively sanguine that substitution effects are not driving our primary findings.

5 Private provider incentives for drug-specific cost-sharing

Our findings suggest that, unlike public prescription drug plans, private plans vary cost sharing considerably across drugs, setting greater cost-sharing for more elastic drugs. This qualitative relationship appears robust to attempts to address a variety of potential contaminants in what is, in the end, a cross-sectional correlation. In this final section, we provide additional corroborative support for our analysis by showing that it is not merely an empirical regularity but also one that, at least within the context of the highly stylized theoretical model, is the socially optimal direction to set cost-sharing and is also the optimal strategy for a profit maximizing monopolist or duopolist.

The intuition for why a private firm's incentives are aligned with the social optimum is quite simple for the case of a monopoly provider. An insurance contract is essentially a two-part tariff in which the provider can charge both a fixed fee (premium) and a variable price per claim (co-insurance). The optimal strategy for this type of two-part tariff is well-known: a profit maximizing monopolist should set the variable price to maximize consumer surplus, and then extract as much of this surplus as possible via the premium. Thus, the co-insurance design should maximize consumer (and hence social) surplus. While the intuition for the duopoly case is more nuanced, the same forces are in play: the duopolists attempt to maximize consumer surplus through the co-insurance, and then compete with each other

for market share via premium setting. We formalize this intuition below.[15]

5.1 Setup

We consider an environment where there exists only one drug. The social marginal cost of producing the drug is w, which we normalize to be a unit cost $w = 1$. There exists a mass of individuals, who all have the same probability of a health shock λ. We assume that the health shock can be completely mitigated if the individual takes the drug. The monetized disutility from the health shock is x, which we assume to be homogeneous across individuals.

We assume that the disutility from the untreated health shock is unknown ex ante, and is drawn from a uniform distribution $x \sim U[0, K]$. $K > 1$ is the key parameter that guides the extent of moral hazard (i.e. the price elasticity of demand in our empirical results). If $x > 1$, the individual would purchase the drug even at full cost (of $w = 1$); in this case there is no moral hazard and full insurance is efficient. Once $x < 1$, however, individuals would respond to price, and only purchase the drug if the coverage is generous enough. Thus, the higher is K, the more likely it is that $x > 1$, and the less responsive individuals are to the price of the drug.

Individuals are risk averse and have a CARA utility over realized utility $u_i(z) = -exp(-\varphi_i z_i)$, where z_i is the individual's realized utility and φ_i is the coefficient of absolute risk aversion. The coefficient is individual-specific and guides the heterogeneity in insurance preferences across individuals. Each individual has the opportunity to purchase an insurance contract. The insurance contract is a pair of premium π and out-of-pocket price $p < 1$. The out-of-pocket price is the theoretical analog of the empirical co-insurance rate. The individual's certainty equivalent $V(p; \phi)$ for a contract (π, p) equates the utility from paying V with certainty to the expected utility from having coverage p. In other words, V implicitly solves

$$-exp(-\varphi_i(z_i - V)) = \tag{5}$$
$$-(1-\lambda)exp(-\varphi_i z_i) - \lambda Pr(x > p)exp(-\varphi(z-p)) - \lambda \int_0^p \frac{1}{K} exp(-\varphi_i(z_i - x))dx,$$

where with probability $(1-\lambda)$ individuals do not experience a health shock. With probability λ they experience a health shock x, and either pay p if the disutility from the health shock

[15] We have not worked out the case of perfect competition, but we think that the predictions for equilibrium cost-sharing across drugs of different elasticities are less obvious there, and would likely depend on a variety of modeling assumptions, such as the order of decisions, the rationing of consumers, etc.

is greater than p, or pay x if the disutility of the shock is less than p. Rearranging terms and simplifying, we obtain:

$$V(p;\varphi_i) = \frac{1}{\varphi_i} \ln \left[(1-\lambda) + \lambda \Pr(x > p) \exp(\varphi_i p) + \lambda \frac{1}{K} \frac{1}{\varphi_i} (\exp(\varphi_i p) - 1) \right]. \tag{6}$$

Using this framework, no insurance is equivalent to a contract of ($\pi = 0$, $p = 1$). Individual's willingness to pay for a contract that offers co-insurance p is given by the difference between her certainty equivalent for that co-insurance and her certainty equivalent from no insurance:

$$WTP_i(p) = V(1;\varphi_i) - V(p;\varphi_i). \tag{7}$$

Insurer's expected profits from a contract (π, p) that is sold to consumer i is:

$$\Pi_i = \pi - \lambda(1-p) \Pr(x > p). \tag{8}$$

That is, the insurer collects the premium π and with probability λ has to pay $(1-p)$ for the drug if the individual decides to purchase the drug. The latter happens if the realization of the monetized value of the health shock is greater than the out of pocket price p, i.e. if $x > p$. Insurer's total profits from selling a contract (π, p) is

$$\Pi = \int I(WTP_i(p) > \pi) \Pi_i di, \tag{9}$$

and total welfare from selling (π, p) is then:

$$TS = \int I(WTP_i(p) > \pi)(\Pi_i + WTP_i(p) - \pi) di. \tag{10}$$

We now consider several scenarios of market structure to highlight the equilibrium relationship between moral hazard – measured by K – and risk exposure in the contract, measured by the co-insurance rate p. A higher K implies lower moral hazard, since it implies a higher chance that the monetized value of the health shock x is greater than the social cost of the drug w, and hence the individual would want to purchase the drug regardless of the share of the cost p that she must pay out of pocket. The individual's exposure to risk is increasing in the out-of-pocket price p; with $p = 0$ the individual is fully insured against fluctuations in her realized utility resulting from health shocks.

5.2 Relationship between co-insurance and moral hazard

Social Optimum We start with a social optimum that demonstrates the classic trade-off between moral hazard and risk protection in an optimal insurance setting. The socially optimal price p maximizes total welfare (defined by equation 10); it is given by the p that solves $\lambda(1-p) = V(1;\varphi_i) - V(p;\varphi_i)$, i.e. that equates the expected cost of coverage with the willingness to pay for insurance. Appendix Figure A2 demonstrates the solution to this problem graphically for a selected set of parameter values. As expected , the social planner sets higher levels of risk protection (lower p) in cases where the extent of moral hazard is lower (K is higher).

This results is not specific to our highly stylized setting. As noted in the introduction, it is a classic theoretical result (Feldstein, 1973; Besley, 1988). It does, however, rely on a key assumption that absent insurance (i.e. with no consumer cost sharing) individuals would purchase the socially optimal amount of drugs. Recent papers have challenged this assumption, noting that the patent system marks up drug prices above social marginal costs and thus inefficiently reduces unsubsidized drug consumption (Lakdawalla and Sood, 2009). In addition, failures of rationality may produce sub-optimal drug purchase decisions (Baicker et al., 2015). Our analysis of the social optimum also abstracts from the possibility that individuals may have different social welfare weights. If, for example, drugs with higher elasticities of demand tend to be consumed by individuals who are sicker and thus perhaps assigned higher weights in the social planner's objective, this would affect the social optimum; it would not however affect the private firm's optimal cost sharing which depends only on the extent of moral hazard and not on the characteristics of the affected individuals.

Private monopoly Consider now the case of a monopolist insurer. In this case, the monopolist sets price p that maximizes profits, given by equation (9). We solve this problem numerically for a range of parameter values; Appendix Table A3 reports the results. Comparing the results across different values of K, we see that the optimal level of cost sharing p decreases with K. That is, the monopolist offers more risk protection in cases that have less moral hazard, which is qualitatively similar to the direction by which p would change with K in the social optimum. The intuition is simple and well understood. Demand is decreasing in both the price of insurance π and the cost sharing rate p. Comparing increases in π and in p that would result in the same increase of expected profits, the latter would raise risk exposure, and thus would lead to a greater demand response by risk averse individuals. This means that the monopolist would optimally set p at its socially efficient level, and then

set premium to maximize profits. While this sharp result is driven by our assumption that moral hazard is homogeneous and is not correlated with risk aversion, the overall qualitative intuition is more general.

Private duopoly In the duopoly problem, each insurer sets premiums and prices (π, p) in a Nash equilibrium. To avoid boundary cases, we assume that each insurer is a monopolist against a fraction $\kappa < 0.5$ of the people, and competes for the remaining $1 - 2\kappa$ share of the market. If the other firm sets (π_{-j}, p_{-j}), firm j solves:

$$\begin{aligned} \max_{\pi_j, p_j} \Pi &= \kappa \int I(WTP_i(p_j) > \pi_j)\Pi_i di + \\ +(1-2\kappa) \int I(WTP_i(p_j) &> \pi_j \ \& \ \ WTP_i(p_j) - WTP_i(p_{-j}) > \pi_j - \pi_{-j})\Pi_i di. \end{aligned} \tag{11}$$

To solve the duopoly problem, we need to find (π^*, p^*) for each (π_{-j}, p_{-j}); we then look for a symmetric Nash equilibrium in which $\pi^* = \pi_{-j}$ and $p^* = p_{-j}$.

In the duopoly case, we have the extra parameter κ that indexes the degree of competition between the two insurers. The monopoly case is a special case when $\kappa = 0.5$, while $\kappa = 0$ results in perfect competition with total surplus equal to the social planner's case. In all intermediate values of the competition parameter, we find a large multiplicity of equilibria; the monopoly solution is almost always an equilibrium, and therefore in Appendix Table A3 we report, in each case, the most competitive equilibrium, which generates the lowest profits. Consider an intermediate case with $\kappa = 0.4$; we get patterns that are very similar to the monopolist case. The insurers set lower cost-sharing and higher premiums for more risk averse consumers, and total surplus increases when individuals are more risk averse. Turning to our key comparison, the simulation of the model predicts that for all combinations of parameter values on consumer risk aversion and competition, increasing the moral hazard parameter K leads to lower cost-sharing for the drug. Hence, profit-maximizing incentives in this set-up of the model lead to an inverse gradient between moral hazard and risk protection that is also present in the social planner's solution.

6 Conclusion

In debates over whether to have private provision of public insurance, two arguments are often advanced in favor of private provision. First, private provisions may result in more and better choices for consumers. Second, competition among private insurers may lead to more

efficient provision of the goods or services in question. A substantial empirical literature has analyzed the first of these arguments, but there is relatively little work on the second.

In this paper we investigate a specific efficiency issue: the design of consumer cost-sharing, which trades off risk protection and moral hazard. The textbook public finance discussion assumes that while the public sector has a comparative advantage in combating adverse selection, it does not have a comparative advantage over the private market in ameliorating moral hazard. Our results here go further, to suggest that in fact, the *private sector* may have a comparative advantage in addressing moral hazard through efficient benefit design.

Our empirical setting is Medicare Part D. We have three main findings. First, we exploit the discrete change in price at the donut hole to estimate and document substantial variation in the price elasticity of demand across drugs. This heterogeneity exists within and across broad therapeutic classes and exhibits intuitive patterns.

It also suggests that optimal cost-sharing may differ across drugs and therapeutic classes. However, as with many other publicly provided prescription drug plans, the government-defined standard benefit plan for Part D features uniform consumer cost-sharing across drugs. By contrast, our second finding is that private insurers in Medicare Part D vary cost-sharing substantially across drugs within a plan.

Third, we find that private insurers in Medicare Part D vary cost-sharing in the socially optimal direction: they set higher consumer cost sharing (less risk protection) for drugs that exhibit a higher price elasticity of demand (i.e. greater degree of moral hazard). Consistent with this empirical finding, we provide a stylized conceptual framework which suggests that market forces may indeed lead to efficient benefit design: profit-maximization incentives lead to the same gradient in the trade-off between risk protection and moral hazard as in the optimal insurance contract. Our empirical and theoretical results thus suggest that the private sector may have a comparative advantage over the public sector in the "production" of insurance.

An interesting question that our analysis does not address is why public insurance plans do not also vary pricing of drugs in what the neo-classical theory would suggest is the socially optimal direction. One possible explanation is a basic "costs of complexity" story to determine drug-specific demand elasticities and set cost-sharing accordingly, interacted with the lack of profit-seeking incentives that might induce designers to incur those costs. Alternatively, there may be political economy concerns about who and how the pricing decisions would be made, thus pushing toward uniformity in cost sharing. Finally, there may be equity concerns across individuals; for example, if the social planner assigns different

social welfare weights to individuals with different diseases (treated by different drugs), that could affect the socially optimal cost-sharing across drugs relative to the benchmark model.

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Figure 1: Standard Defined Benefit (2008)

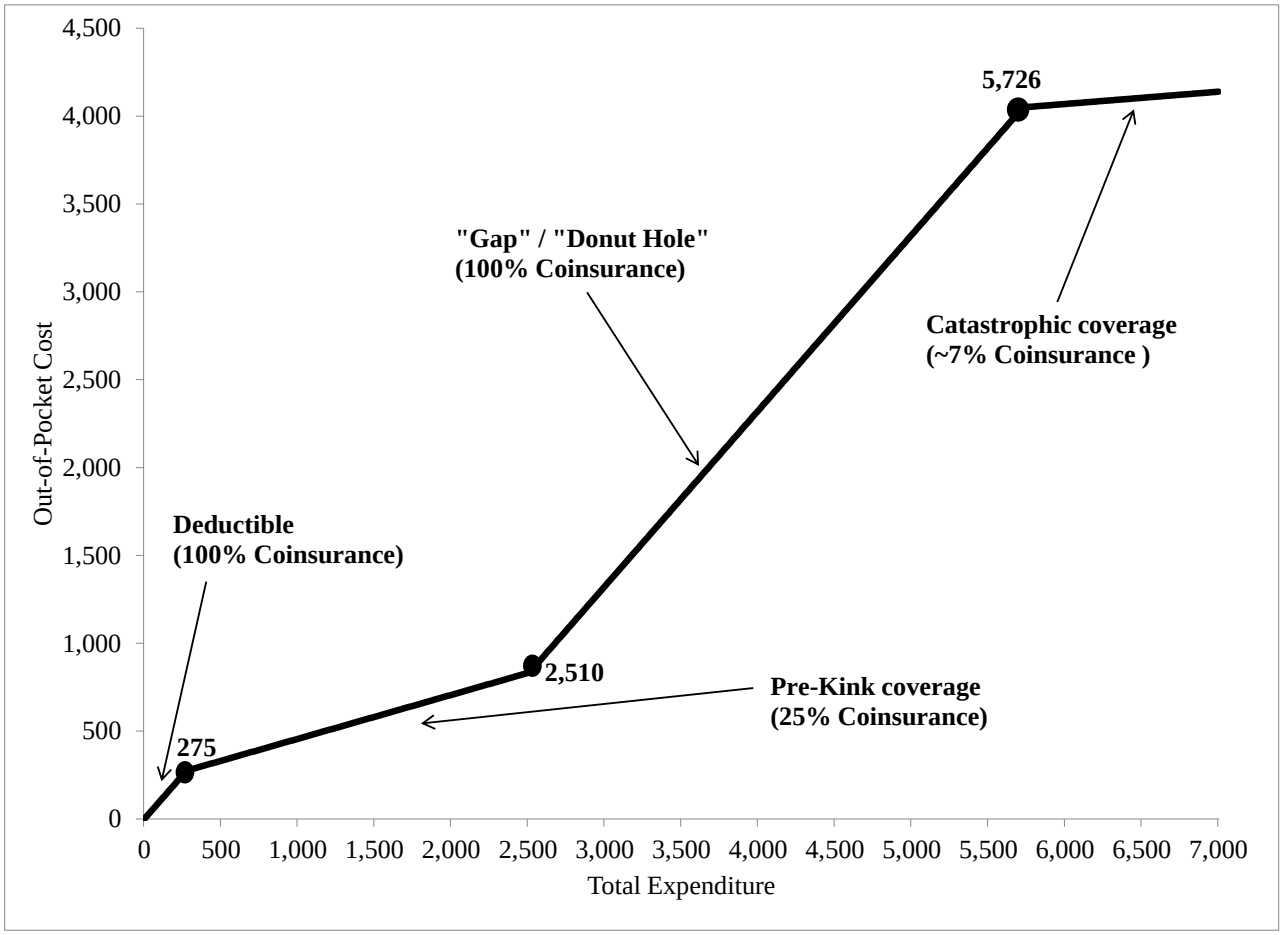
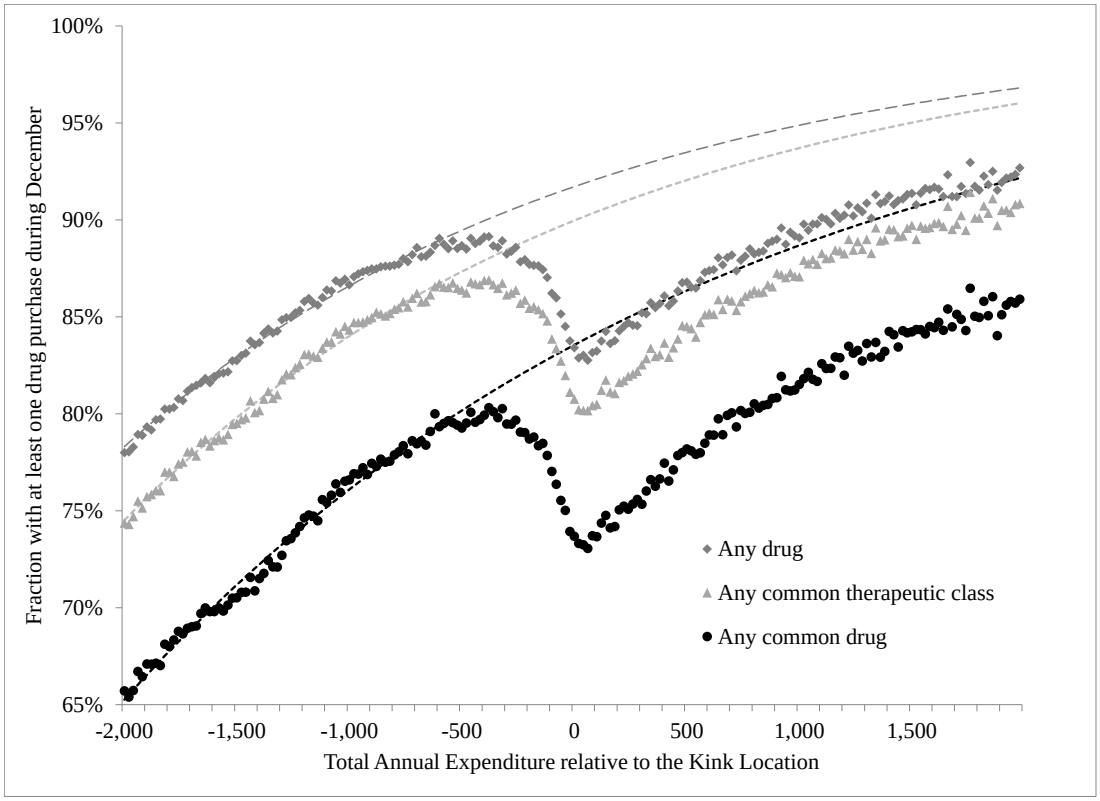


Figure shows the Part D Standard Defined Benefit (SDB) in 2008. The exact thresholds of the deductible, donut hole, and the catastrophic level increased over time. For example, the deductible increased from $250 in 2006 to $310 in 2011, and the donut hole level increased from $2,250 in 2006 to $2,840 in 2011.

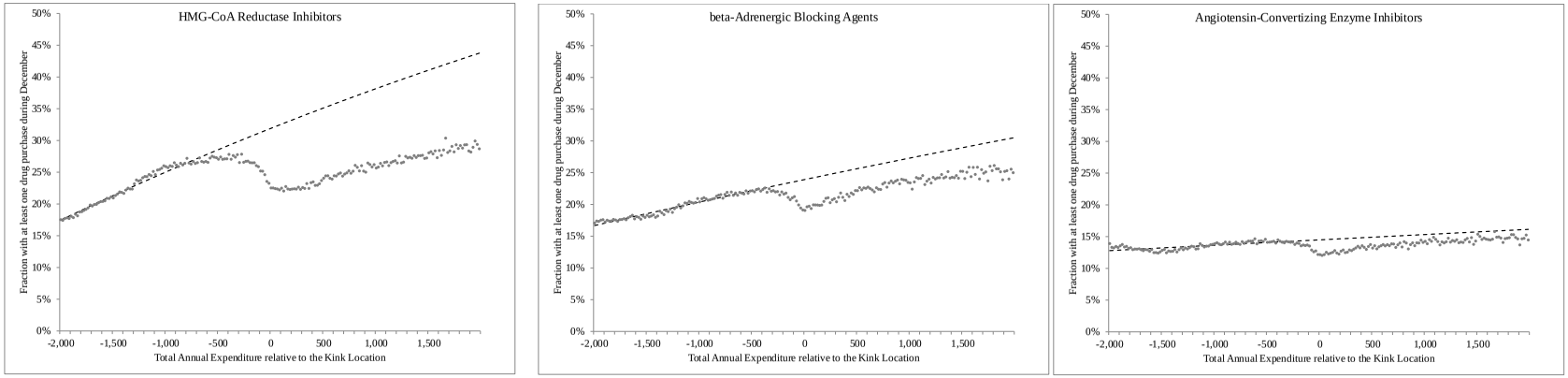
Figure 2: Claim propensity in December as a function of annual spending - pooled estimates



These three graphs plot the share of individuals within a $20 dollar spending bin that filled a claim in December for (i) any drug - marked with dark gray squares; (ii) any common therapeutic class - marked with light gray triangles; or (iii) any common drug - marked with black dots. The top scatterplot for "any drug" is an updated version (that is, additional years of data are included) of Figure IV in Einav et al. (2015). The spending bins are recorded on the x-axis; the spending is calculated as relative to the kink location in the corresponding year. Each of the three dotted lines plots predictions from a regression described in Section 3.2, which is fitted using observations that are to the left of -$500.

Figure 3: Claim propensity in December as a function of annual spending

(a) Top 3 Common Therapeutic Classes



(b) Top 3 Common Drugs

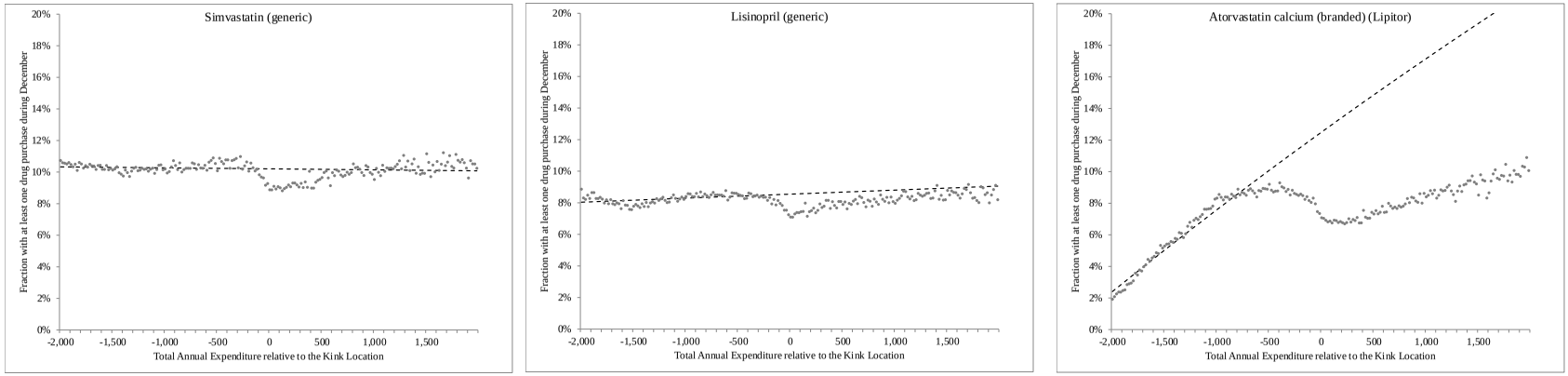
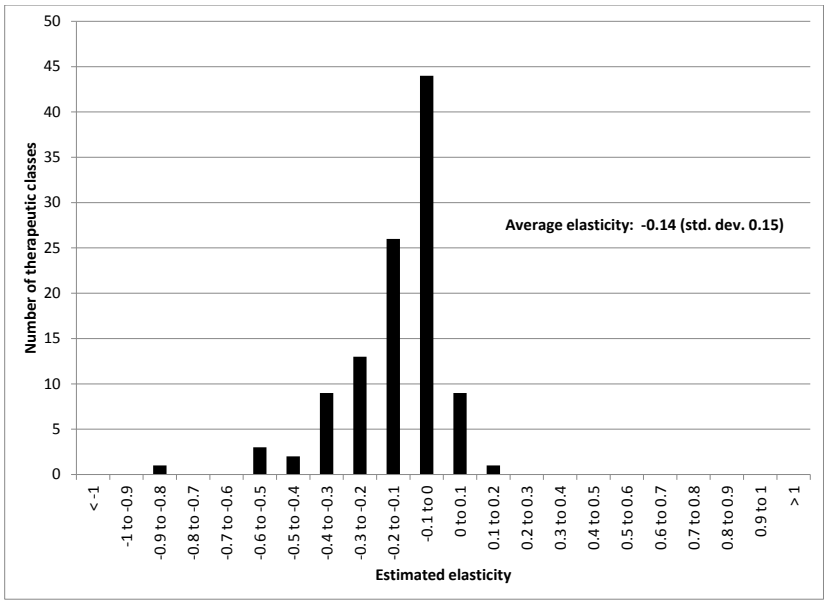


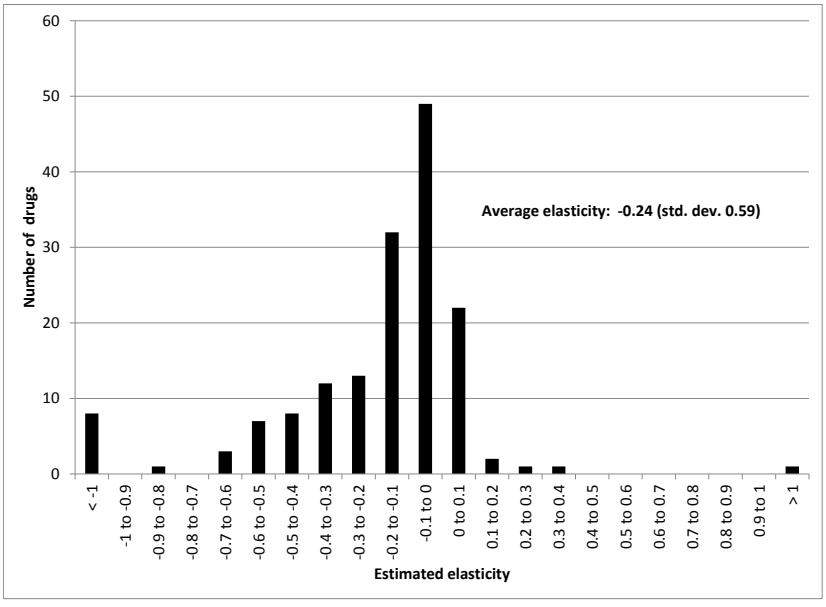
Figure shows the probability of filling a claim in December, for the top three "common" therapeutic classes (top panel) and the top three "common" drugs (bottom panel). The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location; we bin spending in $20 bins. The vertical axis is the fraction of individuals within each bin with at least one claim in December associated with the drug (or class). The dashed lines are generated from the estimates of equation (2), as described in Section 3, where we fit the line on all individuals whose spending is $500 below the kink location and lower.

Figure 4: Distribution of elasticity estimates

(a) Common Therapeutic Classes



(b) Common Drugs



Figures show the distribution of the estimated elasticities across the 108 "common" therapeutic classes (top panel) and 160 "common" drugs (bottom pane). Appendix Tables A4 and A5 report the complete list.

Figure 5: Correlation between Tier 3 placement and Drug Elasticity

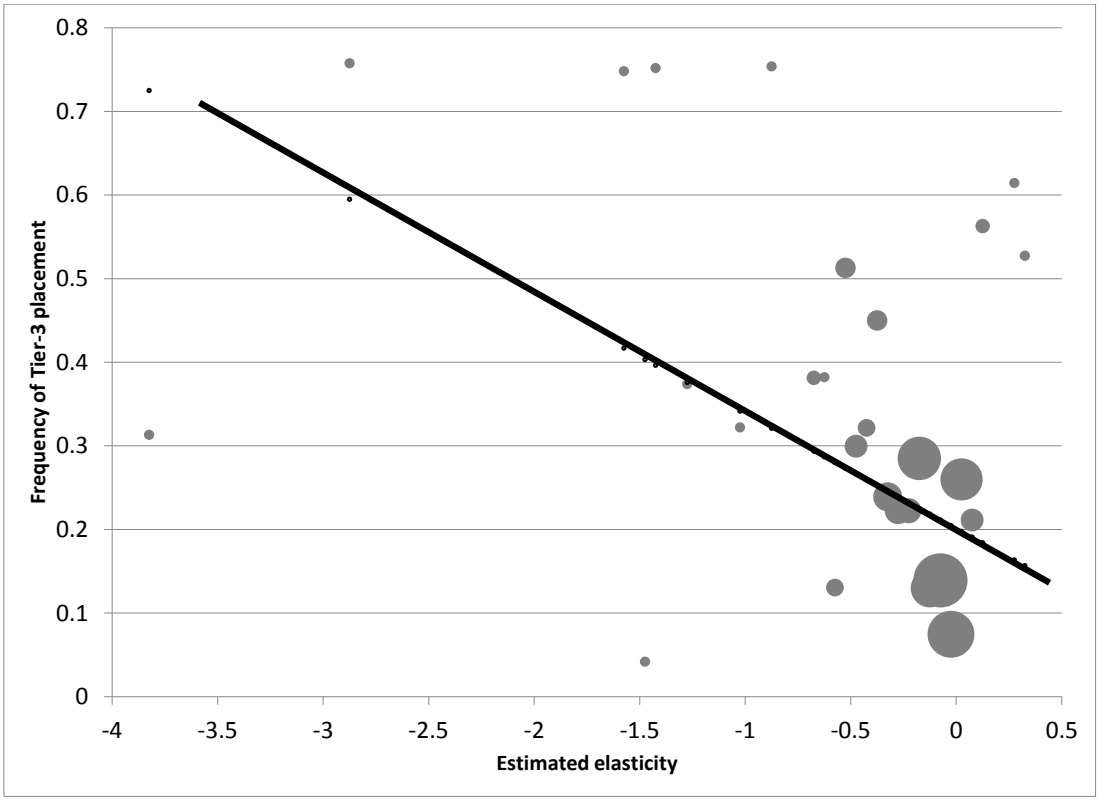
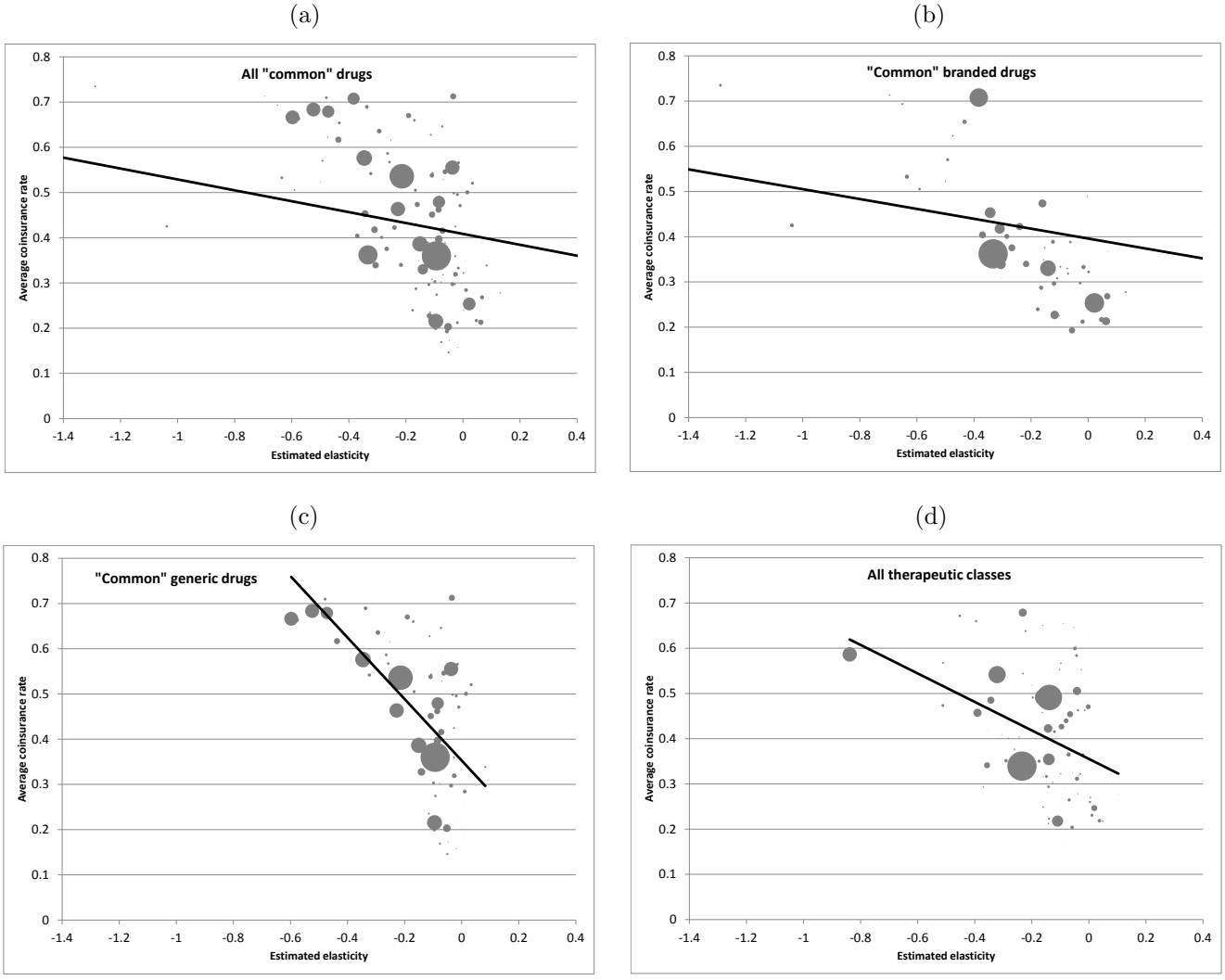


Figure shows the correlation between the probability of a drug being placed in Tier 3 (which corresponds to the highest consumer cost-sharing) on the vertical axis and the estimated drug elasticity (on the horizontal axis). Each circle represent a set of drugs whose estimated elasticity falls in the same elasticity bin of size 0.05. The size of the circle represents the number of drugs in each bin. The vertical axis is the frequency (across formularies) with which drugs in the set are placed in Tier 3. The regression line is the fitted line across all the circles, weighting each data point by the number of drugs in that bin.

Figure 6: Correlation between Co-insurance and Elasticity



Figures shows the correlation between the average co-insurance for a drug (or class) on the vertical axis and the estimated elasticity for the drug (or class) on the horizontal axis. Average co-insurance is defined as the pre-gap co-insurance rate. Each circle corresponds to a specific drug (or class); circle sizes are proportional to the number of claims for each drug (or class) in the data. For ease of graphical presentation, the figures are limited to estimated elasticities between 0 and -1. This omits 11% of claims from panel a (common drugs), 27% of claims from figure b (common branded drugs), 2% of claims from panel c (common generic drugs), and 6% of claims from panel d (common therapeutic classes). Fitted regression lines are in all panels; these are fitted using equal weights for all drugs, and include the data points that are outside of the elasticity range shown.

Table 1: Baseline Beneficiary Sample

	Mean	Std. Dev.	10th pctile	90th pctile
Age	75.6	7.7	67	87
Female indicator	0.65			
Whilte indicator	0.95			
Annual total spending ($US)	1,910	2,977	76	3,977
Annual out-of-pocket spending ($US)	757	937	27	1,872
Annual claim propensity				
Number of claims	31.2	26.6	3	67
Number of branded claims	13.7	14.9	0	33
Number of generic claims	17.5	17.2	1	40
Share with at least one claim	0.95			
Share with at least one branded claim	0.86			
Share with at least one generic claim	0.90			
December claim propensity				
Number of claims	2.71	2.80	0	6
Number of branded claims	1.10	1.51	0	3
Number of generic claims	1.61	1.93	0	4
Share with at least one claim	0.75			
Share with at least one branded claim	0.53			
Share with at least one generic claim	0.63			

Table based on our baseline sample described in Section 3. The unit of observation is a beneficiary-year. The sample covers 6,520,707 beneficiary-years that represent 2,022,527 unique beneficiaries.

Table 2: Elasticity estimates for ten largest common drugs and therapeutic classes

Therapeutic Class (1)	Drug example (2)	Claim share (3)	%ΔQ (4)	%ΔOOP (5)	Estimated elasticity (6)
HMG-CoA Reductase Inhibitors	Lipitor	0.077	-31.9	136.1	-0.23 (0.002)
beta-Adrenergic Blocking Agents	Propranolol	0.067	-17.4	125.5	-0.14 (0.003)
Angiotensin-Converting Enzyme Inhibitors	Lisinopril	0.047	-13.9	87.8	-0.16 (0.007)
Thiazide Diuretics	Diuril	0.045	-27.1	84.2	-0.32 (0.006)
Thyroid Agents	Levothyroxine	0.038	-17.9	21.4	-0.84 (0.031)
Dihydropyridines	Amlodipine	0.031	-19.4	138.1	-0.14 (0.004)
Proton-pump Inhibitors	Omeprazole	0.030	-26.7	243.0	-0.11 (0.002)
Selective Serotonin-reuptake Inhibitors	Prozac	0.023	-15.9	111.5	-0.14 (0.007)
Angiotensin II Receptor Antagonists	Losartan	0.022	-29.2	74.8	-0.39 (0.007)
Opiate Agonists	Morphine	0.022	-5.5	132.0	-0.04 (0.007)

Drug name (1)	Brand/Generic (2)	Claim share (3)	%ΔQ (4)	%ΔOOP (5)	Estimated elasticity (6)
Simvastatin	Generic	0.034	-10.8	116.4	-0.09 (0.006)
Lisinopril	Generic	0.028	-12.4	57.8	-0.21 (0.015)
Atorvastatincalcium	Brand	0.022	-48.3	145.1	-0.33 (0.002)
Levothyroxinesodium	Brand	0.021	-21.5	14.5	-1.48 (0.057)
Levothyroxinesodium	Generic	0.018	-13.6	39.4	-0.35 (0.025)
Amlodipinebesylate	Generic	0.018	-17.5	115.9	-0.15 (0.007)
Omeprazole	Generic	0.017	-24.2	254.3	-0.10 (0.003)
Warfarinsodium	Generic	0.017	-18.9	83.1	-0.23 (0.009)
Hydrocodonebitartrateandac	Generic	0.017	-3.8	102.2	-0.04 (0.010)
Hydrochlorothiazide	Generic	0.016	-20.4	38.9	-0.52 (0.023)

Table reports the estimated elasticities for the ten most frequently claimed therapeutic classes (top panel) and drugs (bottom panel). Column (3) reports the share of each class' claims in the baseline sample. Column (4) reports the estimated percentage change in the observed (relative to the predicted) claim propensity in December for individuals who enter the donut hole. Column (5) reports the associated percentage change in the out-of-pocket price. Elasticities -- reported in clumn (6) -- are then estimated based on equation (1), with standard errors in parenthesis (based on 100 bootstrap samples from which we estimate the change in claim propensity). See Section 3 for more details.

Table 3: Elasticity differences by drug categories

	Mean elasticity	Std. Dev.
Acute drugs	-0.12	0.34
Chronic drugs	-0.45	0.84
Non-maintenance drugs	0.01	0.49
Maintenance drugs	-0.30	0.60
Branded drugs	-0.34	0.79
Generic drugs	-0.13	0.15
Predominantly non-maintenance class[a]	-0.10	0.09
Predominantly maintenance class[a]	-0.17	0.17

Table reports (unweighted) average (and std. dev.) estimated elasticities for different subsets of drugs (and therapeutic classes). See on-line appendix for details of how these classifications are constructed.

[a] We consider a class as "predominantly maintenance" if the majorty of the associated drugs are classified as to maintenance drugs; in most therapeutic classes all drugs are either maintenance or not.

Table 4: Plan design and drug pricing

	No. of all drugs	No. of "Common" drugs	Share generics	OOP ($US)[a]	Total cost ($US)[a]	Co-insurance[a]	Claim share (all drugs)	Claim share ("common" drugs)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3-Tier plans (8% of enrollees; 12% of plans)								
Tier 1	1,732.5	72.7	0.652	4.1	21.9	0.18	0.060	0.062
Tier 2	857.0	39.4	0.119	36.4	130.5	0.28	0.019	0.018
Tier 3	485.6	12.0	0.046	77.6	218.3	0.44	0.003	0.002
4-Tier plans (81% of enrollees; 61% of plans)								
Tier 1	1,806.3	72.6	0.646	6.4	21.5	0.30	0.581	0.616
Tier 2	846.5	38.8	0.111	40.5	141.0	0.29	0.189	0.170
Tier 3	828.7	27.6	0.092	68.0	131.5	0.53	0.043	0.025
Tier 4	275.5	3.7	0.054	199.6	682.7	0.29	0.001	0.000
5-Tier plans (9% of enrollees; 21% of plans)								
Tier 1	1,506.0	62.1	0.630	6.7	20.3	0.34	0.059	0.064
Tier 2	882.1	40.6	0.391	34.2	114.0	0.31	0.022	0.021
Tier 3	784.0	30.0	0.076	62.8	133.3	0.50	0.009	0.007
Tier 4	658.4	22.0	0.168	66.3	193.8	0.37	0.001	0.001
Tier 5	276.4	4.2	0.106	199.4	651.3	0.31	0.000	0.000

Table uses our baseline sample described in Section 3. Each cell in the table reports average across plans that have the associated number of tiers. Column (1) reports the average number of drugs (defined here by the number of NDC11 codes on the formulary), column (2) reports the number of "common" drugs, and column (3) reports the share of all drugs that are generic. Columns (4) and (5) report, respectively, the average out-of-pocket and total cost per claim (for "pre-gap" claims) for all drugs. Column (6) converts the out-of-pocket costs to a co-insurance rates for all drugs. For each plan and tier we calculate the aggregate co-insurance as the ratio of OOP spending in that plan-tier to total spending on drugs in that plan-tier. We then average across plans. Columns (4), (5), and (6) reported weighted average (by plan enrollment), while the other columns are not weighted. Columns (7) and (8) record the share of each tier's claims out of, respectively, all claims and "common drugs" claims in the sample.

[a] OOP cost, total cost, and co-insurance rate are based only on claims that are above the deductible and under the donut hole.

Table 5: Relationship between elasticity of common drug and its tier-positioning

	Dependent Variable: Estimated demand elasticity					
Sample	All drugs & plans	All drugs & plans	4-tier plans	High frequency drugs	All drugs & plans	"Lower subst." drugs
	(1)	(2)	(3)	(4)	(5)	(6)
High co-insurance (Tier 3)	-0.122	-0.119	-0.120	-0.074	-0.210	-0.163
	(0.007)	(0.006)	(0.008)	(0.005)	(0.007)	(0.016)
Formulary Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Drug price included	No	No	No	No	Yes	No
R-squared	0.011	0.016	0.014	0.015	0.054	0.021
No. of Obs.	50,086	50,086	29,865	34,854	50,086	13,829
Mean of Dep. Var.	-0.211	-0.211	-0.213	-0.200	-0.211	-0.246
Std. Dev. Of Dep. Var.	0.477	0.477	0.483	0.260	0.477	0.591

Table shows the relationship between the estimated demand elasticity of each drug and its tier placement, as in equation (3). We report the coefficient on being in Tier 3, relative to tiers 1 or 2; indicator variables for higher tiers are included in the regression (but not reported). The unit of observation is a drug-by-formulary-by-tier. Standard errors in parentheses are clustered at the formulary-tier level. Column (4) restricts the analysis to the 96 of our 160 "common drugs" that have at least 300,000 claims over our sample period. Column (5) adds a control for the total cost of the drug by year. Column (6) restricts the analysis to the 38 drugs for which substitution to other drugs is less likely.

Table 6: Relationship between co-insurance and elasticity

	Dependent Variable: Co-insurance rate						
Sample	All drugs & plans	All drugs & plans	High frequency drugs	All drugs & plans	"Lower subst." drugs	Branded drugs	Generic drugs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Drug-level analysis							
Estimated demand elasticity	-0.197	-0.198	-0.323	-0.166	-0.167	-0.182	-0.641
	(0.046)	(0.047)	(0.073)	(0.039)	(0.056)	(0.035)	(0.075)
Formulary fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Drug price included	No	No	No	Yes	No	No	No
R-squared	0.065	0.324	0.363	0.415	0.435	0.271	0.518
No. of Obs. (plan years)	654,043	654,043	521,144	654,043	197,281	277,585	376,458
Mean of Dep. Var.	0.435	0.435	0.441	0.435	0.452	0.400	0.462
Std. Dev. Of Dep. Var.	0.306	0.306	0.304	0.306	0.318	0.266	0.330
Panel B. Class-level analysis							
Estimated demand elasticity	-0.303	-0.305	-0.315	-0.252			
	(0.064)	(0.065)	(0.074)	(0.052)			
Formulary fixed effects	No	Yes	Yes	Yes			
Drug price included	No	No	No	Yes			
R-squared	0.029	0.304	0.339	0.386			
No. of Obs. (plan years)	586,735	586,735	463,207	586,735			
Mean od Dep. Var.	0.408	0.408	0.416	0.408			
Std. Dev. Of Dep. Var.	0.267	0.267	0.267	0.267			

Table shows the relationship between a drug's (Panel A) or class' (Panel B) pre-gap co-insurance rate and its estimated elasticity. The unit of observation is a drug (or class) by plan. Standard errors in parentheses are clustered at the drug (or class) levels.