Drug Rebates and Formulary Design: Evidence from Statins in Medicare Part D

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Abstract

In contrast to many countries, drug prices in Medicare Part D are determined by privately negotiated rebates between insurance plans and drug manufacturers. What would happen in equilibrium if rebates for a blockbuster drug were increased? We use moment inequalities to estimate formulary-contingent rebates for branded statins in 2010. We show rebates have large effects on formulary design and heterogeneous effects on consumer surplus. If rebates reduced U.S. prices to match Canada, Crestor and Lipitor preferred-tier placement would increase by 19 percentage points, cost-sharing for beneficiaries buying branded statins would fall by 8%, and consumer surplus would increase by 1.8%.

Keywords: Formularies, Insurance, Moment Inequalities, Rebates

1 Introduction

A controversial aspect of the Medicare Part D program, which provides drug insurance to the vast majority of Americans older than 65, is that drug prices are determined by rebates that are negotiated by private insurance companies and drug manufacturers. Detractors of the status quo often argue that the government should negotiate on behalf of insurers because

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it could leverage its buying power to obtain larger rebates. However, there is no evidence on how well the current system, where private firms negotiate rebates, works. Nor is there evidence on how changing rebates in Part D would affect insurance plan design or consumer surplus.

This paper models how rebates affect insurance benefit design in a competitive equilibrium and quantifies how changes in rebates affect consumer surplus. We present the first paper to model insurers' equilibrium formulary placement decisions for branded drugs. This model allows us to estimate rebates that are commercially secret and simulate several counterfactual scenarios to understand how consumer surplus is affected by the resulting distribution of formularies. With our estimates of status-quo rebates and several counterfactuals, we provide an in-depth analysis on the role of rebates in Medicare Part D market, which we believe could be an important input to recent policy proposals for Part D.

Medicare Part D started in 2006 and is a large government program that provides drug insurance to over 40 million beneficiaries in almost 1,000 plans and costs the government nearly $100 billion annually. An important feature of Part D is that insurance is provided by private insurers who compete to enroll beneficiaries of the Part D program. Plan formularies, which specify the list of drugs that an insurance plan covers and the associated cost-sharing rules, are a key dimension of plan competition. These formularies are also important determinants of consumer surplus because they determine the copays and coinsurance rates that beneficiaries pay for drugs covered by their insurance plan.

The leverage that insurers have when they negotiate rebates with drug manufacturers comes from their control over the formulary placement of drugs on their plans. Almost all Part D plans use tiered formularies, which place each covered drug on a tier, and enrollees have to pay larger out-of-pocket costs for drugs on higher tiers. If an insurer places a branded drug on the "preferred" tier of their formulary, copays for the drug are lower, and demand is higher. Alternatively, for drugs on the "non-preferred" tier, copays are higher, and demand is lower. Finally, for drugs excluded from the formulary, enrollees on the plan must pay list price. Institutionally, drug manufacturers offer insurers (typically through intermediaries called Pharmacy Benefit Managers) rebates for branded drugs that are per unit discounts off of list price and are contingent on the tier their drug is placed on. The rebates that result from this process, however, are not publicly known.

We focus on branded statins in 2010. Statins comprised 6% of all prescriptions filled on Part D in 2010, which is the most recent year for which Lipitor (a blockbuster statin produced by Pfizer) and Crestor (a newer and more potent statin produced by AstraZeneca)

were both on patent. These two branded drugs also faced competition from three main generic alternatives: Lovastatin, Pravastatin, and Simvastatin.

We substantially extend the models used to analyze insurer incentives in Part D. Specifically, we account for two key features of competition in Part D. First, we model branded drug formulary placement, which is a key dimension of Part D plan differentiation. Second, we simultaneously model both plan demand and statin demand to capture selection in plan choice due to statin preferences. This is important because statins treat chronic underlying health conditions, and thus when consumers choose their plans, they are likely to have knowledge of their need for statins and of which particular statin works best for them (statins vary in their strength and associated side effects).

We specify a demand model in which each consumer makes an optimal statin choice given their plan's copays for the various statins and their individual preferences; and plan demand is modeled by having each consumer choose among plans taking account of their anticipated statin demand (as well as plan characteristics), with knowledge of their individual statin preferences. This model is particularly well suited to the Medicare Part D environment because it allows for both observed and unobserved heterogeneity in statin preferences to drive plan selection.

With demand estimates in hand, we calculate how insurer profits depend on their formulary choices. We show how to use plans' observed formulary choices to estimate the unobserved rebates for Crestor and Lipitor. In particular, we use a moment inequality approach that finds the rebates that rationalize the formulary choices observed in the data. A key advantage of estimating rebates using insurers' formulary choices is that it allows us to be agnostic about the particular form of bargaining between insurers and drug manufacturers. For example, with our moment inequalities approach, we can consistently estimate mean rebates even if AstraZeneca offers extra rebates on Crestor to insurers who place other AstraZeneca drugs on the preferred tier. Our model captures an important institutional aspect of the structure of rebates in Part D; rebates are formulary-contingent. Drug manufacturers are willing to pay larger rebates to have their branded drugs placed on the preferred tier of the formulary.

We find that drug manufacturers pay large rebates to Part D insurers. Our moment inequality approach provides set estimates of rebates. The mean of our estimates of the per-unit rebate for preferred tier placement is 37.3% for Crestor and 36.2% for Lipitor. However, our set estimates are consistent with large asymmetries in rebates across branded statin manufacturers.

There is substantial interest in rebate policy reform. However, because rebates are secret, there is little evidence on how they affect the copays that Part D beneficiaries incur. We use our rebate estimates to quantify how changing rebates would affect the insurance market equilibrium including formulary design, cost sharing, premiums, consumer surplus, and insurer profits.[1] We begin by analyzing formulary design. Increasing Lipitor rebates from 35% to 50% results in an 18 percentage point increase in the share of large plans that place Lipitor on the preferred tier. In contrast, increasing the Crestor rebate from 35% to 50% increases the Crestor preferred-share by 11 percentage points and *decreases* the Lipitor preferred-share by 2 percentage points (despite holding Lipitor rebates fixed). Thus increasing the Crestor rebate hurts some Lipitor users because insurers try to steer statin users towards Crestor.

After quantifying the effects of rebates on formularies, we use our counterfactuals to answer three main questions: (i) How well does the status quo system, where insurers negotiate rebates, work? (ii) What would happen if manufacturers were prohibited from paying insurers rebates? (iii) What would happen if Part D rebates brought branded statin prices into line with Canadian prices? Conceptually, the answer to these questions all depend on whether or not the associated rebates result in equilibrium formularies that give Part D beneficiaries sufficient plan choice; can people find a plan that covers their preferred branded statin and their other non-statin drugs?

Our estimates are consistent with the Part D status quo performing well in terms of consumer surplus in the market for statins (importantly, the statin market has branded and generic therapeutic substitutes, and the Part D status quo may not work as well with other market structures). Specifically, our estimated rebates are consistent with the status quo achieving well over half of the available consumer surplus in the statin market. We explain this result by analyzing counterfactual plan choices and statin utilization. When branded statin rebates increase, more formularies place branded statins on the preferred tier, but branded statin utilization hardly changes. Thus, there are enough plans covering branded statins on the preferred tier under the status quo.

In contrast, any reduction in rebates results in sharp decreases in consumer surplus. If rebates were prohibited (we explore intermediate counterfactuals as well), the share of plans that cover both Crestor and Lipitor on the preferred tier would fall precipitously by 66

[1]The presence of Low Income Subsidy (LIS) beneficiaries results in discontinuous profit functions for Part D insurers (e.g., Decarolis, Polyakova, and Ryan 2020). We follow the literature and endogenize premiums in Part D assuming that insurers set premiums on the basis of their non-LIS demand (e.g., Starc and Town 2020).

percentage points. As a consequence, the average cost-sharing for branded statins (across equilibrium plan offerings) would increase drastically, Crestor utilization would fall by 25% and Lipitor utilization would fall by 35% and consumer surplus would fall commensurately. Premiums move by roughly an order of magnitude less than cost-sharing.

If rebates were increased, so that the price of branded statins with preferred tier placement matched Canadian prices, average cost sharing for beneficiaries buying branded statins would fall by 7.09% for Crestor and 8.75% for Lipitor. Under Canadian prices, utilization of branded statins would not increase much and thus changes in consumer surplus mostly are due to changes in price (as opposed to an increase in quantity). Ultimately, matching Canadian prices would increase consumer surplus by 1.80%. In contrast, insurer profits would increase by 6.72%.

This paper contributes to a growing literature that studies supply-side models of non-premium aspects of insurance plan design. Formularies are high-dimensional objects that list the cost-sharing rules for all drugs covered on an insurance plan. Andersen (2017), Lavetti and Simon (2018), and Starc and Town (2020) summarize formularies by the number of drugs covered or average out-of-pocket costs and study unintended consequences of Part D rules.[2] In contrast, in this paper, we focus on a specific therapeutic class and model formulary design in terms of the *tier placement* of each branded drug. This allows us to analyze concrete formulary changes that insurers could make in response to changes in rebates (e.g., a plan could move a branded drug from the preferred tier to the non-preferred tier). Ho (2006) suggested studying the consumer welfare effects of restrictive formularies using this detailed *tier placement* approach; here we implement her suggestion and also study the supply-side effects.

This paper also contributes to the endogenous product positioning literature. We use moment inequalities to estimate unobserved per unit rebates and model formulary design. A common methodological challenge in the application of moment inequalities is selection (Pakes 2010), which, in our setting, arises because firms choose formularies based on unobserved heterogeneity in rebates. We address this by imposing a restricted form of rebate

[2] Carey (2017) studies the effect of incomplete risk adjustment on plan design. Decarolis and Guglielmo (2017) study enrollment reform and plan design. Kakani, Chernew, and Chandra (2020) and Feng and Maini (2021) provide interesting analyses of net prices dynamics using data from SSRHealth. The SSRHealth net price data is novel and useful, however it does not directly measure the rebates that insurers face, which we estimate here, for two reasons. First, SSRHealth net prices are not formulary contingent; second, they are net anything that pharmaceutical companies can legally use to reduce their revenues when they file their 10-K (for example point-of-sale coupons and payments to wholesalers).

heterogeneity that is a natural fit for our institutional setting: unobserved rebate heterogeneity varies across insurers, but is constant within insurer. With insurer-specific structural errors, we address selection by combining the approaches in Eizenberg (2014) and Wollmann (2018) and using support bounds and reweighting. Our paper also provides a nice setting in which to study endogenous product positioning because the cost of changing formularies is low and, as a consequence, they are frequently changed every year. Thus, we study endogenous product positioning without the dynamic concerns present in settings with large fixed costs of entry.

The rest of this paper is structured as follows. In Sections 2 and 3, we present institutional background and data. In Section 4, we describe our simultaneous model of demand and our model of insurer formulary setting. Section 5 covers estimation for both demand and supply. In Section 6, we report our demand and rebate estimates. Section 7 reports the results from our counterfactual analyses. In Section 8, we conclude.

2 Institutional Background

This section describes the institutional details relevant to our demand model, our formulary equilibrium model, and our counterfactual analyses. We split the institutional details into three subsections: Medicare Part D, statins, and drug rebate setting.

2.1 Medicare Part D

Medicare Part D is a voluntary, prescription-drug insurance program. All Medicare beneficiaries are eligible to enroll in Part D, and enrolling is typically financially favorable because the government pays a subsidy of at least 74.5% of base premiums.[3] As a consequence, enrollment is high; close to 60% of Medicare beneficiaries enrolled in a Part D plan in 2010. A key component of Medicare Part D is that benefits are administered by private insurers who compete over enrollees; the idea is to leverage competition to keep program costs low.

Medicare beneficiaries can enroll in Part D plans between October 15 and December 7 each year with coverage starting on January 1 the following year. Beneficiaries who are on Medicaid or have incomes less than 150% of the poverty level receive the Low Income

[3]For regular beneficiaries, the subsidy is roughly 74.5%. Most of the subsidy directly reduces premiums. The rest of the subsidy reduces out-of-pocket costs for beneficiaries who have exceeded the catastrophic threshold, which was set at $4,880 in annual out-of-pocket costs in 2010. For low-income beneficiaries, described in detail later, the government further subsidizes both premiums and out-of-pocket costs.

Subsidy (LIS), which reduces out-of-pocket costs to between $0 and $6.30 per fill. The LIS also covers up to 100% of monthly premiums for LIS beneficiaries who enroll in low premium ("below-benchmark") plans.[4] Each Medicare beneficiary is assigned to one of 34 geographical regions (based on their state of residence) and can enroll in PDPs from their region. To facilitate plan choice, the government runs a website that allows beneficiaries to compare plans.

Part D insurance plans are divided into two types: stand-alone Prescription Drug Plans (PDPs) and Medicare Advantage Prescription Drug Plans (MAPDs). We restrict our analysis to the PDP market. MAPDs cover hospital care in addition to drug insurance and face complicated incentives, which would distract from the focus of this paper and has been studied in depth elsewhere (Lavetti and Simon 2018 and Starc and Town 2020).

Plans compete on financial characteristics (copays, coinsurance, and premiums) as well as formularies (the list of covered drugs and their associated tiers). In 2010, more than 90% of plans used tiered formularies where each drug is put on a tier, e.g., generic, preferred branded, non-preferred branded, specialty, or excluded. Most plans cover thousands of drugs. As a consequence, formularies are high-dimensional objects. The Center for Medicare and Medicaid Services (CMS) specifies two main requirements for PDP formularies. First, every formulary must include two drugs per therapeutic class. Second, every plan must cover all drugs in six protected therapeutic classes.[5] Beyond these two rules, plans have substantial freedom to design their formularies and, as we document below, the variation in observed formularies generates large variation in annual OOP costs for the same beneficiary in different plans. In addition to formulary requirements, CMS also imposes actuarial requirements on PDPs. Plans must be at least as generous as the Standard Benefit Schedule (SBS), which is not tiered, unlike the vast majority of PDPs. Appendix A has further details on the SBS.

[4]Each year, the Center for Medicare and Medicaid Services (CMS) calculates benchmarks (in each of the 34 Part D regions) using a weighted average of Part D plan premiums. Plans that offer basic Part D coverage with premiums no larger than the regional benchmark are "below-benchmark." LIS beneficiaries also qualify for full subsidies in plans that are under the regional benchmark plus a *de minimis* threshold of $1 or $2. The *de minimis* rule reduces the number of plans that change benchmark status from year to year. Plans can change below benchmark status from year to year, and LIS beneficiaries in a plan that loses below benchmark status are randomized into new below benchmark plans unless they opt out and pay the premium difference.

[5]These classes are anticonvulsants, antidepressants, antineoplastics, antipsychotics, antiretrovirals, and immunosuppressants.

2.2 Statins

To estimate our drug-demand model, we focus on the therapeutic class of HMG-CoA Reductase Inhibitors (statins), which are lipid-lowering drugs that are taken daily as a preventative for cardiovascular disease.[6] In 2010, statins were the largest therapeutic class of drugs in Part D by fills. Moreover, in 2010, five statins comprised more than 98% of the market: from newest to oldest, they are Crestor, Lipitor, Simvastatin, Lovastatin, and Pravastatin. In 2010, Crestor, manufactured by AstraZeneca, and Lipitor, manufactured by Pfizer, were both on-patent branded drugs. Plans place these branded statins on the preferred branded or non-preferred branded tiers of their formularies or exclude them from the formulary altogether. Lovastatin, Pravastatin, and Simvastatin are all generic statins and as such are always on the generic tier of formularies. We focus on Crestor and Lipitor because we model the formulary placement of branded drugs and how it responds to changes in rebates.

2.3 Rebate Setting

The final component of the institutional background relevant to our analysis concerns rebate setting. Part D consists of more than 1,000 insurance plans offering thousands of drugs. As a consequence, negotiating rebates for every branded drug is complicated. This has led to large intermediaries, called Pharmacy Benefit Managers (PBMs), negotiating drug rebates on behalf of many insurers. The PBM market is highly concentrated, with five firms dominating the market in 2010.

Drug manufacturers offer insurers (through PBMs) formulary contingent rebates, so that AstraZeneca will pay insurers a large rebate when Crestor is on the preferred tier and a small rebate (or no rebate at all) when Crestor is on the non-preferred tier. The negotiations between PBMs and drug manufacturers are secret. Since little is known about how the negotiations take place or what model would accurately represent them, we take an approach to estimating rebates based off estimating insurer profit functions and using data on insurers' observed formulary decisions.[7] In 2010, 98.9% of all Direct and Indirect Remuneration to insurers was in the form of manufacturer rebates (Schmidt and Suzuki 2022).

[6] Statins are differentiated on several dimensions besides out-of-pocket costs. First, statins have different levels of effectiveness in terms of reducing low-density lipoprotein cholesterol (LDL-C). Second, statins can have different adverse side effects. The most common, although still rare, side effect that people experience is muscle pain. The presence of side effects may be linked to the mechanism by which statins work: Crestor and Pravastatin are hydrophilic, while Lipitor, Simvastatin, and Lovastatin are lipophilic.

[7] A 2010 government report provides some information about rebates (Office of Inspector General 2010).

3 Data

We use data from the Center for Medicare and Medicaid Services (CMS) in 2010. We use four main datasets that included information on: (i) plan choices and demographic variables, (ii) plan characteristics, (iii) formulary data, (iv) Part D claims data. We also use inpatient, outpatient, and physician claims data from 2009 to calculate prescription drug risk scores (which are predictions of drug utilization) using the CMS algorithm.

3.1 Beneficiary Data

We start with a 20% random sample of Medicare beneficiaries in 2010. For each beneficiary, we observe demographic data on age, sex, and ZIP code of residence; and Part D plan choices.

We impose similar sample restrictions to prior papers studying Medicare Part D; we exclude beneficiaries who are younger than 65, who do not have full-year coverage on Part A and B, who enroll in a Part C plan for any month, who do not enroll in Part D for any month, who switch PDPs or LIS status mid-year, or who die mid-year. There are two main differences between our sample restrictions and those of prior papers. First, we do not exclude LIS beneficiaries because they account for 32.1% of our sample and thus their demand is important for formulary design. Second, we restrict to statin users because we do not think that anticipated statin utility is likely to be a significant determinant of plan choices for people who do not yet need statins.[8] After imposing all of these sample restrictions, we are left with 737,057 beneficiaries. Appendix Table 1 reports summary statistics for the beneficiaries that survive our sample restrictions.

3.2 Plan Data

We restrict our sample to plans with at least 1,000 enrollees (after beneficiary sample restrictions) to ensure we have enough observations in each plan to estimate our model.[9] In our resulting sample, each region has between 5 and 26 plans. For each plan, we observe enrollment and the financial characteristics relevant to beneficiary plan choice (along with formulary design, which is described in the next subsection). We exclude Employer Group

[8] We define a beneficiary to be a statin user if they have 30 days supply for at least 75% of the months that they are enrolled in Part D, e.g., 270 days supply for a full year beneficiary and 90 days supply for a beneficiary who is enrolled for four months.

[9] This restriction results in us excluding 4 Part D regions (Alaska, Hawaii, New Mexico, and Nevada) because these regions have at most one plan in our data with 1,000 or more enrollees.

Table 1: Formulary Design for Branded Statins

	Lipitor Tier		
Crestor Tier	Preferred	Non-Preferred	Excluded
Preferred	208 (53.2%)	72 (18.4%)	31 (7.9%)
Non-Preferred	10 (2.6%)	44 (11.3%)	1 (.3%)
Excluded	10 (2.6%)	0 (0%)	15 (3.8%)

Notes: Each cell shows the number of plans (percent of plans) with the indicated formulary placement for Crestor and Lipitor. The sample consists of the 391 plans with at least 1,000 enrollees. Alaska, Hawaii, New Mexico, and Nevada are excluded because of sample size restrictions. Finally, 42 plans are excluded because they use the standard benefit schedule as opposed to a tiered formulary.

Waiver Plans because they are not open to general enrollment. This reduces the number of plans in our data from 1,542 to 431, which account for 86% of total enrollment across Part D regions. Appendix Table 2 reports summary statistics relating to the formulary design of the plans in our data. Nearly all (90.0%) of the plans in our data are tiered.

3.3 Formulary Data

In 2010, the typical tiered formulary had separate tiers for generic drugs, preferred branded drugs, non-preferred branded drugs, and specialty drugs.[10] Table 1 enumerates the combinations of tier placement for Crestor and Lipitor for the plans in our data. Just over half (53.2%) of plans have both Crestor and Lipitor on the preferred branded tier. 11.3% of plans have both drugs on the non-preferred branded tier. There is a clear asymmetry between the two branded statins with Crestor generally getting preferential formulary treatment; Crestor is in a favored position on 26.6% of plans while Lipitor is only in a favored position on 5.2% of plans.

Table 2 shows that branded statin formulary placement is strongly related to statin demand. For example, on plans that place both Crestor and Lipitor on the preferred tier, 9.4% of enrollees buy Crestor, and 24.8% of enrollees buy Lipitor. In contrast, on plans that place Crestor on the preferred tier and Lipitor on the non-preferred tier 14.7% of enrollees buy Crestor, and only 4.8% of enrollees buy Lipitor. These drastic changes in demand may reflect both selection and moral hazard. For example, beneficiaries who know that they prefer Lipitor may choose a plan where Lipitor is preferred (and these beneficiaries are high

[10] A small share of tiered formularies split generic drugs into preferred and non-preferred generics.

Table 2: Branded Statins Market Shares by Formulary Design

	Lipitor Tier		
Crestor Tier	Preferred	Non-Preferred	Excluded
Preferred	9.4%, 24.8%	14.7%, 4.8%	8.4%, 0%
Non-Preferred	7.1%, 30.9%	8.4%, 13.2%	9.6%, 0%
Excluded	0%, 32.4%	0%, 0%	0%, 0%

Notes: Each cell shows the market share of Crestor (before the comma) and Lipitor (after the comma) among beneficiaries on plans with the indicated formulary placement for Crestor and Lipitor.

cost in terms of statins because they do not use generics). However, even absent this plan selection channel, copay differences can induce differential statin choice with implications for plan costs. For example beneficiaries who are in plans that place Crestor on the preferred tier and Lipitor on the non-preferred tier will face a copay differential that may induce them to purchase Crestor. The model of demand that we present in the next section accounts for both of these effects.

3.4 Drug Claims Data

We observe claim-level data for all Part D fills for all beneficiaries in our sample. For each fill, we observe the specific drug, the date of the fill, the quantity supplied, and the OOP cost that the beneficiary has to pay. We also observe the list price associated with each claim.[11] The mean list price per pill for Crestor and Lipitor are $4.08 and $3.92 per pill respectively. This list price determines beneficiaries' OOP costs in the deductible region as well as for plans that use coinsurance.[12]

We use the change in annual OOP costs as the price that statin users consider when they make their statin and plan choices: we think of this as modeling a situation where beneficiaries use the CMS calculator to determine their annual costs of each statin under various plans. The calculator takes into account the copays or coinsurance for each statin as well as nonlinearities in the price schedule, including the deductible and the coverage gap. Beneficiaries then compare their annual OOP costs under each statin relative to their annual

[11] The list price differs from the cost because it does not account for rebates.

[12] The list price is also relevant for OOP costs in the Medicare Part D "donut hole" (details are in Appendix A).

OOP costs if they do not buy any statin. We provide details on the construction of these annual OOP costs, including further institutional detail, in Appendix A.

Table 3: Statin Summary Statistics

	Non-LIS			LIS		
	Annual OOP		Market	Annual OOP		Market
	Mean	S.D.	Share	Mean	S.D.	Share
	(1)	(2)	(3)	(4)	(5)	(6)
Crestor	\$568	\$402	8.1%	\$39	\$99	11.2%
Lipitor	\$586	\$380	19.4%	\$43	\$119	23.3%
Lovastatin	\$80	\$62	8.6%	\$12	\$9	7.5%
Pravastatin	\$82	\$62	12.1%	\$12	\$10	8.9%
Simvastatin	\$80	\$63	51.7%	\$11	\$9	49.1%
Beneficiaries	737,053					

Notes: This table reports summary statistics on annual OOP costs and market shares for each statin for non-LIS and LIS beneficiaries. Annual OOP summary statistics are calculated on the sample of beneficiaries who chose the relevant statin. Appendix A provides details behind annual OOP cost calculations.

Table 3 reports statin-related summary statistics using the claims data. Columns (1), (2), and (3) report statistics for non-LIS beneficiaries and Columns (4), (5), and (6) report statistics for LIS beneficiaries. First, consider non-LIS beneficiaries. The mean annual OOP costs from buying Crestor (instead of no statin) is \$568. Lipitor is slightly more expensive with a mean annual OOP cost of \$586. The standard deviations show substantial variation in the annual OOP cost of branded statins across beneficiaries.[13] LIS beneficiaries' annual OOP costs for statins are substantially less than that of non-LIS beneficiaries. The lower annual OOP costs that LIS beneficiaries face appear to translate into larger markets shares for branded statins: 23.3% of LIS beneficiaries buy Lipitor and 11.2% buy Crestor, whereas 19.4% and 8.1% of non-LIS beneficiaries buy Lipitor and Crestor respectively.

[13]Two factors account for the variation in annual OOP costs across beneficiaries. First, different beneficiaries face different copays for the same drug based on the plan they choose and its formulary placement of branded statins. Second, beneficiaries who purchase a lot of other drugs are more likely to reach the coverage gap region of Part D coverage, which increases annual costs because most plans provide no coverage in the coverage gap.

4 Model

The model has three stages. In stage 0, manufacturers and PBMs negotiate to determine rebates. In stage 1, insurers choose the formulary placement of statins on all of their plans. In stage 2, beneficiaries observe plan characteristics and choose a plan, and statin users choose which statin to purchase. We describe the model in reverse order by beginning with beneficiary demand. Although rebate setting is an important component of the economic environment that we study, we estimate rebates and quantify counterfactuals in a manner that avoids requiring us to take a stand on how rebates are set. As a consequence, we do not describe stage 0 of the model.

4.1 Demand

The main goal of the demand side model is to quantify the effects of branded statin formulary placement on statin demand and plan demand, which inform the profit effects that insurers consider under different formulary alternatives.

For each statin user enrolled in a stand-alone Part D Plan, we estimate a simultaneous demand model; statin users make their decisions over plans and statins at the same time.[14] A key advantage of a simultaneous model is that it explicitly allows for selection based on both observed and unobserved preferences. This is important because statins are taken daily, so most statin users know their statin preferences before they choose their plans; our model assumes that people search out plans that have good cost-sharing arrangements for their preferred statin. We first specify the statin demand component of the model. We then use the indirect utility from statins to specify the plan demand component of the model.

In each Medicare Part D regional market $r = 1, ..., R$, plan $j = 1, ..., J_r$ covers a subset of statins K_j.[15] Each plan's formulary specifies the tier placement of branded statins $f_j \in F$ where F denotes the set of possible formulary configurations for branded statins, e.g., Crestor preferred and Lipitor non-preferred, or Crestor non-preferred and Lipitor excluded.

Statin user $i = 1, ..., N$ chooses both a plan and a statin. We group each statin user into

[14] This simultaneous approach to estimating demand in a setting with bundled goods is similar to the strategy used Lee (2013), and Crawford, Lee, Whinston, and Yurukoglu (2018). Several papers have used a sequential approach to estimating demand in settings with a similar structure, e.g., Ho (2006), Gowrisankaran, Nevo, and Town (2015), and Ho and Lee (2017).

[15] Statins are packaged at different dosages (e.g., 10mg, 20mg, 40mg). In our data, different dosages of the same statin are always placed on the same formulary tier and thus have the same cost-sharing rules, so we abstract from dosage when we consider our model of statin choice.

one of four risk types, denoted by t, and allow utility parameters to differ across types.[16] The utility from choosing statin k on plan j is given by

$$v_{ijkt} = -\alpha_t^{OOP} OOP_{ijkt}(f_j) + \alpha_t^x x_{ikt} + \xi_{kt} + \varepsilon_{ikt}, \tag{1}$$

where OOP_{ijtk} is the annual out-of-pocket (OOP) costs for statin k, x_{ikt} are observed enrollee characteristics, and ξ_{kt} is a statin fixed effect.Although utility management is sometimes used to make branded drugs harder to purchase, we do not include it in our utility specification because it was very infrequently used to restrict access to statins in Part D according to the CMS data, e.g., 0.28% of beneficiaries are on plans that require prior authorization for Crestor or Lipitor. The error term, ε_{ikt}, is assumed to be IID and Type 1 Extreme Value. It is individual and brand specific, so unobserved preferences for branded statins do not depend on the identity of the plan in which the user is enrolled.

Annual OOP costs, OOP_{ijkt}, depend on the formulary placement of branded statins f_j as well as other cost-sharing rules of the plan (e.g., the rest of the formulary, copays, and the deductible) and non-statin drug purchases. We calculate OOP_{ijkt} for any statin choice on every plan using the cost calculator approach that has been used in many Part D papers.[17] This approach uses data on observed formularies, plan cost-sharing rules, and the assumption that non-statin drug choices are unaffected by plan choice (i.e., no moral hazard on non-statin drug choices).[18] Implementation details for our cost calculator are in Appendix A. Importantly, we explicitly model how statin choice is affected by plan characteristics and especially branded statin formulary placement.

The model includes both observed and unobserved individual heterogeneity. We use statin fixed effects, ξ_{kt} to capture unobserved statin quality. Observed consumer heterogeneity is captured in two ways. First, the model is estimated separately by risk type. Second, x_{ikt} includes median income (at the 5-digit ZIP code) and age interacted with an indicator for branded statins. Because beneficiaries know their statin tastes before they choose

[16] Non-LIS beneficiaries are grouped based on terciles of the CMS 2009 RxCCS hierarchical risk score (risk score). LIS beneficiaries are grouped together. Finally, new non-LIS beneficiaries are assigned to the middle risk score tercile because we cannot calculate a risk score for them. Decarolis, Polyakova, and Ryan (2020) and Starc and Town (2020) use similar risk type groups to estimate Part D plan demand.

[17] E.g., Abaluck and Gruber (2011), Abaluck and Gruber (2016), Heiss, Leive, McFadden, and Winter (2013), Ho, Hogan, and Scott Morton (2017).

[18] An alternative to the no moral hazard assumption, used in Heiss, Leive, McFadden, and Winter (2013), maintains that beneficiaries choose the cheapest drug by therapeutic class in each plan. In principle, this paper's analysis could be redone under this alternative assumption, but at a considerable extra computational expense. For non-statin drugs excluded from the formulary, we assume beneficiaries choose an alternative drug on the same tier.

their plans, unobserved taste heterogeneity in statin preferences affects plan demand (e.g., Equations (2) and (3) below).

We are able to include statin fixed effects while still estimating the coefficient on annual OOP costs because of individual-level variation in annual OOP costs. This variation comes from the interaction between the nonlinear price schedule inherent to Part D plan design and non-statin drug spending. We assume that, conditional on the individual-level heterogeneity in our model, differences in annual OOP costs that arise from the nonlinear schedule are uncorrelated with statin-specific preferences. We provide further details in Appendix A.

Accounting for individual heterogeneity in statin tastes is important for estimating a plan's profit from various formulary changes because individual heterogeneity implies that (plan conditional) statin choice probabilities do not have the IIA property. Thus, when an insurer places both Crestor and Lipitor on the preferred branded tier, they account for the fact that removing Crestor from the formulary may drive many consumers to Lipitor to the extent that younger beneficiaries, for example, are more likely to choose both Crestor and Lipitor (as opposed to moving to the high market share Simvastatin).

The utility-maximizing statin choice for beneficiary i of type t on plan j, and the utility from this choice are defined as

$$k^*_{ijt} = \underset{k \in K_j}{\operatorname{argmax}}\, v_{ijkt}, \qquad v^*_{ijt} = \max_{k \in K_j} v_{ijkt}. \tag{2}$$

We next describe the demand model for plans based on optimal statin choice and utility. The utility from choosing plan j comes from statins and non-statin characteristics of the plan, and is given by

$$u_{ijt} = \beta^{v^*}_t v^*_{ijt} - \beta^p_t p_j + \beta^x_t x_j + \zeta_{jt} + \tau_{ijt}, \tag{3}$$

where p_j is the plan premium, which does not vary across types,[19] x_j is a vector of observed plan characteristics, ζ_{jt} is unobserved plan quality,[20] and τ_{ijt} error term that is assumed to be IID and Type 1 Extreme Value.[21]

The v^*_{ijt} term, which captures statin utility, adds an important dimension to the specification. The v^*_{ijt} implies that beneficiaries know their statin preferences when they choose their plan and that beneficiaries who have strong preferences for a specific statin prefer plans where that statin is cheap. The plan covariates, x_j, are standard and include the annual

[19] As we discuss in Section 5, we assume that p_j is endogenous and employ Hausman instruments that consist of the enrollment-weighted mean of the insurer's similar plans in other Part D markets.

[20] This is often denoted with ξ, e.g., in Berry, Levinsohn, and Pakes (1995), but we already used ξ in the statin choice model.

[21] As in Abaluck and Gruber (2011), we only model the choices of beneficiaries who enroll in a stand-alone Part D Plan. Thus, we normalize the mean utility of an arbitrary plan in each region.

deductible, the presence of gap coverage, enhanced plan status, and formulary generosity summary statistics such as the number of drugs covered on the plan, the number of drugs on each tier, and cost sharing on each tier (copay or coinsurance rate), insurer (e.g., United Healthcare) fixed effects, Part D market fixed effects and plan age. We include plan age as a component of plan utility to account for plan inertia.[22] Unobserved plan quality is captured by ζ_{jt} and implies that we need an instrumental variable for premiums. Individual heterogeneity in plan utility is captured through risk types and through the maximized statin utility term, which captures observed and unobserved heterogeneity in statin preferences.

We assume that statin user i chooses plan j to maximize Equation (3). However, maximizing Equation (3) involves maximizing Equation (1) as a subproblem; when beneficiaries choose their plans, they account for the fact that they will make the best statin choice available on each plan. To calculate plan choice probabilities we rewrite Equation (3) as

$$u_{ijt} = \delta_{jt} + \beta_t^{v^*} v_{ijt}^* + \tau_{ijt},$$

where the mean utility term δ_{jt} is defined as

$$\delta_{jt} = -\beta_t^p p_j + \beta_t^x x_j + \zeta_{jt}. \tag{4}$$

Our model has two sets of demand-side parameters. Let $\theta_t^k = (\alpha_t^{OOP}, \alpha_t^x, \xi_{kt})$ and $\theta_t^j = (\beta_t^{v^*}, \beta_t^p, \beta_t^x)$ denote vectors that collect the parameters from the statin utility component of demand in Equation (1) and the plan utility component of demand in Equation (3) respectively. We write choice probabilities as explicit functions of the formulary placement of branded statins, which is critical to our model of supply.

The conditional probability that beneficiary i of type t chooses statin k given that they are on plan j is given by the usual logit formula:

$$s_{ikt|j}(f_j, \theta_t^k) = \frac{\exp(-\alpha_t^{OOP} OOP_{ijkt}(f_j) + \alpha_t^x x_{ikt} + \xi_{kt})}{\sum_{k' \in K_j} \exp(-\alpha_t^{OOP} OOP_{ijk't} + \alpha_t^x x_{ik't} + \xi_{k't})} \tag{5}$$

As the choice probabilities make clear, we model statin demand as a static choice. There are two reasons behind our decision to use a static model of statin demand. First, statins are used as a prophylactic for a chronic underlying condition: hyperlipidemia (high cholestrol). As such, most statin users take statins every day of the year. Moreover, in our data, statin users typically buy a single type of statin, e.g., Crestor or Simvastatin.[23] Second, in the context of statins, we believe that dynamics would not add much and would distract from the important

[22] A theoretical justification for this approach is given in Decarolis, Polyakova, and Ryan (2020).

[23] 94.7% of statin users in our data buy a single type of statin.

novel component of our drug demand model, which focuses on selection of statin users into plans (on the basis of observed and unobserved preferences) and is important in our context precisely because statin users need statins every day and have a lot of experience with statins prior to plan choice.[24]

The probability that beneficiary i of type t chooses plan j depends on all formularies that are available in a region because they determine plan utilities through the maximized statin utility term. Letting p_{-j} and f_{-j} denote the formularies of plans other than j in the same region, the plan choice probabilities are

$$s_{ijt}(f_j, p_j, f_{-j}, p_{-j}, \theta_t^j, \theta_t^k) = \frac{\exp(-\beta_t^p p_j + \beta_t^x x_j + \beta_t^{v^*} v_{ijt}^*(f_j, \theta^j) + \zeta_{jt})}{\sum_{j'=1}^{J_r} \exp(-\beta_t^p p_{j'} + \beta_t^x x_{j'} + \beta_t^{v^*} v_{ij't}^*(f_{j'}, \theta^j) + \zeta_{j't})}. \quad (6)$$

Thus, plans' statin formulary placement decisions have both intensive and extensive margin effects. On the intensive margin, placing branded statins on the preferred tier induces plan enrollees to buy more branded statins, which are expensive from insurers' perspective. On the extensive margin, placing branded statins on the preferred tier increases plan market share. The cost of a beneficiary depends on the characteristics of the type of beneficiaries that endogenously select into each plan based on plan characteristics that include the formulary placement of branded statins, premiums, and the formulary treatment of non-statin drugs. We model this selection explicitly and provide more details on how this selection affects firm profits below; the key point is that our demand model allows us to calculate each beneficiary's plan choice probabilities for any set of formularies in the market, which allows us to track the consequences of plan selection on firm profits.

4.2 Supply

The most important aspect of rebates in the Part D program is that they are formulary contingent, i.e., they are paid for preferred tier placement. We use the estimates from our demand model to calculate insurer profit functions and infer the formulary–contingent rebates using moment inequalities. This section describes our model of insurer behavior.

Our model is designed to allow us to estimate the rebates for branded statins; it uses necessary conditions implied by profit maximization that are informative about rebates and allows us to avoid modeling other insurance plan characteristics. Specifically, we adopt a moment inequality approach to study formulary design. We allow for a structural error in the sense of Pakes (2010) and Pakes, Porter, Ho, and Ishii (2015). This structural error generates a selection issue that we resolve by combining aspects of the approaches in Eizenberg

[24] Drug demand dynamics have been modeled in depth by Dalton, Gowrisankaran, and Town (2019).

(2014) and Wollmann (2018). In our counterfactuals, we endogenously model branded statin formulary placement.

Our measure of the profit for plan j is the sum of the profits made on each beneficiary i:

$$\hat{\Pi}_j(f_j, p_j, f_{-j}, p_{-j}, r_j) = \sum_{i=1}^{N} \left[s_{ijt}(f_j, p_j, f_{-j}, p_{-j}, \hat{\theta}_t^j, \hat{\theta}_t^k) p_j - c_{ijt}(f_j, p_j, r_j, f_{-j}, p_{-j}, \hat{\theta}_t^j, \hat{\theta}_t^k) \right] \quad (7)$$

where r_j is a vector of statin specific, formulary-contingent rebates that are received by plan j, which we discuss at length below. In this representation, everything that is not premium revenue is accounted for in the cost term c_{ijt}; for example, formulary-contingent rebates reduce costs as do the legislated Part D direct subsidies paid to insurers on the basis of beneficiary i's risk score.

We account for all types of plan revenue using the same definitions as the CMS Medical Loss Ratio (MLR) reports. Specifically we account for the following four components: beneficiary premiums, direct subsidies, federal reinsurance, and Low Income Premium Subsidy Amounts (LIPSA).[25] Appendix B provides the details as to how we calculate each source of revenue.[26]

We do not assume constant marginal costs and instead use data on each beneficiary's drug insurance claims to calculate costs. We calculate drug claims costs as the total cost of filling Part D claims net of beneficiary out-of-pocket payments, Low Income Cost Sharing Amounts (LICSA), and rebates. We assume that administrative costs per member per month would not change even if plans altered their branded statin formulary placement. As with revenues, Appendix B contains a detailed description of the different components of cost.

We impose two important assumptions that allow us to calculate costs. The assumptions relate to how we calculate non-statin costs and are necessary because we do not estimate demand for non-statin drugs. First, we assume no moral hazard on non-statin drugs, so that we can calculate non-statin drug costs on any plan for each individual's observed choices. This no moral hazard assumption is common in Part D plan demand models.[27] Second,

[25] We ignore risk corridors, which account for less than 1% of revenue across all therapeutic drug classes (as opposed to only statins) for PDPs in the MLR Public Use Files.

[26] Revenues also depend on rebates because federal reinsurance payments are made on the basis of the cost of drugs net of rebates. We account for these payments in our profit calculations. Details are in Appendix B.

[27] E.g., Abaluck and Gruber (2011) and Abaluck and Gruber (2016) use this assumption to calculate the out-of-pocket costs that Part D beneficiaries would have spent on plans that they did not choose. When beneficiaries buy non-statin drugs that are excluded from the formulary of other plans in their region, we assume they would have replaced the drug with a different drug of the same cost.

we assume that the rebate for all branded non-statin drugs is 13.8%.[28] With these two assumptions and the institutional accounting details in Appendix B, we calculate plan costs as a function of selection.

We assume that manufacturers offer per unit rebates off of list price that are paid after a drug is purchased from a pharmacy. This assumption is consistent with descriptions of the Part D environment (Conti, Frandsen, Powell, and Rebitzer 2021, Government Accountability Office 2019). Our approach is robust to the possibility that there is unobserved heterogeneity in per unit rebates across insurers in the Part D market; this is discussed at length below.

In order to focus attention on the role of formularies and rebates, it is helpful to rewrite our profit measure. Equation (7) expresses profits in a standard way as revenues minus costs. To operationalize our moment inequalities, it helps to focus attention on the linearity of rebates. Thus we write the profit for plan j as

$$\hat{\Pi}_j(f_j, p_j, f_{-j}, p_{-j}, r_j) = \overbrace{A_j(f_j, p_j, f_{-j}, p_{-j})}^{\text{Profit Net of Rebate}} + \overbrace{\sum_{k \in K_j^b} \underbrace{r_{jk}(f_j)}_{\text{Percent Rebate}} \underbrace{L_{jk}(f_j, p_j, f_{-j}, p_{-j})}_{\text{List Price}}}^{\text{Rebate Discount}} \quad (8)$$

where K_j^b is the set of branded statins covered on plan j, r_{jk} is the rebate for statin k on plan j, L_{jk} is the total cost at list prices for statin k on plan j (which is a function of both plan demand and statin demand conditional on plan choice), and A_j captures all other determinants of plan profits.[29] This representation makes clear that profits are increasing in rebates and that profits are linear in rebates conditional on demand (for both plans and statins) — rebates are per unit discounts off list price.

To allow for unobserved heterogeneity in rebates, we write them in the following form:

$$r_{jk}(f_j) = \gamma_k(f_j) + \nu_{2j} \quad (9)$$

where $\gamma_k(f_j)$ is the mean rebate for drug k under formulary f_j and ν_{2j} is the deviation from the mean and captures plan-specific heterogeneity.[30] This heterogeneity could reflect the

[28] In 2014, the mean branded drug rebate was 17.5% according to the CMS Manufacturer Rebate Summary Report. In 2010 and 2014, overall manufacturer rebates were, respectively, 11.3% and 14.3% based on the Medicare Trustees Reports. We assume that the mean non-statin branded drug rebate in 2010 is 13.8% (calculated from $.175 \times .113/.143$).

[29] The government pays 80% of catastrophic coverage region costs net of manufacturer rebates. We account for this when we calculate our profit functions.

[30] In an earlier version of this paper, we allowed for rebates on the non–preferred tier and also for rebates to depend on the formulary status of competitors, but found no evidence for either type of rebate and thus assume that such rebates are not used for statins.

fact that insurers use different PBMs and, as a consequence, obtain different rebates. Given this motivation, we assume that an insurer is offered the same rebate menu for all of its plans, that is, rebate heterogeneity is constant across plans within an insurer. To introduce this formally, let $\nu_{2,h}$ denote the idiosyncratic component of the rebate offered to insurer h and $h(j)$ denote the insurer that owns plan j. Then we have

$$\nu_{2j} = \nu_{2,h(j)}, \quad j = 1, ..., J.$$

Next, we specify assumptions on insurer's information set, $\mathcal{I}_h$. We assume that $\nu_{2,h}$ is unpredictable before rebate menus are observed; specifically, we assume

$$\mathbb{E}[\nu_{2,h}|\mathcal{I}_h] = 0. \tag{10}$$

However, insurers observe rebates, and hence $\nu_{2,h}$, before they design their formularies. Thus their formulary choice contain information about $\nu_{2,h}$. Let f_h be a vector that collects the formularies of insurer h's plans. Then

$$\mathbb{E}[\nu_{2,h}|\mathcal{I}_h, f_h] \neq 0.$$

This generates a selection issue in the estimation, which frequently arises in moment inequality models and is discussed in Pakes, Porter, Ho, and Ishii (2015). We discuss how we overcome this selection issue at length in Section 5. Even though rebate heterogeneity is not formulary specific, it still has incentive effects on formulary design because rebates are per unit and multiply demand.

In addition to the structural error, we assume that there is measurement error, $\nu_{1j}(f_j)$, that is mean zero even conditional on formulary choices; $\mathbb{E}[\nu_{1j}(f_j)|\mathcal{I}_{h(j)}, f_{h(j)}] = 0$. Measurement error captures the difference between insurer j's expectation of its profits and our profit measure:

$$\mathcal{E}[\Pi_j(f_j, p_j, f_{-j}, p_{-j}, \gamma, \nu_{2,h(j)})|\mathcal{I}_{h(j)}] = \hat{\Pi}_j(f_j, p_j, f_{-j}, p_{-j}, r_j) + \nu_{1j}(f_j). \tag{11}$$

where we let $\mathcal{E}(\cdot|\mathcal{I}_h)$ denote the insurer h's expectation conditional on its information set. We discuss the implications of measurement error in Section 5 below.

The profit function for insurer h is the sum of the profits for plans owned by h, $J_h = \{j = 1, \dots J : h(j) = h\}$. Then insurer h's expectation of its profits is

$$\mathcal{E}\left[\Pi_h(f_h, p_h, f_{-h}, p_{-h}, \gamma, \nu_{2,h})|\mathcal{I}_h\right] = \sum_{j \in J_h} \mathcal{E}\left[\Pi_j(f_j, p_j, f_{-j}, p_{-j}, r_j)|\mathcal{I}_h\right], \tag{12}$$

where p_h are the premiums on insurer h's plans and f_{-h} and p_{-h} are the formularies and premiums of other insurers.

We assume that insurers simultaneously design their plans by choosing branded statin formulary tier placement, premiums, and all other plan characteristics to maximize their profits. A necessary condition implied by profit maximization is the following: If insurer h chooses branded statin formulary placement f_h instead of f_h', then the insurer must expect profits to be higher under f_h than f_h'. Thus, we have

$$\mathcal{E}(\Pi_h(f_h, p_h, f_{-h}, p_{-h}, \gamma, \nu_{2,h})|\mathcal{I}_h) \geq \mathcal{E}(\Pi_h(f_h', p_h, f_{-h}, p_{-h}, \gamma, \nu_{2,h})|\mathcal{I}_h) \quad \forall f_h'. \tag{13}$$

Inequality (13) is a direct implication of insurers' revealed preferences. We have suppressed many arguments of the profit function because they are held fixed on both sides of the inequality.[31] The key point is that given all of the other plan design choices that characterize the Nash equilibrium, it must be the case that changing the formulary weakly lowers insurer profits. This inequality is the key to our moment inequality strategy for estimating rebates, which we operationalize below.

5 Estimation

5.1 Demand

We estimate the model by simulating maximum statin utility and then using a Method of Simulated Moments estimator. We estimate the two sets of parameters, θ^j and θ^k, jointly using moments from beneficiaries' statin and plan choices.

Combining the statin and plan components of the model, we use Equations (5) and (6) to calculate the unconditional probability that beneficiary i of type t chooses statin k as

$$s_{ikt}(\theta^j, \theta^k) = \sum_{j=1}^{J_r} s_{ijt}(\theta^j, \theta^k) s_{ikt|j}(\theta^k). \tag{14}$$

First, we the use following set of moments based on unconditional statin choice probabilities

$$\mathbb{E}[(y_{ikt} - s_{ikt}(\theta^j, \theta^k)) z_{it}^k] = 0 \quad k \in \{1, ..., K\} \tag{15}$$

where y_{ikt} is an indicator that is one if beneficiary i of type t chooses statin k, $z_{it}^k = (1, a_{it}, i_{it})'$ is the vector of instruments. Here a_{it} denotes the age of beneficiary i, and i_{it} denotes the median income of beneficiary i (based on 5-digit ZIP codes). The second and third sets of moments equate the average age and income of beneficiaries who buy each type of statin in the data and the model. For each type, we obtain 15 moments from Equation (15).

[31] For example, insurer profits depend on deductibles and the formulary treatment of non-statin drugs.

Second, we use moments based on plan characteristics. In particular, we use the following sample moments:

$$\mathbb{E}[\zeta_{jt}(\theta^j, \theta^k) z_j^j] = 0, \tag{16}$$

where z_j^j is an $M^j \times 1$ vector consisting of the exogenous plan characteristics and the premium instrument for plan j. For each type, we obtain 39 moments from Equation (16), so we have 54 moments in total.[32] To account for premium endogeneity we follow the approach in Decarolis, Polyakova, and Ryan (2020) and Starc and Town (2020), and use a Hausman instrument, which measures the premium of similar plans offered by the same insurer in other Part D markets. This Hausman instrument is valid under the assumption that the difference in premiums for similar plans across Part D markets captures national-level costs, but is unrelated to market-specific demand.

In order to calculate sample moments based on Equations (15) and (16) at a candidate parameter vector (θ^j, θ^k), we need to calculate the statin and plan choice probabilities implied by the model. Due to the simultaneous estimation of statin and plan demand, there is no closed-form solution for $s_{ijt}(\theta^j, \theta^k)$, so we simulate it. Let s_{ijt}^{sim} denote the simulated values (details on the simulation are in Appendix C).

The stacked sample analogs of Equations (15) and (16) are given by

$$g_t(\theta^j, \theta^k) = \begin{bmatrix} \frac{1}{N_t} \sum_{t(i) \in t} (y_{ikt} - s_{ikt}^{sim}(\theta^s, \theta^p)) z_{it}^k \\ \frac{1}{J} \sum_{j=1}^{J} \zeta_{jt}(\theta^j, \theta^k) z_j^j \end{bmatrix},$$

where $J = \sum_{r=1}^{R} J_r$ is the total number of plans. To obtain ζ_{jt} we first calculate s_{ijt}^{sim} as described in Appendix C and then use the BLP contraction. We estimate the parameters by minimizing the following objective function

$$Q(\theta^j, \theta^k) = g_t(\theta^j, \theta^k)' W_t g_t(\theta^j, \theta^k). \tag{17}$$

Here $g_t(\theta^j, \theta^k)$ is a 54×1 vector and W_t is a 54×54 positive definite weight matrix. We calculate standard errors by bootstrapping our procedure 100 times.

5.2 Supply

We use necessary conditions implied by insurers' profit-maximizing branded statin formulary placement to construct a moment inequality estimator, which we use to recover unobserved rebates. We first develop intuition behind our approach to estimating rebates, and then work out simple inequalities for the special case of a single–plan insurer. We then discuss the

[32] Out of the 39 moments that we obtain from Equation (16), 29 correspond to region fixed effects.

general inequalities that we take to the data; many of the details are relegated to Appendix D.

To develop some intuition behind what drives our rebate estimates, reconsider Table 1, which shows the distribution of branded statin formulary placement for the plans in our data. Consider a rebate menu that offered 100% rebates for branded statins on the preferred tier. Under such a menu, insurers would face no cost from branded statins. Every insurer would place both Crestor and Lipitor on the preferred tier because that would increase plan demand and premium revenues without increasing costs. Given that Table 1 shows that only half of the plans in our data actually place both Crestor and Lipitor on the preferred tier, we know that many formulary inequalities based off Inequality (13) would be violated with a rebate menu that had preferred tier rebates of 100%, thus, we reject such a rebate menu. On the other extreme, consider a case with no (0%) rebates. Then insurers would face large costs from branded statins, and our profit functions imply that most plans would remove both Crestor and Lipitor from their formularies. However, only 4% of plans exclude both Crestor and Lipitor from their formularies; as a consequence, we reject the no rebate case.

The remainder of this section develops an approach to estimating rebates that accounts for selection effects due to rebate heterogeneity $\nu_{2,h}$ that is observed by insurers, but not by the econometrician. Inequality (13) is the basis for our moment inequality approach. However, as stated in Equation (11), we measure profits with error. After substituting Equations (11) and (12) into Inequality (13) we obtain

$$\sum_{j \in J_h} \left[\hat{\Pi}_j(f_j, p_j, f_{-j}, p_{-j}, r_j(f_j)) + \nu_{1j}(f_j) \right] \geq \sum_{j \in J_h} \left[\hat{\Pi}_j(f'_j, p_j, f_{-j}, p_{-j}, r_j(f_j)) + \nu_{1j}(f'_j) \right] \quad \forall f'_h \tag{18}$$

Inequality (18) holds for any vector of branded statin formularies f'_h that was not chosen, however we restrict attention to comparisons that change one plan formulary at a time. Suppose that insurer h chooses formulary f_j for plan j instead of f'_j. Then substituting Equations (8) and (9) into Inequality (18), and suppressing many function arguments, we have

$$\begin{aligned} \sum_{j \in J_h} \Delta A_j(f_j, f'_j) + \sum_{j \in J_h} \sum_{k \in K_j^b} \gamma_k(f_j) \Delta L_{jk}(f_j, f'_j) + \sum_{k \in K_j^b} (\gamma_k(f_j) - \gamma_k(f'_j)) L_{jk}(f'_j) \geq \\ - \sum_{j \in J_h} \sum_{k \in K_j^b} \Delta L_{jk}(f_j, f'_j) \nu_{2,h} - \sum_{j \in J_h} \Delta \nu_{1j}(f_j, f'_j). \end{aligned} \tag{19}$$

where the Δ operator is defined in terms of formulary differences, e.g., $\Delta A_j(f_j, f'_j) = A_j(f_j) - A_j(f'_j)$.

Inequality (19) can be rearranged to provide a bound on $\nu_{2,h}$. When we take sample averages across insurers, the measurement error term $\Delta\nu_{1j}(f_j, f_j')$ averages out. Thus, the direction of the bound depends on the sign of

$$\sum_{j \in J_h} \sum_{k \in K_j^b} \Delta L_{jk}(f_j, f_j').$$

Inequality (19) can be simplified and rearranged to give an intuitive bound on formulary-contingent rebates for single-plan insurers. Suppose that single-plan insurer h chooses f_h to cover Crestor on the preferred tier and exclude Lipitor. Compare profits with the case where f_h' excludes both branded statins. Then, ignoring measurement error, which averages to zero across insurers, Inequality (19) can be rearranged as

$$\Delta A_h(f_h, f_h') \leq r_{hc}(f_h) L_{hc}(f_h).$$

where L_{hc} is the cost of Crestor for insurer h at list price and r_{hc} is the rebate for placing Crestor on the preferred tier. This Inequality is much simpler than Inequality (19) because many terms are zero. This occurs for two reasons: first, we restrict attention to single–plan insurers, and second we focus on a comparison that involves excluding branded statins from the formulary, whence insurers do not cover any associated costs. The left-hand side of the inequality is the change in all non-rebate components of profits on plan h between formularies f_h and f_h'. The right-hand side of the inequality is the rebate payment. The inequality can be further rearranged to provide an intuitive lower bound on the Crestor rebate. If the Crestor rebate were very low, for example if there were no rebate, then excluding Crestor would look more enticing because the insurer would pay close to the full cost of Crestor. Since the insurer covered Crestor, we infer that the rebate cannot have been too small, hence we obtain a lower bound.

The intuition from the single plan insurer extends generally. Specifically, comparing a plan with branded statin formulary f_j to f_j' provides a lower bound on $\nu_{2,h}$ when the coverage of branded statins is reduced (e.g, moving from preferred to excluded) and provides an upper bound on $\nu_{2,h}$ when coverage is increased. The sign of these bounds follow from the properties of demand (negative own-price elasticities and positive cross-price elasticities for substitutes) and the details can be found in Appendix D. Specifically based off Inequality (19), for any

vector of mean rebates γ, define the following quantity

$$\mathcal{B}_j(\gamma, f_j, f_j') = -\Big(\sum_{j\in J_h}\sum_{k\in K_j^b}\Delta L_{jk}(f_j, f_j')\Big)^{-1}\times \tag{20}$$
$$\left(\sum_{j\in J_h}\Delta A_j(f_j, f_j') + \sum_{j\in J_h}\sum_{k\in K_j^b}\gamma(f_j)\Delta L_{jk}(f_j, f_j') + \sum_{k\in K_j^b}(\gamma_k(f_j) - \gamma_k(f_j'))L_{jk}(f_j')\right).$$

In two cases, we cannot calculate bounds from the data because there is no way to increase (decrease) coverage relative to the formulary that places both branded statins on the preferred tier (excluded from the formulary), so we follow Eizenberg (2014) and use support bounds. Fortunately, in our setting there are natural support bounds implied by the fact that rebates can be no less than 0% and no more than 100%. This observation can be combined with Equation (9) to obtain the following bounds based on the support of the rebates:

$$-\min_{k\in K_j^b}\{\gamma_k(f_j)\} \le \nu_{2,h} \le 1 - \max_{k\in K_j^b}\{\gamma_k(f_j)\}. \tag{21}$$

We combine the bounds from the data in Equation (20) with the support bounds in Inequality (21) for estimation.

The lower bound function is defined as follows:

$$\mathcal{L}_j(\gamma, f_j, f_j') = \begin{cases} \mathcal{B}_j(\gamma, f_j, f_j') & \text{if } f_j \text{ does not exclude both Crestor and Lipitor} \\ -\min_{k\in K_j^b}\{\gamma^k(f_j)\} & \text{else} \end{cases} \tag{22}$$

The upper bound function $\mathcal{U}_j(\gamma, f_j, f_j')$ is defined similarly. Then, for every plan j, at the true vector of rebates γ_0, either

$$\mathcal{L}_j(f_j, f_j', \gamma_0) + \Delta\nu_{1j}(f_j, f_j') \le \nu_{2,h} \le \mathcal{U}_j(f_j, f_j', \gamma_0) + \Delta\nu_{1j}(f_j, f_j') \tag{23}$$

or a very similar pair of inequalities holds.[33]

Because we can calculate $\mathcal{L}_j$ and $\mathcal{U}_j$ for every plan j, we can take averages that do not condition on formulary choices as in Eizenberg (2014). Since insurers vary in the number of plans they offer and $\nu_{2,h}$ is constant across plans within insurer, we follow Wollmann (2018) and weight our bounds by the inverse of the number of plans offered by each insurer. Thus we calculate sample moments that first average across plans within an insurer and then average across insurers; by Equation (10), at the true rebate parameter vector γ_0, we have

$$\mathbb{E}[\mathcal{L}_j(\gamma_0, f_j, f_j')|\mathcal{I}_h] \le \mathbb{E}[\nu_{2,h}|\mathcal{I}_h] = 0. \tag{24}$$

[33]Specifically, if plan j places both Crestor and Lipitor on the preferred tier, then there is no $\Delta\nu_{1j}(f_j, f_j')$ term in the upper bound. Likewise if plan j excludes both Crestor and Lipitor, then there is no $\Delta\nu_{1j}(f_j, f_j')$ term in the lower bound.

If z_j is in insurer $h(j)$'s information set and if w is a nonnegative function, then by the Law of Iterated Expectations

$$\mathbb{E}[\mathcal{L}_j(\gamma_0, f_j, f_j')w(z_j)] \leq 0. \tag{25}$$

With $m = 1, ..., M^r$ instruments z_j^m, we have M^r moments corresponding to Inequality (25). For all m, and any rebate vector γ, we define

$$Q_m^{\mathcal{L}}(\gamma) = \max\left\{\mathbb{E}[\mathcal{L}_j(\gamma, f_j, f_j')w(z_j^m)], 0\right\} \tag{26}$$

and the sample analog is

$$\hat{Q}_m^{\mathcal{L}}(\gamma) = \max\left\{\frac{1}{H}\sum_{h=1}^{H}\frac{1}{J_h}\sum_{j\in J_h}\mathcal{L}_j(\gamma, f_j, f_j')w(z_j^m), 0\right\}, \tag{27}$$

which measure the extent to which sample analog of Inequality (25) is violated for instrument m. Let $Q_m^{\mathcal{U}}$ and $\hat{Q}_m^{\mathcal{U}}$ be upper bound functions defined analogously to the lower bound functions. The identified set is defined as

$$R^I = \{\theta : Q_m^{\mathcal{L}}(\theta) = 0 \text{ and } Q_m^{\mathcal{U}}(\theta) = 0, m = 1, ...M^r\}. \tag{28}$$

To use Equation (26) for inference, we follow Chernozhukov, Chetverikov, and Kato (2019), which develops a procedure for inference with many moment inequalities. The method is applied separately at each candidate rebate vector and is particularly well suited for our model because the number of moment inequalities is not negligible relative to the sample size. The details of the estimation procedure are given in Appendix D.

For methodologically similar approaches to supply-side estimation, see Eizenberg (2014) and Wollmann (2018). Relative to those papers, in our setting, firms have many options for each decision and, due to the institutions, the parameters that we recover are per unit rebates as opposed to fixed costs. Both differences play important roles in our approach. Having many formulary configurations allows us to reduce our reliance on the support bounds that Eizenberg (2014) uses. Estimating per unit rebates allows us to model selection with firm specific (but not choice specific) structural errors while Wollmann (2018) used choice specific (but not firm specific) specific errors.

6 Estimation Results

6.1 Demand

Table 4 reports estimates from minimizing the simultaneous demand model objective given in Equation (17). Panel A reports statin utility parameters ($\hat{\theta}_t^j$). Panel B reports plan utility

parameters ($\hat{\theta}_t^k$). The model is estimated separately for each risk group, and the results are reported in the respective columns. Allowing the parameters to differ by risk group is one dimension by which the model accounts for individual heterogeneity.

Starting with Panel A, we find intuitive coefficients on out-of-pocket statin costs $\hat{\alpha}_t^{OOP}$. LIS beneficiaries, who by definition have low income, are most sensitive to statin out-of-pocket costs with a coefficient of 4.343. Among non-LIS beneficiaries, $\hat{\alpha}_t^{OOP}$ decreases by risk score tercile. Our estimates of mean drug quality show that Lipitor is preferred to Crestor by all risk types. Older beneficiaries have a smaller preference for branded statins. Excepting LIS beneficiaries, people in higher income ZIP codes prefer branded statins. The negative income coefficient for LIS beneficiaries may reflect that higher income LIS beneficiaries have higher cost sharing.

Turning to Panel B, for all risk types, we find a positive coefficient on maximized statin utility $\hat{\beta}_t^{v^*}$. As in Decarolis, Polyakova, and Ryan (2020), the magnitude of the premium coefficient decreases with risk score. Non-LIS beneficiaries prefer plans with lower deductibles, gap coverage, and more drugs covered by the formulary. The coefficient on plan age is positive, which is consistent with prior studies and with the observation that older plans have higher market share.

LIS beneficiaries have a substantially smaller premium coefficient. Combined with a large estimate for $\hat{\alpha}_t^{OOP}$, this is consistent with LIS beneficiaries choosing plans on the basis of formulary coverage as opposed to premiums. For LIS beneficiaries who know which drugs they will take, under existing Part D rules, formulary coverage can matter more for annual Part D costs (premiums plus out-of-pocket costs), than premiums. Since the Low Income Premium Subsidy Amount (LIPSA) covers a proportion of the base premium, the negative coefficient on gap coverage is intuitive because plans with gap coverage have supplemental premiums that are not covered by LIPSA.

We calculate the elasticities of demand for statins and plans. We report elasticities for non-LIS beneficiaries. We estimate that the (conditional on plan choice) own-price elasticities for Crestor and Lipitor with respect to annual OOP costs are -2.0 and -2.1 respectively. The (conditional) cross-price elasticities are .25 and .47 respectively.[34] We find that the elasticity of plan demand with respect to premiums among statin users is -2.7. This implies that statin users are less elastic than Part D beneficiaries overall.

[34]We focus on conditional elasticities (i.e., elasticities of $s_{ikt|j}$) because they have closed-form expressions in our model. Calculating unconditional statin demand elasticities requires calculating expensive numerical derivatives. The unconditional elasticities must be smaller than the conditional elasticities; unconditional elasticities allow for the possibility that plan choice changes while statin choice does not.

Table 4: Simultaneous Demand Estimates

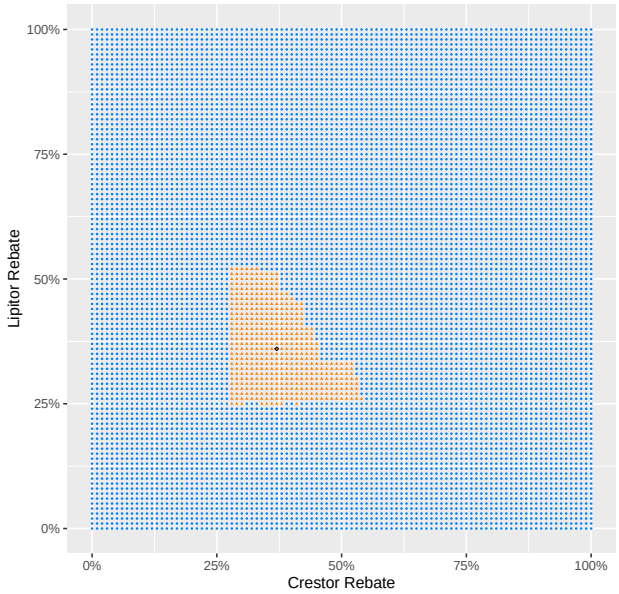
	Risk Type (2009 Risk Score Tercile)			
	Lowest	Middle	Highest	LIS
	(1)	(2)	(3)	(4)
	Panel A. $(\hat{\theta}_t^j)$			
OOP Price Sensitivity $\hat{\alpha}^{OOP}$	3.586	3.428	3.254	4.343
	(.345)	(.228)	(.151)	(.302)
Crestor Quality	1.231	1.295	1.020	1.531
	(.399)	(.125)	(.051)	(.075)
Lipitor Quality	2.067	2.022	1.680	2.062
	(.710)	(.119)	(.050)	(.078)
Age / 100 $\times \mathbb{1}$(Branded)	-2.175	-2.187	-1.518	-2.263
	(.327)	(.214)	(.081)	(.242)
log(Income) $\times \mathbb{1}$(Branded)	.218	.202	.153	-.910
	(.516)	(.267)	(.058)	(.391)
	Panel B. $(\hat{\theta}_t^k)$			
Maximized Statin Utility $\hat{\beta}^{v^*}$	3.512	3.484	3.239	3.674
	(.030)	(.037)	(.051)	(.033)
Premium	-.0826	-.0750	-.0690	-.0024
	(.021)	(.020)	(.019)	(.019)
Annual Deductible	-.0094	-.0091	-.0081	.0036
	(.0007)	(.0007)	(.0007)	(.0007)
Any gap coverage indicator	1.722	1.746	2.175	-.257
	(.818)	(.760)	(.737)	(.735)
Number of drugs covered	.0024	.0023	.0024	.0004
	(.0002)	(.0002)	(.0002)	(.0002)
Plan Age	.421	.38	.485	.191
	(.077)	(.072)	(.069)	(.069)

Notes: This table reports estimates from the simultaneous demand model described in Section 4.1. In particular, we minimize the objective in Equation (17) separately for each tercile of risk score and for LIS beneficiaries. All models also include the following components (coefficients not reported) in θ^j: region fixed effects, an enhanced plan indicator, the number of drugs on the generic tier, and the number of drugs on the preferred tier.

6.2 Supply

Figure 1 plots the 90% confidence set for the mean rebates paid to insurers when they place branded statins on the preferred tier. The figure shows that we estimate rebates that are bounded away from 0% and 100%. The set is small; we reject 9717 out of the 10201 rebate parameter vectors that we consider. The mean rebates for parameter vectors that are not rejected is $(37\%, 36\%)$, which we use as a reference point in our counterfactuals below.

Figure 1: Estimates of Branded Statin Rebates on Preferred Tier



Notes: This figure plots the 90% confidence set for the mean rebates paid to insurers when they place branded statins on the preferred tier. Blue circles are rejected from the confidence set. Orange triangles cannot be rejected. The open black diamond corresponds to the midpoint of the rebate parameter vectors in the confidence set. We estimate rebates on a grid from 0% to 100% in 1% increments. We reject 9717 of the 10201 rebate parameters.

Table 5 reports the projection of our 90% confidence set onto single dimensional rebates. The projected confidence set for AstraZeneca's Crestor is $[28\%, 54\%]$ while for Pfizer's Lipitor it is $[25\%, 52\%]$.[35] Despite the fact that Lipitor was the incumbent branded statin with a big market share advantage (21% compared to 9% for Crestor), the confidence sets are symmetric. However, we cannot rule out asymmetric rebates either.[36]

While the rebates paid to Part D insurers are secret, CMS does observe them and reports

[35]The rebates that we estimate are the rebates the insurers receive. Manufacturers pay slightly larger rebates because PBMs keep a wedge. Our approach of estimating rebates based off insurer decisions is not informative about the size of the wedge. Our counterfactuals focus on consumer surplus and insurer profits,

Table 5: Branded Statin Rebate Estimates

	Confidence Set
Crestor Preferred	[28%, 54%]
Lipitor Preferred	[25%, 52%]
Number of insurers	45
Number of plans	431

Notes: This table reports the projection of our 90% confidence sets for estimated branded statin rebates.

on the aggregate level annually. In 2010, the average annual Part D rebate was 11.3%.[37] By 2014, the average annual Part D rebate was 14.3%. Moreover, in 2014, CMS released the only summary of Part D rebates using total branded drug costs as the denominator (as opposed to all drug costs). Total Part D rebates accounted for 17.5% of branded drug costs in 2014.[38] Maintaining the same ratio as in 2014, we calculate that Part D rebates were 13.8% of branded drug costs in 2010. Thus, we estimate that branded statin rebates were larger than average Part D branded drug rebates in 2010. The same 2014 CMS data reports that the average annual branded cardiovascular drug rebates in 2014 was 26.3% (unfortunately, this is the most disaggregated level of rebates in the CMS report). Using the same rescaling as before, we calculate that branded cardiovascular drug rebates in 2010 were around 20.7%. Thus we estimate that branded statin rebates were substantially larger than other cardiovascular drugs.

Three facts may account for the large rebates for branded statins relative to all branded cardiovascular drugs. First, averaging over all branded cardiovascular drugs captures some drugs that are unlikely to have any rebate (e.g., on patent drugs with no competitors in their class) and these zeros will reduce the average. Second, in 2010 statins were a therapeutic class with exactly two competing branded manufacturers—moreover there was a sharp asymmetry with the dominant blockbuster drug Lipitor having more than twice the market share of Crestor—and this may have encouraged the branded statin manufacturers to offer large rebates in order to obtain a good formulary position. Third, as mentioned previously, in

and for these quantities, the rebate that insurers receive is the relevant rebate.

[36]SSRHealth data for 2010 estimates average US total discounts for Crestor and Lipitor of 32.7% and 40.6% respectively. While, our set estimates include these points, it is important to recognize that these net prices reflect rebates paid to insurers as well as other reductions (such as rebates paid to wholesalers) and are not formulary contingent.

[37]Table IV.B8 of 2018 Trustees of Medicare Annual Report.

[38]CMS 2014 Manufacturer Rebate Summary Report.

2010 statins were the largest therapeutic class of drugs covered on Part D (by number of fills) and thus market size may have an effect on the rebates that are offered.

SSRHealth provides another external data source (used in Kakani, Chernew, and Chandra (2020) and Feng and Maini (2021)) that can be compared to our estimates. In 2010, SSRHealth reports an average net-to-gross discount of 40.58% for Crestor and 32.70% for Lipitor. These net-to-gross discounts are inside our confidence set. However, SSRHealth net-to-gross discounts could be lower than our formulary-contingent rebates because it averages across all prescriptions filled (many of which are for non-preferred formulary placement and receive little or no rebate). On the other hand, SSRHealth net-to-gross discounts could be larger than our formulary-contingent rebates because they include direct discounts to wholesalers and payments to pharmacies.

The rebate estimates presented in this section are a key starting point for our counterfactual analyses. Mean branded statin rebates were estimated based off revealed preferences of insurers in a way that is agnostic about the rebate setting model and is robust to unobserved heterogeneity in rebates. The counterfactuals in the next section consider the consequences of different rebate menus on insurer formulary choice, beneficiary welfare, and firm profits.

7 Counterfactuals

Our counterfactuals quantify the effects of changing branded statin rebates on consumer surplus, formularies, and insurer profits. There is substantial policy interest in changing Part D rebate policy and in reducing drug prices more generally. These policies will have direct first-order effects on the costs that insurers face under different formularies. Thus understanding how rebates affect equilibrium formularies is an important question that we quantify for the first time. We first describe our counterfactual methodology for calculating formulary equilibria as a function of branded statin rebates. Then we present the counterfactual results.

7.1 Counterfactual Methodology

We present counterfactuals under two different assumptions: a model with (i) fixed premiums and (ii) endogeneous premiums. Due to computational complexity of endogeneizing both formularies and premiums, our main counterfactual analyses hold premium fixed. However, we present some results with endogenous premiums to understand its effect on consumer surplus.

A Nash equilibrium of the formulary game involves each insurer choosing the formularies for their plans optimally given the formularies of their competitors. In terms of the profit function in Equation (12), a Nash equilibrium obtains if every insurer h solves

$$\max_{f_h} \mathcal{E}\left[\Pi_h(f_h, p_h, f_{-h}, p_{-h}, \gamma, \nu_{2,h})|\mathcal{I}_h\right]. \tag{29}$$

We are interested in policy reforms where all insurers receive the same rebates and then set their formularies.[39,40]

There are two important assumptions implicit in Equation (29). First, we only allow insurers to change their formularies as branded statin rebates change, i.e., we hold fixed other plan characteristics including premiums and the level of copays (or coinsurance) associated with each formulary tier. Thus, our paper is complementary to many papers that allow premiums to change, but keep formularies and other plan characteristics fixed. Changing rebates for any one class of branded drugs is unlikely to have a large effect on premiums or the level of copays associated with each formulary tier.[41] Second, we hold list prices fixed in all of our counterfactuals. Relaxing this assumption is difficult to the extent that list prices are set based on profits earned by manufacturers across insurance market segments (e.g., Medicare, Medicaid, and commercial). This assumption is stronger for larger changes in rebates. However, many of our counterfactuals consider different rebate menus that are either within or near our estimated set of rebates (which are all consistent with the status quo list prices in terms of our supply-side model of rebates).

Because of the large number of market configurations, calculating the Nash equilibrium for all plans is computationally intractable.[42] Thus, we assume that the formulary choice for all small plans is fixed; a similar approach is used in Eizenberg (2014). By changing their formularies, insurers can differentiate their plans, attract consumers who value high rebate statins, and steer existing enrollees towards high rebate statins. By modeling the formulary

[39]Thus, in these counterfactuals there is no rebate heterogeneity and $\nu_{2,h} = 0$.

[40]Two examples include prohibiting manufacturers paying insurers rebates and government-negotiated rebates.

[41]Statins, which were the largest therapeutic class of drugs by fills in 2010, only comprise around 5% of insurer costs. (To calculate this number, we applied an average branded rebate of 13.8% to all branded drugs (based off calculations in Section 6).) As a consequence, changing branded statin rebates is unlikely to lead insurers to make large changes to the copays for each formulary tier because those copays are set on the basis of thousands of drugs that account for the remaining 95% of costs. By a similar logic, changing branded statin rebates is unlikely to have a large effect on premiums.

[42]The mean number of plans per region (after our sample restrictions) is 14. Thus there are roughly 9^{14} possible market configurations per region, so simulating demand for every possible market configuration is infeasible.

choices of large plans, we account for the demand responses of 62% of beneficiaries on average (unweighted, across markets) while keeping the number of formulary configurations that we need to simulate tractable.[43]

While our main counterfactual analyses hold premiums fixed, we report results from some calculations intended to gauge the magnitude of the effect of rebaters on premiums. Specifically, for half-a-dozen formulary configurations, we solve for the fixed point of the premium first-order condition within each Part D region.[44] We follow the literature endogenizing premiums in Part D and assume that insurers set premiums on the basis of their non-LIS demand (e.g., Starc and Town (2020)).[45]

7.2 Counterfactual Results

In our counterfactuals, we focus on understanding how formularies and consumer surplus would change under various rebate menus. We vary branded statin rebates for preferred formulary placement from 0% to 100% (in 5% increments) and assume that there is no rebate for being on the non-preferred tier. There is no guarantee that the profit functions that we estimate support a unique, pure-strategy Nash equilibrium at every counterfactual rebate menu that we consider. We find a unique equilibrium for 429 out of our 441 conterfactuals. For the remaining 12 cases, we do not find any pure strategy equilibria and use linear interpolation to quantify outcomes in these counterfactuals; however, given the game that we analyze has a finite number of players and a finite strategy space, there exists a mixed strategy equilibrium.

7.2.1 Consumer Surplus Effects of Branded Rebates

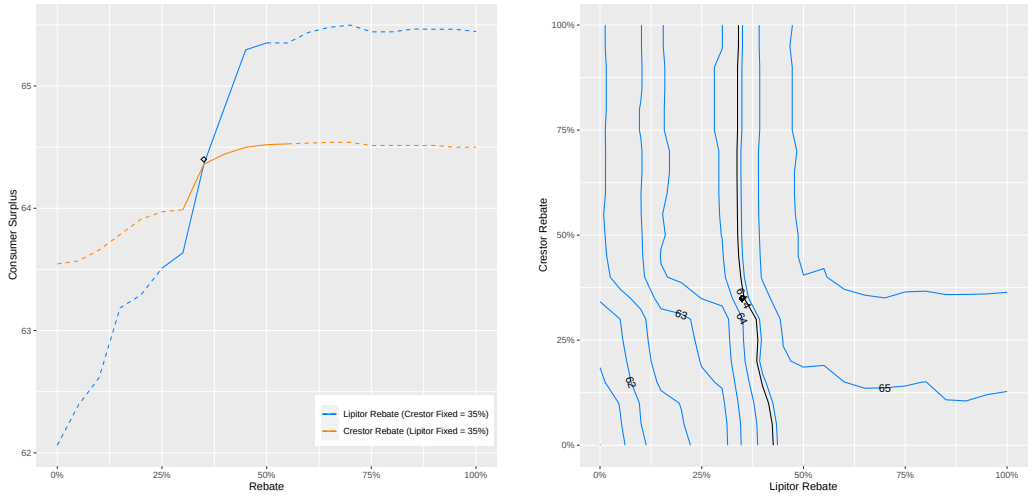
Our first set of counterfactual results focus on how changing rebates for different drugs affects consumer surplus. Figure 2 illustrates that the effect of rebates on consumer surplus are subtle. In Panel (a), we show how consumer surplus changes in each branded statin rebate (holding fixed the competing branded statin rebate). The black diamond at 35%

[43] Appendix Table 3 reports the mean, minimum, and maximum cumulative market share across all Part D markets as a different number of the largest plans in each market are accumulated. We allow the 4 largest plans in each region to change their branded statin formulary placement in response to rebates.

[44] Because plan demand from non-statin users is important for premium setting, we estimate plan non-statin demand solely for the purpose of these calculations. The estimates are in Appendix Table E.

[45] Since LIS beneficiaries are relatively premium inelastic and comprise a substantial proportion of the Part D market and because the LIS benchmark may meaningfully constrain Part D premiums, these premium calculations should be interpreted cautiously, however we believe that they provide intuitive and useful guidance on how changing rebates could affect premiums.

Figure 2: The Effect of Each Statin Rebate on Consumer Surplus



(a) Single Rebate Changes

(b) Consumer Surplus Isocurves

(for both Crestor and Lipitor) are close to the mean rebates in our estimated set. As Lipitor rebates increase from 35% to 50% consumer surplus increases by 1.53%. In contrast, increasing Crestor rebates beyond 35% has no effect on consumer surplus. To investigate this further, we plot consumer surplus isocurves in rebate space in Panel (b). When Crestor rebates are above 35%, the consumer surplus isocurves are vertical. Thus increasing Crestor rebates beyond 35% does not increase consumer surplus at any level of Lipitor rebates. Panel (b) also shows that the effect of rebates on consumer surplus exhibits diminishing returns because the space between isocurves increases as rebates get larger.

Figure 2, Panel (a) is consistent with the idea that current system in Part D, which has insurers negotiated rebates with drug manufacturers, works well for the setting of branded statins (where there are two competing branded drugs and several generic alternatives). To see this clearly, each of the lines in Figure 2, Panel (a) has a dashed component and a solid component. The solid component indicates the rebates that are inside our estimated confidence set (e.g., orange triangles in Figure 1) while the dashed component corresponds to rebates outside our estimated confidence set. The dashed lines for both series essentially reach the maximum of each respective series. This means that our estimated confidence set is consistent with the status quo maximizing consumer surplus in the market for statins. Since rebates in our model are set identified, we report the upper and lower bound on the share of possible consumer surplus that is consistent with our estimates. For Crestor, our estimates are consistent with the status quo achieving between 44–99% of available consumer

surplus, while for Lipitor our estimates are consistent with the status quo achieving between 42–96% of available consumer surplus.

The effect of rebates on consumer surplus is nonlinear and heterogeneous across drugs. Policy reform that results in uniform rebates, such as prohibiting drug manufacturers from paying Part D insurers rebates, is likely to have heterogeneous and possibly unintended consequences. To understand why there are such heterogeneous effects of rebates on consumer surplus, we quantify how rebates affect formularies.

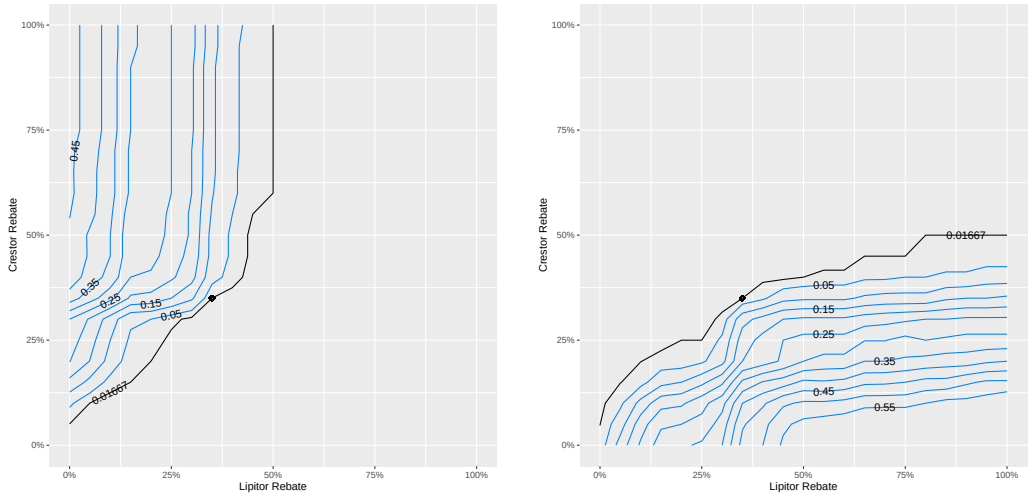
7.2.2 Formulary Effects of Branded Rebates

Panel (a) of Figure 3 shows that the share of large insurers with Crestor on the preferred tier and excluding Lipitor, intuitively, is increasing in the Crestor rebate and decreasing in the Lipitor rebate. Rebates have a large effect on formulary design. Near the mean of our estimated rebates (35% for each statin), the share of preferred/excluded plans is less than 2%. In contrast, increasing the Crestor rebate to 40% and decreasing the Lipitor rebate to 30% changes the share of preferred/excluded plans to more than 15%. This large effect on insurers' formularies is induced through a small change of rebates (that stays within our estimated set of rebates), which suggests that this result is likely robust to endogenizing manufacturer list prices. The insurers that choose preferred/excluded formularies benefit from higher Crestor rebates through two channels; they select Crestor users and they steer statin users to Crestor. Panel (b) shows a symmetric situation for the share of plans with Lipitor on the preferred tier and excluding Crestor. Figures for other formulary configurations and the market shares of each branded statin are in Appendix Figures 2 and 3.

Table 6, Panel A, shows large differences in the share of plans choosing each formulary configuration across several rebate menus. In Column (1), which corresponds to the mean rebates from our set estimates, 90% of insurer formularies place Crestor and Lipitor on the same tier. In Column (2), increasing the Crestor rebate to 50% results in a 2 percentage point *decrease in Lipitor* being placed on the preferred tier. Even though, the Lipitor rebate was not changed, increasing the Crestor rebate prompts insurers to try to steer people away from Lipitor and thus some Lipitor users on are hurt by the increase in Crestor rebates; we discuss this point further below.

When Lipitor rebates increase to 50%, in Column (3), the share of plans with Lipitor on the preferred tier increases (from 75% to 93%). Since the rebate menus in Columns (1)-(3) are all consistent with our set estimates of rebates, these results are likely to be robust to endogenizing list prices. In Column (5), we consider prohibiting manufacturers paying Part

Figure 3: The Effect of Statin Rebates on Formularies



(a) Preferred/Excluded Share

(b) Excluded/Preferred Share

D insurers any rebates. We find that the share of plans placing both Crestor and Lipitor on the preferred tier would fall by 66 percentage points to 6% (from all drugs on the subset of beneficiaries who use statins). Even small reductions in rebates, as shown in Column (6), which reports a counterfactual for the smallest rebates in our confidence set, shows large reductions in preferred tier placement of branded statins.

7.2.3 Other Effects of Branded Statin Rebates

Branded statin rebates directly affect insurance costs and hence formulary design. However, the ultimate factors that determine the value of Part D insurance to beneficiaries are their bottom line cost-sharing and premiums.

Table 6, Panel B, reports the effect of rebates on beneficiary cost-sharing, consumer surplus, and insurer profits. All of the effects on beneficiaries are mediated by the formulary effects discussed in the previous subsection because rebates have no direct effect on beneficiaries. In Columns (2), (3), and (4), we explore the effect of increasing rebates on consumer cost-sharing. These numbers are relevant to proposals for government-negotiated Part D rebates.[46] Increasing either the Crestor or Lipitor rebate from 35% to 50% results in a 7% or 8% reduction in consumer cost-sharing for the respective branded statin. In contrast, removing branded statin rebates in Column (5) results in large increases in branded statin

[46]E.g., The Lower Drug Costs Now Act aims to increase rebates for some drugs with government negotiation.

cost-sharing in excess of 50%.[47] Column (6) shows that even modest reductions in branded statin rebates lead to large increases in beneficiary cost sharing.

Table 6: Counterfactual Results

	(1)	(2)	(3)	(4)	(5)	(6)
Crestor Rebate	0.35	0.50	0.35	0.50	0.00	0.30
Lipitor Rebate	0.35	0.35	0.50	0.50	0.00	0.25
A. Formulary Effects						
Crestor Tier/Lipitor Tier						
Preferred/Preferred	0.72	0.73	0.78	0.92	0.06	0.55
Non-Preferred/Preferred	0.01	0.00	0.06	0.02	0.03	0.00
Excluded/Preferred	0.02	0.00	0.09	0.00	0.03	0.00
Preferred/Non-Preferred	0.05	0.11	0.00	0.00	0.00	0.03
Non-Preferred/Non-Preferred	0.10	0.06	0.05	0.05	0.29	0.17
Excluded/Non-Preferred	0.00	0.00	0.00	0.00	0.13	0.01
Preferred/Excluded	0.02	0.08	0.00	0.00	0.00	0.03
Non-Preferred/Excluded	0.00	0.00	0.00	0.00	0.01	0.00
Excluded/Excluded	0.08	0.02	0.02	0.02	0.45	0.22
B. Other Counterfactual Effects						
% Change in Crestor cost-sharing	–	-7.38%	1.61%	-7.09%	59.25%	19.77%
% Chang in Lipitor cost-sharing	–	1.02%	-8.75%	-8.75%	50.44%	22.59%
% Change in Consumer Surplus	–	0.24%	1.53%	1.80%	-5.21%	-1.92%
% Change in Insurer Profits	–	2.81%	4.11%	6.72%	-10.25%	-2.56%
Crestor Market Share	0.08	0.08	0.08	0.08	0.06	0.08
Lipitor Market Share	0.22	0.22	0.23	0.23	0.15	0.22
C. Premium Effects						
% Change in Premiums	–	-0.89%	2.02%	2.80%	5.63%	-2.57%

Notes: Each column reports counterfactual outcomes for the given pair of rebates for preferred placement. The share of plans choosing each formulary configuration for Crestor and Lipitor is shown in the first 9 rows, e.g., Preferred/Excluded refers to plans that place Crestor on the preferred tier and exclude Lipitor from the formulary. As discussed in the text, we report the premium calculations based off insurer profits functions ignoring demand from LIS beneficiaries (following the literature). Thus, we separate out the premium effects into a separate panel.

[47] The effect would be even larger if it were not for the donut hole, which results in many beneficiaries in 2010 facing high cost-sharing even when branded statins are on the preferred tier.

Changes in cost-sharing result in changes in consumer surplus. Two subtle insights emerge from our analysis. First, increases in branded statin rebates reduce cost sharing, but they have almost no effect on branded statin utilization. The reason for the lack of a utilization effect is that beneficiaries already have many options for plans with preferred tier branded statins in the status quo. As a consequence, increasing rebates for branded statins only results in small increases in consumer surplus because all of the consumer surplus effects are coming from lower prices—as opposed to increased utilization of branded statins. In contrast, removing branded statin rebates results in a Crestor utilization falling by 25% and Lipitor utilization falling by 35% and consumer surplus falling by 5.21%. Second, increasing Crestor rebates alone (to 50%) only increases consumer surplus by 0.24% and part of the explanation for this small average effect on consumer surplus is that some Lipitor users face *higher Liptor prices* when Crestor rebates increase because Lipitor preferred tier placement falls.

7.2.4 Premium Effects of Branded Statin Rebates

Table 6, Panel C, presents results on how branded statin rebates affect premiums in Part D. First, changes in branded statin rebates have small effects on premiums relative to their effects on cost-sharing, e.g., when rebates are removed, premiums increase by 5.63% and thus the change in premiums is a full order of magnitude smaller than the change in cost-sharing. Second, premiums always move in the the same direction as Lipitor preferred tier formulary placement. When rebates for Lipitor increase, plans take advantage of low cost Lipitor by moving Lipitor on to the preferred tier. This increases the quality of plans for statin users and thus plans increase their premiums.

7.2.5 Comparison With Canada

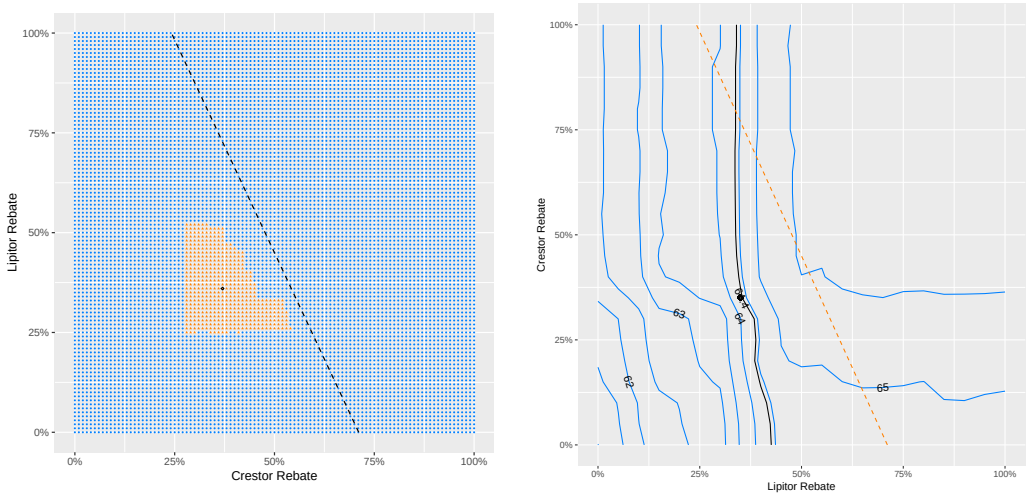
One widely-considered policy proposal is to impose a most-favored-nation clause that limits the prices that Part D insurers pay on the basis of prices paid in other countries. In Figure 4, we benchmark our results against the case where Part D insurers obtained rebates large enough to equate Part D prices with those paid by provincial Canadian governments.[48] If the rebate for both Crestor and Lipitor were 48.4%, then Part D insurers that place branded statins on the preferred tier would face the same mean cost for branded statins as the

[48] We use data on the mean price of branded statins in Canada from Dubois, Gandhi, and Vasserman (2019) to calculate the rebates that Part D insurers would need to receive, for preferred placement of branded statins, in order to match prices in Canada (details are in Appendix F).

Canadian government.

In Panel (a) of Figure 4, the dashed black line shows the pairs of rebates that are consistent with Part D insurers obtaining the same mean branded statin prices as Canada (we use a line because we only have data on mean branded statin prices in Canada). Since the dashed black line does not intersect our estimated set, Part D insurers paid higher prices than Canada even with rebates for preferred placement. This comparison, of the price paid by insurers who place branded statins on the preferred tier, could not be made using data on average net prices such as those used in Kakani, Chernew, and Chandra (2020) and are only possible because we estimate formulary-contingent rebates. In Panel (b) of Figure 4, if all insurers could obtain prices as low as those in Canada by placing branded statins on the preferred tier, then consumer surplus would be on the orange dashed line. Comparing Columns (1) and (4) in Table 6, we see consumer surplus under Canadian prices increases by 1.8%.

Figure 4: Comparison to Canada



(a) Rebates and Prices

(b) Consumer Surplus

8 Concluding Remarks

In this paper, we estimate a simultaneous model of Medicare Part D plan demand and statin demand for the population of statin users. We use these demand estimates to construct insurer profit functions and model insurers' formulary placement of branded statins. Insurers account for endogenous selection of beneficiaries into plans and the implied effect on the distribution of drug costs that they face. We use our model of formulary placement to

quantify how changes in branded statin rebates would affect branded statin formulary design, statin demand, plan demand, consumer surplus, and insurer profits.

We use revealed preference arguments operationalized with moment inequalities to partially identify unobserved formulary-contingent rebates. We estimate that rebates for preferred placement of branded statins are between 25–54%. We show that the status quo, with private insurers negotiating rebates, works well from a consumer surplus perspective in the market for statins, which has two competing branded and drugs and several generic options (however, this result may not hold for other market structures). Increasing rebates can create winners and losers due to endogenous formulary design; we show that relative to our estimated rebates, increasing only Crestor rebates results in more plans advantaging Crestor on the formulary and fewer plans advantaging Lipitor. This creates winners (Crestor users) and losers (Lipitor users) and no net effect on consumer surplus. This paper contributes to our understanding on how policy would affect aspects of insurance plan design beyond premiums. We provide the first evidence on how formularies would endogenously respond to changing rebates. Changing rebates has important, but subtle effects on formulary design.

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Online Appendix

Appendix A Annual OOP Costs and the SBS

We assume that beneficiaries consider the effect of statin choice on their total annual drug spending. Thus we define the price of Crestor as the difference between annual drug spending when Crestor is chosen and when no statin is chosen.

Before we describe the calculation of annual OOP costs, we need to describe the SBS and the different coverage regions of Part D plans. Panel (a) of Appendix Figure 1 shows the SBS in 2010. The y-axis shows the annual out-of-pocket (OOP) cost to a beneficiary as a function of the annual list price of drugs (x-axis). The marginal cost of filling a prescription for beneficiaries who choose plans that use the SBS is a piecewise constant function (given by the slope of the function in Panel (a) of Appendix Figure 1). In the deductible region, beneficiaries pay 100% of the list price for any prescriptions that they fill. In the initial coverage region, beneficiaries pay 25% of the list price of drugs. In the coverage gap, beneficiaries once again pay 100% of the list price of drugs. Finally, for beneficiaries whose annual OOP costs exceed \$4,880 (which we translate to average annual list prices in the figure), the marginal cost of filling further prescriptions is 5% of the list price. Despite the fact that more than 90% of plans are tiered and hence are more complicated than the SBS, all Part D plans have nonlinear pricing based on the same coverage regions although some plans remove the deductible or provide some cost-sharing in the coverage gap.

Because of the nonlinear price schedule in Medicare Part D, the effect of different statin choices on total annual drug spending varies across beneficiaries based on how much they spend on non-statin drugs. Given the institutions, the annual OOP cost $OOP_{ijkt}(f_j)$ for beneficiary i of type t choosing statin k on plan j can be written as

$$OOP_{ijkt}(f_j) = oop_{jk}(g^{ns}_{ijkt}(h_{it}, \eta_{it}, f_j). \tag{30}$$

oop_{jk} is a known function (of plan cost-sharing rules) that maps non-statin drug spending g^{ns}_{ijkt} and plan formularies f_j (which, with abuse of notation, in this section refers to the tier placment of all drugs and the associated copays and coinsurance rates) into annual OOP costs for statins OOP_{ijkt}. non-statin drug spending g^{ns}_{ijkt} depends on beneficiary health h_{it} and preferences η_{it}. We observe g^{ns}_{ijkt} for the actual statin choices that beneficiaries make, however, because of the nonlinear cost-sharing schedule in Part D, we do not observe g^{ns}_{ijkt} for statin choices that beneficiaries could have made. In order to calculate g^{ns}_{ijkt} for every statin,

we assume no moral hazard on non-statin drugs.[49] This means that when we calculate the cost of statins on each plan, we hold fixed the non-statin drug choices of each beneficiary. In the context of plan demand, this assumption has been used by many papers following the seminal paper by Abaluck and Gruber (2011).

Panel (b) of Appendix Figure 1 illustrates an important source of beneficiary-level variation in statin prices in our paper.(where statin prices are defined in terms of total annual OOP costs). The figure shows the relationship between the total annual OOP cost of drugs (the y-axis) and the annual list price of a statin (the x-axis) for beneficiaries who spend different amounts on other (non-statin) drugs. For beneficiaries who do not buy any non-statin drugs, annual OOP costs are given by the solid line, which exactly corresponds to the schedule in Panel (a). Importantly, changes in non-statin drug spending shift the nonlinear schedule to the left by an amount determined from the known function oop_{jk}; the dashed lines show the schedules when annual spending on other drugs is \$250 or \$1,000. The effect of non-statin drug spending on statin prices is nonlinear. With moderate non-statin drug spending, branded statin purchases may fall into the coverage gap region making branded statins very expensive. In contrast, beneficiaries with very high non-statin drug spending may reach the catastrophic coverage region, when the marginal cost of branded statins is relatively low.

Annual OOP costs $OOP_{ijkt}(f_j)$ raise endogeneity concerns in our model if the preferences that determine non-statin drug spending η_{it} are correlated with preferences for statins ε_{ikt} conditional on the control variables in our model. We assume that the individual-level heterogeneity that we specify in our model captures the component of η_{it} that is correlated with ε_{ikt}.

[49] We also assume that beneficiaries would not change the timing of their drug purchases if they changed statins.

Appendix B Revenue and Cost Accounting

B.1 Revenues

As discussed in the text, we follow the CMS Medical Loss Ratio (MLR) reporting format and separate plan revenue into 4 components: beneficiary premiums, direct subsidies, federal reinsurance, and Low Income Premium Subsidy Amounts (LIPSA), but we ignore risk corridors, which account for less than 1% of revenue in the MLR Public Use Files.

The revenue for plan j from enrolling beneficiary i is

$$R_{ij}(p_j) = p_j + p_j^{LIPSA} + SUB_{ij} + RE_{ij} \tag{31}$$

where p_j is the annual premium paid on plan j, p_j^{LIPSA} is the Low Income Premium Subsidy Amounts, SUB_{ij} is the direct subsidy payments to plan j that is risk adjusted on the basis of individual i's historical medical utilization, RE_{ij} are reinsurance payments to plan j for beneficiary i that cover most of the cost for drug fills made after the catastrophic coverage threshold has been reached.[50]

For each plan j, and for each branded statin formulary arrangement f_j, we calculate each of the following sources of annual revenue:

1. *Beneficiary premiums* (p_j). Beneficiaries must pay a monthly premium for basic drug coverage on their plan and also any supplemental premium for "enhanced" drug coverage. The monthly premium for basic drug coverage for a plan is equal to the base premium plus the difference between the plan's bid and the national average bid amount. We observe the premium for basic coverage and supplemental coverage in our data.

2. *LIPSA* (p_j^{LIPSA}). The government subsidizes premiums for LIS beneficiaries (the subsidy can cover up to 100% of the premium and depends on the beneficiaries' cost-sharing group, which is a function of income and is observed in our data). We observe the size of LIPSA payments for each cost-sharing group on every plan.

3. *Direct subsidy* (SUB_{ij}). The government pays each plan a monthly direct subsidy per enrollee. For each one of a plan's enrollees, the government pays the plan a monthly amount equal to the product of the plan's bid and the enrollee's risk score less the beneficiary premium (and LIPSA if applicable):

$$SUB_{ij} = CCS_i \cdot BID_j - (p_j + p_j^{LIPSA}). \tag{32}$$

[50] The catastrophic coverage region started once beneficiaries spent more than $4,880 in annual out-of-pocket costs in 2010

We use the CMS risk score software to calculate each beneficiary's risk score based off their claims data. We observe plan bids (see below).

4. *Federal Reinsurance* (RE_{ij}) The government also pays plans for 80% of the cost of drugs that enrollees purchase once they reach their annual out-of-pocket threshold (net of point-of-sale pharmacy discounts and manufacturer rebates). Let CC_{ijd} denote the total cost of drugs purchased beyond the out-of-pocket threshold (net of point-of-sale discounts) by beneficiary i on plan j on drug type d ($d \in \mathcal{D} = \{K_j, \mathcal{G}_j, \mathcal{B}_j\}$ where plan j covers statins, K_j , non-statin generics, $\mathcal{G}_j$, and branded non-statin drugs, $\mathcal{B}_j$).

$$\begin{aligned} RE_{ij}(f_j, \theta^k, \gamma) = .8 \cdot \sum_{k \in F_j^b} (1-\gamma) \cdot CC_{ikj} \cdot s_{ik|j}(f_j, \theta^k) \\ + .8 \cdot CC_{ij\mathcal{G}_j} \\ + .8 \cdot (1-\gamma^{\mathcal{B}}) \cdot CC_{ij\mathcal{B}_j}. \end{aligned} \tag{33}$$

We assume that generic manufacturer rebates are zero (including generic statins). Based off data from CMS and the Medicare Trustees Reports, we assume that the average manufacturer rebate for branded non-statin drugs, $\gamma^{\mathcal{B}}$, is 13.8%.[51] Finally, we estimate statin rebates as a function of formularies. Thus, we quantify revenues due to federal reinsurance for any counterfactual set of plan choices.

Several of the components of plan revenue depend on bids that plans make to CMS for each Part D plan that they want to offer. A plan's bid specifies the monthly revenue requirement that the plan needs to cover its costs (for basic coverage) and a profit margin. A plan's premium for basic drug coverage is equal to the bid minus the base premium. We observe each plan's premium for basic coverage and we calculate the base premium using public data.[52] Thus we observe plan bids.

[51] In 2014, the mean branded drug rebate was 17.5% according to the CMS Manufacturer Rebate Summary Report. In 2010 and 2014, overall manufacturer rebates were, respectively, 11.3% and 14.3% based off the Medicare Trustees Reports. Rescaling gives $13.8\% = 17.5\% \times 11.3\%/14.3\%$.

[52] The base premium is calculated as a proportion of the national average bid amount (weighted by lagged enrollment). In 2010, the national average bid amount was \$88.34 and the base premium was \$31.94.

B.2 Costs

The expected cost to plan j from enrolling beneficiary i of type t is

$$\begin{aligned} C_{ij}(f_j, \theta_t^j, r_j) &= \sum_{k \in K_j} s_{ikt|j}(f_j, \theta_t^k) \cdot ([1 - r_{jk}(f_j)] \cdot TC_{jk} - OOP_{ijkt}(f_j) - LICSA_{ijkt}) + C_{ijt}^{NS} \\ &= \sum_{k \in K_j} (f_j, \theta_t^k) \cdot C_{ijk}(f_j, r_{jk}(f_j)) + C_{ijt}^{NS} \end{aligned} \tag{34}$$

C_{ijk} is the cost to plan j from beneficiary i's choosing statin k, C_i^{NS} is the cost that plan j incurs to cover beneficiary i's non-statin drugs. The second line defines C_{ijk} as the total cost of statins (TC_{jk}), net of rebates, less annual OOP contributions, and LICSA payments.

The expected costs for plan j are given by the sum of the costs of the enrollees that endogenously select into plan j. Plan j's expected costs depend on demand for the plan as well as per enrollee costs. Critically, these costs depend on branded formulary placement f_j as well as rebates $r_{jk}(f_j)$. Rebates affect the marginal costs of branded statins and formularies affect the extent of steereing among statins.

Most of the quantities that we require to calculate $C_{ijk}(f_j, r_{jk}(f_j))$ were described in the revenue section above. The only extra quantities that we need are beneficiary OOP payments and LICSA payments (which are observed in the data) and branded statin formularies.

Appendix C Simulating Choice Probabilities

Because there is no closed-form expression for our maximized statin utility, we simulate our choice probabilities. Specifically, in simulation b, we take draws of ε_{ikt}^{b} (we hold these draws fixed for every candidate parameter vector to prevent chatter from causing problems with our simulated estimator). Given these random draws, we calculate and use the simulated quantity v_{ijt}^{*b} instead of v_{ijt}^{*}. The simulated plan utility is given by

$$u_{ijt}^{b} = \delta_{jt} + \beta_{t}^{v^*} v_{ijt}^{*b} + \tau_{ijt}, \tag{35}$$

The simulated probability that beneficiary i chooses plan j is then given by

$$s_{ijt}^{sim}(\theta^{j}, \theta^{k}) = \frac{1}{B} \sum_{b=1}^{B} \frac{\exp(\delta_{jt} + \beta_{t}^{v^*} v_{ijt}^{*b})}{\sum_{j'=1}^{J_r} \exp(\delta_{j't}' + \beta_{t}^{v^*} v_{ij't}^{*b})}, \tag{36}$$

where B is the total number of simulation draws per beneficiary. The simulated probability that beneficiary i chooses statin k substitutes s_{ijt}^{sim} into Equation (14):

$$s_{ikt}^{sim}(\theta^{j}, \theta^{k}) = \sum_{j=1}^{J_r} s_{ijt}^{sim}(\theta^{j}, \theta^{k}) s_{ikt|j}(\theta^{k}). \tag{37}$$

Note that the conditional statin choice probability is a regular logit probability and does not need to be simulated. With our simulated choice probabilities, we can construct our sample moments. Let N_t be the number of beneficiaries in type t and let $t(i)$ be the type of beneficiary i.

Appendix D Details on Moment Inequalities

D.1 Signing Bounds

In this Section, we show that the bounds on $\nu_{2,h}$ in Inequality (19) can be signed based off the properties of demand. For reference, we write Inequality (19) again here:

$$\sum_{j \in J_h} \Delta A_j(f_j, f_j') + \sum_{j \in J_h} \sum_{k \in K_j^b} \gamma_k(f_j) \Delta L_{jk}(f_j, f_j') + \sum_{k \in K_j^b} (\gamma_k(f_j) - \gamma_k(f_j')) L_{jk}(f_j') \geq$$
$$- \sum_{j \in J_h} \sum_{k \in K_j^b} \Delta L_{jk}(f_j, f_j') \nu_{2,h}. \tag{38}$$

where we have dropped the measurement error term because it is mean zero and our estimation procedure averages across insurers. Thus, the direction of the bound depends on the sign of

$$\sum_{j \in J_h} \sum_{k \in K_j^b} \Delta L_{jk}(f_j, f_j'). \tag{39}$$

In our estimation approach, we only consider single plan formulary deviations (even for multi-plan insurers). Without loss of generality, we assume that the formulary change is for plan $j_1 \in J_h$.

If f_{j_1}' increases the OOP cost of a single branded statin while holding the OOP cost for the other branded statin fixed, then we obtain a lower bound on $\nu_{2,h}$. Suppose that under f_{j_1} Crestor is not excluded, but Lipitor is excluded. Let f_{j_1}' exclude both branded statins. Both formularies exclude Lipitor, thus the set of branded statins $K_{j_1}^b$ is just Crestor and k refers to Crestor. Since Crestor's OOP cost on j_1 increased, demand for Crestor on j_1 falls, so $\Delta L_{j_1 k}(f_{j_1}; f_{j_1}') > 0$. The remaining terms in Expression (39) capture the change in the insurer's branded statin costs across all its plans when the formulary on j_1 changes from f_{j_1} to f_{j_1}'. Since branded statins on other plans substitute for Crestor on j_1, these terms are all negative (demand is higher under f_{j_1}'). Since some people substitute to different insurers, Expression (39) is positive. Thus dividing both sides of Inequality (19) by the negative of Expression (39), we get a lower bound for $\nu_{2,h}$.

The argument that shows we obtain upper bounds by considering formulary changes that lower the OOP cost of a single branded statin while holding fixed the OOP cost of the other branded statin has the exact same logic and hence is omitted.

D.2 Estimation

Chernozhukov, Chetverikov, and Kato (2019) proceeds in two steps. The first step is the

selection of moment inequalities that are informative about the parameters. After moment selection, a test statistic is calculated as the maximum of t-type statistics corresponding to each moment inequality. This test statistic is compared to critical values that are calculated using the empirical bootstrap. The test statistic calculated in the second stage is adjusted to account for moment selection in the first stage. This procedure returns an estimated set that includes the value of the true parameter with the desired level of confidence.

As instruments, we use the constant, market size and the number of LIS beneficiaries in the market, all of which are in the firm's information set. Any positive function of these instruments can serve as $w(z_{h_j})$ in Equation (26). We use a step function in our estimation, which takes a value of 1 if the instrument is less than the median and 0 otherwise. Together, this leads to a total of twelve moment inequalities.[53] After defining the set of moment inequalities from these instruments, we follow Chernozhukov, Chetverikov, and Kato (2019) to construct a 90% percent confidence set for the true parameter values.

For estimation, we use three instruments: (i) the constant, (ii) an indicator variable that equals one if the market plan j operates is smaller than the median market size (measured as the number of beneficiaries), and (iii) an indicator variable that equals one if the market plan j operates has LIS beneficiaries less than the median number of LIS beneficiaries. Each instrument generates four moment inequalities: the upper and lower bound for each of the potential two deviations. Therefore, in total, we have 12 moment inequalities.

After constructing these moments, we follow Chernozhukov, Chetverikov, and Kato (2019), which provides a framework to test many moment inequalities. The test can be inverted to obtain an estimated set that contains the true parameter value with the desired confidence level. In particular, Chernozhukov, Chetverikov, and Kato (2019) consider the following null hypothesis

$$E[g_j(X_i, \theta)] \leq 0 \quad \text{for all} \quad j = 1, \ldots, p \tag{40}$$

against the alternative

$$E[g_j(X_i, \theta)] > 0 \quad \text{for some} \quad j = 1, \ldots, p \tag{41}$$

Therefore, one can invert this test to find the set of parameters that fail to reject the null hypothesis. To implement this, we construct the empirical analog of these moments as

[53] Our results are robust to constructing instrument functions in different ways.

follows:

$$Q_m^{\mathcal{L}}(\gamma) = \frac{1}{H}\sum_{h=1}^{H}\frac{1}{K_h}\sum_{k=1}^{K_h}\mathcal{L}_j(\gamma, f_j, f_j')w(z_j) \tag{42}$$

$$Q_m^{\mathcal{U}}(\gamma) = -\frac{1}{H}\sum_{h=1}^{H}\frac{1}{K_h}\sum_{k=1}^{K_h}\mathcal{U}_j(\gamma, f_j, f_j')w(z_j) \tag{43}$$

where $w(z_j)$ is a function that is constructed from the instruments. So our estimation procedure boils down to testing the null hypothesis in Equation (40) using the empirical analog of our moment inequalities given in Equation (42).

Chernozhukov, Chetverikov, and Kato (2019) requires setting two important parameters : β which is used in the moment selection setup and α which is used for computing the critical value (in their notation). The resulting confidence set covers the true parameter value with (1-α)% probability. We set $\beta = .001$ and $\alpha = .1$.

To construct the confidence set, we first fix a parameter value $\bar{\lambda}^k$. For $\bar{\lambda}^k$, we calculate the max-t statistics of $Q_m^{\mathcal{L}}(\gamma)$ and $Q_m^{\mathcal{U}}(\gamma)$ provided in Equation (13) of Chernozhukov, Chetverikov, and Kato (2019). Then, to calculate the corresponding critical value, we apply their algorithm "EB with inequality selection" described in detail in Chernozhukov, Chetverikov, and Kato (2019) (pages 1885, 1886). In particular, we first apply the inequality selection to select the informative moments. Then using the selected moments, we calculate the EB test statistics using bootstrap, where we draw plans with replacements taking into account the plan weights, K_h. This results in a critical value for the max-t test statistics. If the max-t statistics is larger than the critical value, we reject $\bar{\lambda}^k$.

We apply this procedure for all values of λ^k in the grid covering the parameter space. The λ^k values that are not rejected are included in the estimated set.

Appendix E non-statin Users Plan Demand

To calculate how premiums respond to changing rebates, we need to know how plan demand changes for non-statin users (in addition to statin users). We estimate demand for non-statin users by re-estimating our demand model for statin users with non-statin users, but imposing that all of the parameters in the statin utility model are zero. This amounts to assuming that non-statin users have no utility from statins; this rules out the possibility that they anticipate starting statins in the same year as their plan choice and therefore value statin formulary placement. To deal with potential endogeneity in premiums, we use the same Hausman instrument that we used when we estimated demand for statin users. We follow other papers calculating counterfactual premiums by assuming that premiums are based off non-LIS demand (Starc and Town 2020), so we do not estimate statin demand for LIS beneficiaries. The demand estimates are reported in Table 7 below.

Table 7: non-statin User Plan Demand Estimates

	Risk Type (2009 Risk Score Tercile)		
	Lowest	Middle	Highest
	(1)	(2)	(3)
Premium	-.0863	-.0817	-.0731
	(.019)	(.019)	(.019)
Annual Deductible	-.0060	-.0069	-.0064
	(.0007)	(.0007)	(.0006)
Any gap coverage indicator	1.730	1.862	2.162
	(.750)	(.719)	(.688)
Number of drugs covered	.0022	.0021	.0021
	(.0002)	(.0002)	(.0002)
Plan Age	.461	.342	.519
	(.070)	(.067)	(.064)

Notes: This table reports plan demand estimates for non-statin users. We use the same model for non-statin users and statin users except we impose that the utility parameter from statins are zero for non-statin users.

Appendix F Canadian Prices

We calculate mean branded statin rebate that equates the mean price that U.S. insurers pay branded statin manufacturers with the mean price provincial Canadian governments pay using data from Dubois, Gandhi, and Vasserman (2019).[54] Their Table 7.23 shows that in Canada the mean price for branded statins is \$1.77 per pill while in the USA it is \$3.43 per pill. Thus U.S. prices would match Canadian prices if there were a mean rebate of 48.4% = 1 - 1.77/3.43.[55]

Ideally, we would have data on both Crestor prices and Lipitor prices in Canada. However, we only observe a mean price for branded statins. If both Crestor and Lipitor had rebates of 48.4%, then the mean rebate would be 48.4%. To calculate other rebate pairs that are consistent with a mean branded rebate of 48.4%, we assume that Canadian market shares for branded statins are the same as Part D market shares and use this assumption to calculate pairs of Crestor and Lipitor rebates that result in a market-share weighted mean rebate of 48.4%. The market shares for Crestor and Lipitor in Part D are 9.5% and 21.1%. The mean Part D prices for Crestor and Lipitor are \$4.08 and \$3.92 per pill. The market-share weighted mean price for branded statins in Part D is \$3.97.

Let r_C and r_L denote Crestor and Lipitor rebates for preferred placement. The pairs of Crestor and Lipitor rebates that equate Part D insurer prices (with preferred tier placement of branded statins) to prices in Canada solves the following linear equation:

$$1 - \frac{1}{3.97}\left[(1-r_C)\frac{.095}{.095+.211}4.08 + (1-r_L)\frac{.211}{.095+.211}3.92\right] = \frac{1.77}{3.43}. \tag{44}$$

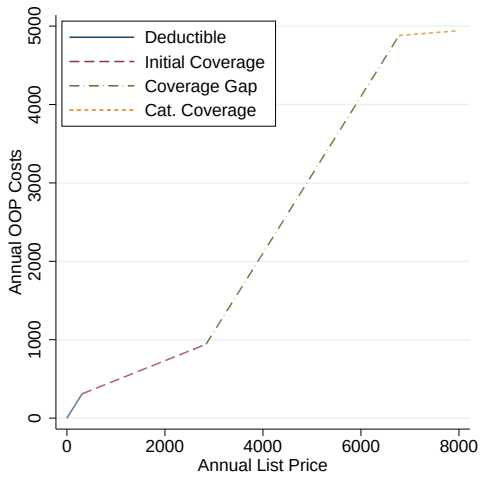
The right-hand side is the mean branded rebate that equates the price for U.S. insurers with the prices in Canada. The term in brackets on the left-hand side gives the market-share, post-rebate weighted price of branded statins in Part D. Thus the left-hand side gives the mean branded rebate in Part D as a function of the Crestor rebate and the Lipitor rebate.

[54] These statin prices are for a hospital setting, however we believe pharmacy prices were similar.

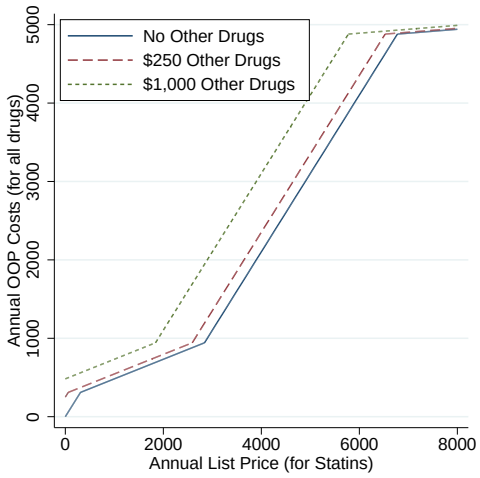
[55] There was exchange rate parity between US dollars and Canadian dollars in 2010.

Appendix G Extra Figures and Tables

Appendix Figure 1: The Standard Benefit Schedule and Annual OOP Costs



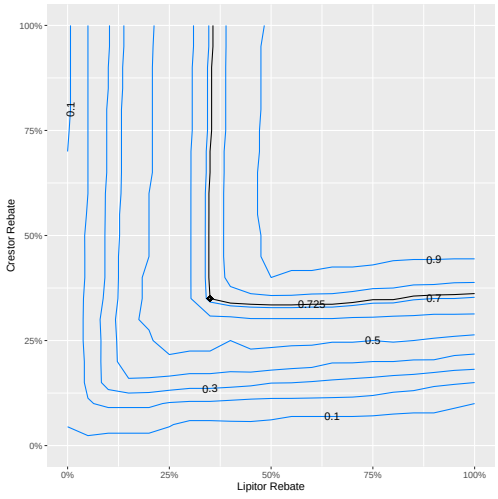
(a) The Standard Benefit Schedule



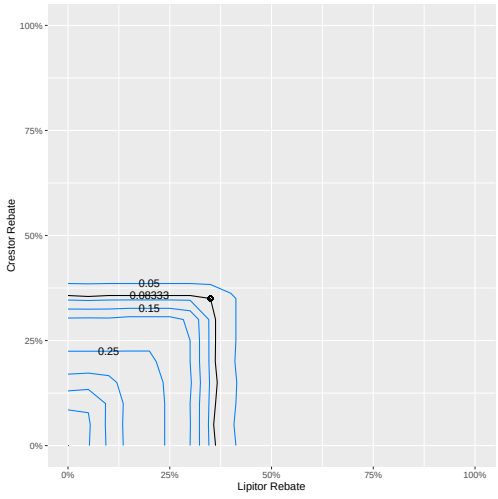
(b) The Effect of non-statin Drug Spending on Annual Statin OOP Costs

Notes: Author's calculation for the Standard Benefit Schedule based on rules provided by CMS.

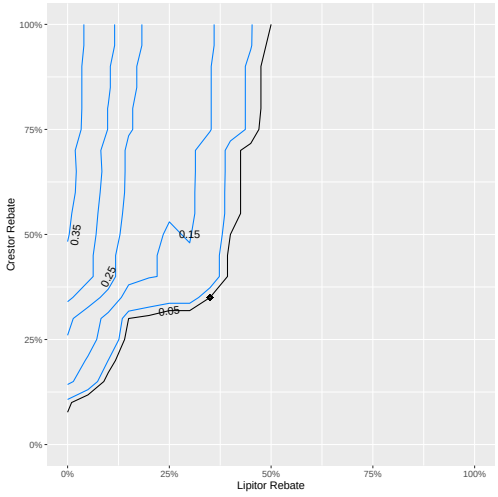
Appendix Figure 2: Equilibrium Preferred Share in Rebate Space



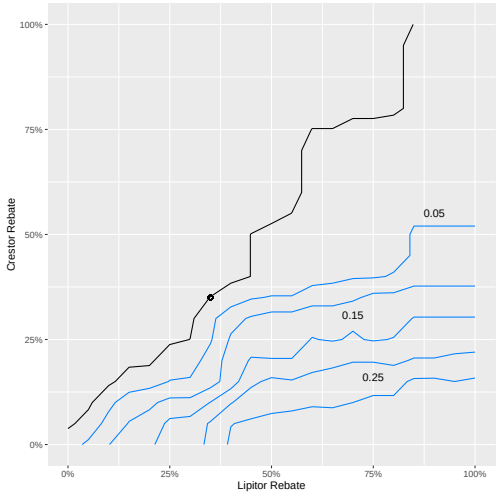
(a) Preferred/Preferred Share



(b) Excluded/Excluded Share



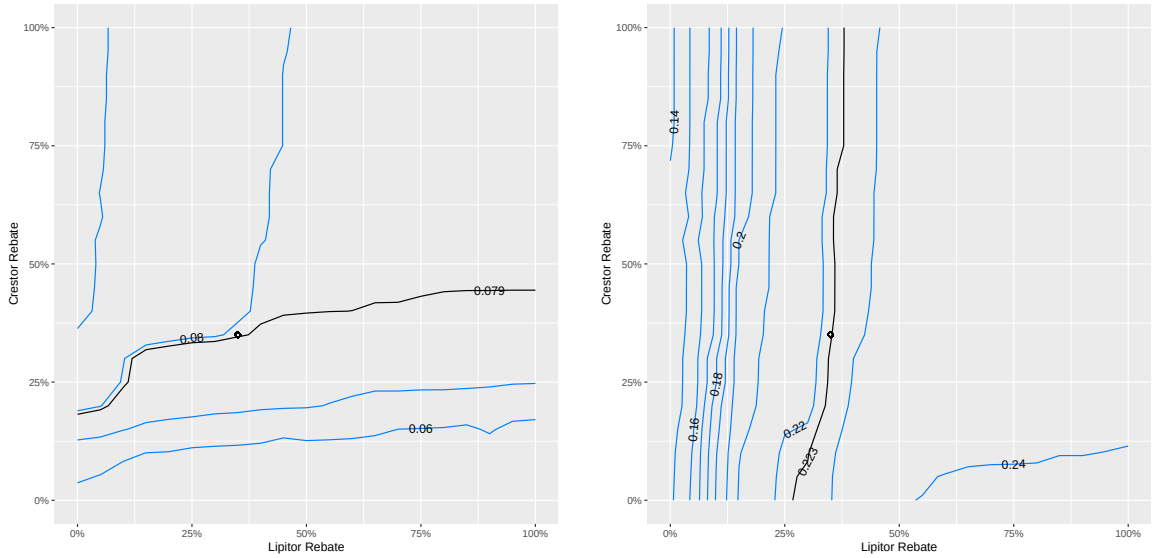
(c) Preferred/non-preferred Share



(d) non-preferred/Preferred Share

Notes: This figure plots the effect of branded statin rebates on the share of plans with each formulary configuration. non-preferred/Preferred means Crestor is on the non-preferred tier and Lipitor is on the preferred tier.

Appendix Figure 3: The Effect of Statin Rebates on Statin Demand



(a) Crestor Market Share

(b) Lipitor Market Share

Notes: This figure plots the effect of branded statin rebates on the demand of branded statins. Panel (a) plots the demand of Crestor and Panel (b) plots the demand of Lipitor.

Appendix Table 1: Beneficiary Summary Statistics

	Mean	Std. Dev.
Age	76.0	7.2
White	86.6%	
Female	61.3%	
Medicaid Eligible	28.2%	
LIS	32.1%	
2009 Part D annual OOP costs ($)	1,054	1,331
2009 Part D fill count	48.4	36.7
Observations (Beneficiaries)	737,053	

Notes: This table reports summary statistics for the beneficiaries in our sample. We do not report the standard deviation for binary variables.

Appendix Table 2: Plan Summary Statistics

	Mean	Std. Dev.	Min	Max
Tiered	90.0%			
Number of Drugs	1,608	373	1,060	2,388
Number of Top 100 Drugs	94.3	2.1	87	96
Share of Top 100 Branded	.95	.06	.77	1.00
Number of Preferred Tier Drugs	642	121	48	821
Number of non-preferred Tier Drugs	330	122	145	769
Preferred Tier Copay ($)	34.4	9.3	4.0	45.0
non-preferred Tier Copay ($)	73.4	17.5	24.0	95.0
Plans		431		

Notes: This table reports formulary design summary statistics for the 431 plans with at least 1,000 enrollees satisfying the sample descriptions described in 3.1 in all Part D regions excluding Alaska, Hawaii, New Mexico, and Nevada. We do not report the standard deviation for binary variables. We use the First DataBank Brand Name Proxy NDC to count the number of drugs. We determine the top 100 drugs in our sample based on the total quantity supplied across all beneficiaries. The copays in the second and third rows from the bottom are calculated on the subset of plans that use copays for those tiers (plans that use coinsurance are excluded).

Appendix Table 3: Cumulative Market Share by Number of Plans Counted

Number of plans	Mean	Min	Max
1	.23	.14	.41
2	.40	.26	.64
3	.53	.36	.83
4	.62	.44	.91
5	.70	.51	.96
6	.76	.56	1.00
7	.81	.61	1.00
8	.85	.65	1.00
9	.88	.70	1.00
10	.91	.73	1.00

Notes: Each row reports statistics that are calculated by including the indicated number of largest plans.