

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

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Abstract

The prices charged for on-patent, branded pharmaceuticals represent a large, and controversial, component of medical spending in the U.S. In contrast to many countries and many other government programs, drug prices in the Medicare Part D program are determined by privately negotiated rebates between insurance plans and drug manufacturers. How big are these rebates? What would happen to formularies, consumer surplus, and firm profits if the government could increase the rebates of a blockbuster Medicare Part D drug? We estimate a simultaneous model of insurance demand and statin demand for the population of statin users in 2010. Our demand estimates allow us to quantify how insurer profits change under different statin formulary structures. We use these profit functions to estimate the rebates for Crestor and Lipitor, two blockbuster drugs of the time using a moment inequality approach; we estimate rebates between 25% and 54% for branded statins. In counterfactuals, we analyze the effect of rebates on formulary design and consumer surplus. We show that increasing only Crestor rebates has no effect on consumer surplus because of offsetting effects on winners and losers. In contrast, increasing only Lipitor rebates does increase consumer surplus. If rebates reduced U.S. prices to match those paid in Canada, then consumer surplus would increase by up to 3.1%.

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

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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 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 prohibiting or changing rebates in Part D would affect insurance plan design or consumer surplus.

This paper quantifies the consumer surplus effects that would arise in Medicare Part D under different levels of rebates. 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. We present the first paper to model insurers' equilibrium formulary placement decisions for branded drugs, and we show how consumer surplus is affected by the distribution of formularies offered in Part D.

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 plans in Part D use tiered formularies that 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, if the drug is placed on the non-preferred tier, copays are higher, and demand is lower. Finally, if the drug is excluded from the formulary entirely, then enrollees on the plan must pay list price for the drug. Institutionally, for branded drugs, drug manufacturers offer insurers (typically, through PBMs) rebates off of list price 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) and

Crestor (more potent and newer, but with different side effects) were both on patent. These two branded drugs also faced competition from three main generic alternatives: Lovastatin, Pravastatin, and Simvastatin.

We specify and estimate a model of the market for Medicare Part D plans that focuses on statins and show how to use this model to estimate the rebates that AstraZeneca and Pfizer offered for Crestor and Lipitor, respectively. We use our estimated rebates to analyze counterfactuals that evaluate the positive and normative effects that would occur if these rebates changed, for example, due to government policy.

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 (whether a branded drug is on the preferred tier, the non-preferred tier, or off the formulary) is a key dimension of Part D plan differentiation. Second, we simultaneously model both plan demand and statin demand to capture adverse selection in plan choice due to statins preferences. This is important because statins treat chronic underlying health conditions, and thus when consumers choose their plans, they are well aware 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 (i) statin users differ along both observed and unobserved taste dimensions (e.g., some may prefer branded drugs, while others may not care); (ii) statin demand within a plan is modeled by having each consumer make an optimal statin choice given their plan's copays for the various statins and their individual preferences, and (iii) plan demand is modeled by having each consumer choose among plans taking account of their anticipated statin demand (as well as other factors) in each candidate plan, with knowledge of their individual statin preferences. This model is particularly well-suited to capturing the adverse selection arising in the Medicare Part D environment because it allows for both observed and unobserved heterogeneity in statin preferences to drive selection. We use our demand model to estimate the profits anticipated by insurers from various formulary choices they could make.

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 inequalities

approach that finds the rebates that rationalize the formulary choices that we observe 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.

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 (partial identification). We estimate that the per-unit rebate paid to plans that place Crestor or Lipitor on the preferred tier is between 25% and 54% of list price. Our estimates are consistent with large asymmetries in rebates across branded statin manufacturers.

We use our rebate estimates to quantify how changing rebates would affect insurance plan design and consumer surplus. We show that if Lipitor rebates increase, then consumer surplus increases. In contrast, if Crestor rebates increase, there is no effect on consumer surplus. Our model of formulary design can explain this result. Increasing Crestor rebates induces some insurers to change their formularies to decrease Crestor copays and increase Lipitor copays; such a formulary change takes advantage of higher Crestor rebates because of both selection and steering effects. However, such a formulary change also creates winners (Crestor users) and losers (Lipitor users) with offsetting effects on consumer surplus. These results suggest a complication for government negotiated rebates: when insurers are free to design their formularies, the effect of reducing the rebate on a single drug depends on many factors for which the government may have limited information.

There is substantial interest in policy reform aimed at targeting rebates.¹ However, because rebates are secret, there is little evidence on how large they are or how they affect the copays that Part D beneficiaries through formularies. We compare the prices that Part D insurers pay to the prices paid by the Canadian government because we think this provides a useful benchmark.

Net of rebates, Part D insurers pay higher prices for branded statins than the prices

¹On the 20th of November 2020, the Trump administration announced a new rule prohibiting insurers from receiving rebates from drug manufacturers on Part D.

paid by the Canadian government. If Part D insurers obtained a 48.4% rebate to place both Crestor and Lipitor on the preferred tier of their formulary, then Part D insurers could match the prices paid by the Canadian government. However, rebates this high are rejected by estimates (Figure 1). Moreover, policy reform that increased Part D rebates so that insurer prices matched Canada’s prices would have important effects on formularies and consumer surplus. Our rebate estimates suggest that consumer surplus for statin users in Part D would increase by as much as 3.1% if Part D insurers could match Canadian prices.

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 demonstrate unintended consequences of Part D rules on formulary design.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 plans could make in response to different changes in rebates (i.e., 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 go beyond her suggestion to also study the supply-side effects.

This paper is related to a growing empirical literature that uses moment inequalities from the Pakes et al. (2015) framework to estimate supply-side parameters that determine the set of products that firms offer in equilibrium.³ A common methodological challenge in the application of moment inequalities arises from selection issues related to the structural error. In our setting unobserved rebate heterogeneity implies that moment inequalities that condition on the formulary choices of insurers do not recover average rebates. We combine the

²Carey (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) study time trends in Part D rebate and list price growth. Feng (2019) studies formularies using data on average drug prices net of rebates and abstracts from the role of insurers.

³Ho (2009) uses moment inequalities to model the determinants of insurers’ hospital networks. Ho and Pakes (2014) use moment inequalities to study how hospital referrals respond to insurer payments. Outside of the insurance setting, Eizenberg (2014) and Wollmann (2018) use moment inequalities to estimate fixed costs of product development and to model product entry.

approaches in [Eizenberg \(2014\)](#) and [Wollmann \(2018\)](#). Specifically, we impose a restricted form of rebate heterogeneity that is a natural fit for our institutional setting: unobserved rebate heterogeneity varies across insurers, but is constant within insurer because rebates. This restriction on the structural error generates a selection issue that we resolve through a combination of using support bounds and reweighting observations.

This paper also contributes to a growing literature on drug demand estimation. While there are many models of Part D plan demand, there are far fewer models estimating demand for specific drugs in Part D, even though drug demand is a critical input into models of drug manufacturer and insurer behavior.⁴ [Carrera et al. \(2018\)](#) estimate demand for statins using data from 12 Fortune 500 firms. [Einav, Finkelstein and Polyakova \(2016\)](#) estimate drug demand in Part D. [Dalton, Gowrisankaran and Town \(2019\)](#) also estimate drug demand in Part D and focus on behavioral models of consumer behavior and estimate a dynamic model of drug choice. [Dubois, Gandhi and Vasserman \(2019\)](#) and [Maini and Pammolli \(2019\)](#) estimate drug demand to study the consequences of international reference pricing policy using structural models of demand for drugs. In contrast to other papers estimating Part D drug demand, we focus on a single class of drugs that treat a chronic condition and define the price of different statins as the increment in annual drug costs. We use this definition of prices to estimate the first model of plan demand that explicitly accounts for utility coming from drug demand (in this case statins).

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 the simultaneous model of demand and the 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 detail relevant to our demand model, our formulary equilibrium model, and our counterfactual analyses. We split the institutional details into

⁴Some papers studying Part D plan demand include [Abaluck and Gruber \(2011\)](#), [Ketcham, Kuminoff and Powers \(2016\)](#), [Abaluck and Gruber \(2016\)](#), [Heiss et al. \(2013\)](#), [Ho, Hogan and Scott Morton \(2017\)](#), [Starc and Town \(2020\)](#), [Decarolis, Polyakova and Ryan \(2020\)](#)

three sections: 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.⁵ 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 that competition will keep program costs low.

Part D insurers are divided into two types: stand-alone Prescription Drug Plans (PDPs) and Medicare Advantage Prescription Drug Plans (MAPDs). Beneficiaries who use traditional Fee-For-Service Medicare for inpatient and outpatient coverage (Part A and Part B) can enroll in PDPs, while beneficiaries who are in private Medicare Advantage plans for inpatient and outpatient services (Part C) can enroll in MAPDs.

In this paper, we restrict our analysis to the PDP market for two reasons. First, because MAPDs cover hospital care in addition to drug insurance, they face complicated incentives, which would distract from the focus of this paper and has been studied in depth elsewhere (e.g., [Lavetti and Simon 2018](#) and [Starc and Town 2020](#)). Second, we have much richer data on beneficiaries in PDPs because they produce claims records on all of their hospital and physician utilization, and we use this data in our analysis.

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 Subsidy (LIS), which reduces out-of-pocket costs to between \$0 and \$6.30 per fill. The LIS also covers between 25% and 100% of monthly premiums for LIS beneficiaries who enroll in low premium (“below-benchmark”) plans.⁶ Plans can change below benchmark status

⁵For 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.

⁶Each year, 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

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. 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. In 2010 every region had at least 30 PDPs. We restrict our sample to plans with at least 1,000 enrollees (after basic sample restrictions) to ensure we have enough observations in each plan to estimate our model. 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. In our resulting sample, the remaining regions have between 5 and 26 plans in each region, and the mean number of plans per region is 14. To facilitate plan choice, the government runs a website that allows beneficiaries to compare plans.⁷

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. 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.⁸ Beyond these two rules, plans have substantial freedom to design their formularies and, as we will 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.

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.

⁷<https://www.medicare.gov/find-a-plan/questions/home.aspx>.

⁸These classes are anticonvulsants, antidepressants, antineoplastics, antipsychotics, antiretrovirals, and immunosuppressants

2.2 Statins

To estimate a drug-demand model, we focus on the therapeutic class of HMG-CoA Reductase Inhibitors (statins). 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.⁹ 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 remove them from the formulary altogether. Lovastatin, Pravastatin, and Simvastatin are all generic statins always placed on the generic tier of insurer formularies. We focus on Crestor and Lipitor because we model the formulary placement of branded drugs and how it responds to changes in rebates.

Statins are lipid-lowering drugs that are taken because they have been proven to prevent cardiovascular disease and related health events. Statins are differentiated on several dimensions besides out-of-pocket costs. First, different statins have different levels of effectiveness in terms of reducing low-density lipoprotein cholesterol (LDL-C). The statins in our data reduce LDL-C by between 20% and 60%. Typically newer statins achieve larger percentage LDL-C reductions. Second, statins can have 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 a difference in the mechanism by which statins work: Crestor and Pravastatin are hydrophilic, while Lipitor, Simvastatin, and Lovastatin are lipophilic.

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 (CVS Caremark, Express Scripts, Medco, OptumRX, and Prime Therapeutics).

⁹We exclude Vytorin, which combines Ezetimibe and Simvastatin.

The rebates that drug manufacturers offer insurers (through PBMs) are formulary contingent 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 private. 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.¹⁰

3 Data

We use data from the Center for Medicare and Medicaid Services (CMS) in 2010. We use four main datasets.¹¹ The first data set records plan choices and demographic variables for beneficiaries in our 20 percent random sample. The second data set describes PDPs' financial characteristics, such as premiums, deductibles, copays, and coinsurance. The third data set contains the formulary placement of every drug for all PDPs in every Part D geographical region.¹² The fourth data set consists of claim-level data on Part D drug fills for all of the beneficiaries in our 20% random sample. We use this data set to construct variables related to the statin component of our demand model, including statin choices and out-of-pocket costs. In addition, we use three files on non-drug utilization in 2009 and 2010 (the inpatient, outpatient, and physician files) to calculate beneficiary risk scores, which are predictions of drug utilization using a CMS algorithm.

¹⁰The rebates that we estimate are the rebates the insurers receive. Typically the rebates insurers receive are smaller than the rebates that manufacturers pay because PBMs keep a wedge. Our approach based off insurer decisions is not informative about the size of the wedge and hence does not pin down the exact size of the rebates payments that manufacturers pay. Our results focus on consumer surplus and insurer profits, and for these quantities, the rebate that insurers receive is the relevant rebate. Moreover, if the government negotiations that we analyze in our counterfactuals can eliminate the PBM wedge, then the benefit of government negotiations be even larger than we find.

¹¹The datasets correspond to 4 CMS files; the Master Beneficiary Summary File, the plan characteristics file, the formulary file, and the Part D Event file.

¹²As described above, we exclude the regions for Alaska, Hawaii, New Mexico and Nevada because they are too small

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, race, 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. The two main differences between our sample restrictions and the sample restrictions in prior papers is that we restrict to statin users, and we do not exclude LIS beneficiaries (they account for 32.1% of our sample).¹³ The age restriction excludes beneficiaries who are Medicare eligible because they are on disability insurance; and because of their age, they typically do not use statins. The remaining sample restrictions focus our analysis on statin users whose coverage does not change within the year. 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. The mean age is 76.0 years. The sample is majority white (86.6%) and female (61.3%). Just over a quarter (28.2%) of the sample are eligible for Medicaid, and almost a third (32.1%) of the sample are LIS beneficiaries.

3.2 Plan Data

For each PDP in the 30 Part D regions we analyze, we observe plan enrollment and the financial characteristics of plans relevant to beneficiary plan choice (along with formulary design, which is described in the next subsection). We exclude Employer Group Waiver Plans because they are not open to general enrollment. We also exclude small plans that have fewer than 1,000 enrollees in our data. This reduces the number of plans in our data from 1,542 to 431; however the 431 remaining plans account for 86% of total enrollment in these 30 regions.

¹³We 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.

Table 1: Formulary Design for Branded Statins

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

Notes: Each cell shows the number 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

Appendix Table 2 reports summary statistics relating to the formulary design of the plans in our data. 90.0% of the plans in our data are tiered. The mean number of drugs covered on each plan is 1,608. There is considerable variation in the number of covered drugs; the standard deviation is 373, with the smallest formulary covering only 1,060 drugs and the largest formulary covering 2,388 drugs. All plans offer an overwhelming majority of the top 100 most purchased drugs (the minimum number covered is 87), but no plans offer all of the top 100 most purchased drugs (the maximum covered is 96). There are 26 branded drugs among the 100 most purchased drugs (Lipitor is the most purchased branded drug, and Crestor is the 5th most purchased branded drug), and all plans cover at least 20 (77%) of them. Plans also differ in how many drugs they place on different tiers of their formularies. On average, for the plans in our sample, there are 642 drugs on tier 2 and 330 drugs on tier 3. For plans that use copays (as opposed to coinsurance) for tiers 2 and 3, the mean copays are \$34.4 and \$73.4 per fill.

3.3 Formulary Data

Formularies specify which drugs are covered and, for tiered formularies, they assign each covered drug with a unique tier that determines cost-sharing. Higher tiers correspond to higher OOP costs for beneficiaries. In 2010, the typical tiered formulary had separate tiers for generic drugs, preferred branded drugs, non-preferred branded drugs, and specialty drugs.¹⁴

Table 1 enumerates the combinations of tier placement for Crestor and Lipitor across large plans (with more than 1,000 enrollees after sample restrictions) in our data. Just over half

¹⁴A small share of tiered formularies split generic drugs into preferred and non-preferred generics.

Table 2: Branded Statins Market Shares by Formulary Design

<i>Crestor Tier</i>	<i>Lipitor Tier</i>		
	Preferred	Non-Preferred	Off
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%
Off	0%, 32.4%	-, -	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.

(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 (18.4% + 7.9% + .3%) while Lipitor is only in a favored position on 5.2% of plans.

Table 2 shows that branded statin formulary placement matters a lot for the branded statin market share of plans. 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 non-preferred tier 14.7% of enrollees buy Crestor, and only 4.8% of enrollees buy Lipitor. These drastic changes in branded statin market share across plans with different formularies reflect both moral hazard and adverse selection: holding fixed enrollment, moving Lipitor off the preferred tier reduces the Lipitor market share because Lipitor is more expensive and so fewer people buy it; in addition, moving Lipitor off the preferred tier induces people who have strong preferences for Lipitor to change plans. 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,¹⁵ the date of the fill, the quantity supplied, and the OOP

¹⁵There are three codes for classifying drugs in our data: the National Drug Code (NDC), which is administered by the Food and Drug Administration; the Chronic Conditions Warehouse (CCW) formulary drug identifier, which is used by CMS to ensure that plans satisfy their formulary requirements; and the

cost that the beneficiary has to pay. We also observe the list price associated with each claim.¹⁶ For plans without gap coverage, beneficiaries’ OOP cost in the coverage gap is the list price. For plans with coinsurance in the coverage gap, beneficiaries’ OOP cost is the coinsurance rate times the list price.

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 modelling 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 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, we focus on non-LIS beneficiaries. The mean annual

First DataBank (FDB) brand name. The CCW code is useful for working with the formulary files. The FDB code is useful for counting the number of drugs on a formulary because it does not distinguish between package size

¹⁶The list price does not reflect the true cost to either Medicare or the PDP because it does not account for rebates [https://www.resdac.org/sites/resdac.umn.edu/files/Part D Event Cost Information \(Slides\).pdf](https://www.resdac.org/sites/resdac.umn.edu/files/Part%20D%20Event%20Cost%20Information%20(Slides).pdf)

OOP costs from buying Crestor (instead of no statin) is \$568. Lipitor is slightly more expensive, and its mean annual OOP cost is \$586. The standard deviations make clear that there is substantial variation in the annual OOP cost of branded statins across beneficiaries. 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. Generic statins annual OOP costs are around \$80, which makes them far cheaper than branded statins.

LIS beneficiaries annual OOP costs for statins is 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.

Table 3 reports data on mean OOP costs in Part D. For each claim, we also observe the list price manufacturers receive (before rebates are paid to insurers). In our data, the mean list price per pill for Crestor and Lipitor are \$4.08 and \$3.92 per pill respectively. Thus on average, Crestor costs insurers 4% more than Lipitor per pill.

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 is to have a model and estimates that quantify the effect of different branded–statin formulary decisions on statin choice and plan choice, which then inform the profit effects plans foresee from different formulary choices.

For each statin user who enrolled in a stand-alone Part D Plan in 30 Part D markets in 2010,¹⁷ we estimate a simultaneous demand model; statin users make their decisions over plans and statins at the same time. A key advantage of a simultaneous model is that it explicitly allows for adverse selection based on both observed and unobserved preferences. As a result, beneficiaries who have strong preferences for expensive branded statins search out plans that have good cost-sharing arrangements for these drugs. This simultaneous approach to estimating demand in a setting with bundled goods is similar to the strategy used in [Crawford and Yurukoglu \(2012\)](#), [Lee \(2013\)](#), and [Crawford et al. \(2018\)](#).¹⁸ 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, plan j covers a subset of statins K_j .¹⁹ 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 off formulary.

Statin user $i = 1, \dots, N$ chooses both a plan and a statin. We group each statin user into one of four risk types, denoted by t , and allow utility parameters to differ across types.²⁰

¹⁷Recall that we exclude plans with fewer than 1,000 enrollees in our data, which results in excluding the four smallest Part D markets (Alaska, Hawaii, Nevada, and New Mexico). As in [Abaluck and Gruber \(2011\)](#), we only model the choice of beneficiaries who choose a stand-alone Part D Plan, excluding employer group waiver plans. Thus, we normalize the mean utility of an arbitrary plan in each region.

¹⁸Several 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 \(2017\)](#).

¹⁹Statins 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. We use statin fixed effects in our specification of statin utility to capture unobserved quality.

²⁰Non-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.

The utility from choosing statin k on plan j is given by

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

where OOP_{ijkt} 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. The error term, ε_{ikt} , is assumed to be IID from a Type 1 Extreme Value distribution. It is individual and brand-specific, so unobserved preference for branded statins does 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 (the rest of the formulary, copays, deductible, and gap coverage) and the nonstatin drugs 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.²¹ This approach uses data on observed formularies, plan cost-sharing rules, and the assumption that nonstatin drug choices are unaffected by plan choice (i.e., no moral hazard on nonstatin drug choices).²² 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; thus, mean statin utility differs by risk type and by observed individual characteristics. Because beneficiaries know their statin tastes before they choose 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

²¹E.g., [Abaluck and Gruber \(2011\)](#), [Abaluck and Gruber \(2016\)](#), [Heiss et al. \(2013\)](#), [Ho, Hogan and Scott Morton \(2017\)](#).

²²An alternative to the no moral hazard assumption, used in [Heiss et al. \(2013\)](#), 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 nonstatin drugs off formulary, we assume beneficiaries choose an alternative drug on the same tier.

from the interaction between the nonlinear price schedule inherent to Part D plan design and nonstatin 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 (for example, the coverage gap) 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 is defined as

$$k_{ijt}^* = \operatorname{argmax}_{k \in K_j} v_{ijk t}, \quad v_{ijt}^* = \max_{k \in K_j} v_{ijk t}. \quad (2)$$

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 nonstatin characteristics of the plan, and is given by

$$u_{ijt} = \beta_t^{v^*} v_{ijt}^* - \beta_t^p p_j + \beta_t^x x_j + \zeta_{jt} + \tau_{ijt}, \quad (3)$$

where p_j is the plan premium, which does not vary across types,²³ x_j is a vector of observed plan characteristics, ζ_{jt} is a plan fixed effect, and τ_{ijt} error term that is assumed to be IID from a Type 1 Extreme Value distribution.

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^p , are standard and include the annual deductible, the presence of gap coverage, enhanced plan status, and formulary generosity measures such as the number of drugs covered on the plan, the number of drugs at each tier

²³As 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.

the tier cost sharing (copay or average value of coinsurance), insurer (e.g., United Healthcare) fixed effects, Part D market fixed effects and plan age.²⁴ Unobserved plan quality is represented by ζ_{jt} and will induce the need for instrumental variables. Individual heterogeneity in plan utility is captured through risk types and through the maximized statin utility term, which captures unobserved heterogeneity.²⁵

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

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

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

$$\delta_{jt} = \beta_t^p p_j + \beta_t^x x_j^p + \zeta_{jt}. \quad (4)$$

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:

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

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 cholesterol). As such most statin users take statins every day of the year.²⁶ Moreover, in our data,

²⁴We include plan age as a component of plan utility to account for plan inertia. A theoretical justification for this approach is given in [Decarolis, Polyakova and Ryan \(2020\)](#). Enhanced plans are Part D plans that cover drugs that are not usually on Part D formularies, or offer extra coverage in the donut hole and charge supplementary premiums.

²⁵Equation (2) shows that v_{ijt}^* includes the contributions of unobserved statin taste shocks ε_{ijkt} .

²⁶96.5% of the statin fills in our data are for 30 days or 90 days.

statin users typically buy a single type of statin, e.g., Crestor or Simvastatin.²⁷ Second, in the context of statins, we believe that dynamics would not add much and would distract from the important novel component of our drug demand model, which focuses on adverse 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.²⁸

The probability that beneficiary i of type t chooses plan j depends all formularies that are available in a region, because they determine plan utilities through the maximized statin utility term, and is given by:

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

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. 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 nonstatin 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

We use the estimates from our simultaneous-demand model to calculate insurer profits under different statin formulary arrangements and use these profits to infer rebates using moment inequalities. This section describes our model of insurer behavior and the assumptions.

Part D insurance plans have many characteristics, including the premium, the formulary, and the deductible. All Part D plans available during the open enrollment period (from

²⁷94.7% of statin users in our data buy a single type of statin.

²⁸Drug demand dynamics have been modeled in depth by [Dalton, Gowrisankaran and Town \(2019\)](#).

October 15 to December 7 each year) are first submitted to CMS in early June. Insurers do not observe each other’s submissions. Thus we model Part D plan design as a simultaneous move game where each insurer chooses all plan characteristics.

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 et al. \(2015\)](#). This structural error generates a selection issue that we resolve by combining aspects of the approaches in [Eizenberg \(2014\)](#) 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 :

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

where r_j are the branded statin 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 insurer h based on 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).²⁹ Appendix B provides all of the details as to how we calculate each source of revenue.³⁰

We do not assume constant marginal costs and instead use data on each beneficiaries 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

²⁹We 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.

³⁰Revenues 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 Federal Reinsurance payments in our profit calculations. Details are in Appendix B.

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 nonstatin costs and are necessary because we do not estimate drug demand for all Part D drugs. First, we assume no moral hazard on nonstatin drugs, so that we can calculate nonstatin drug costs on any plan for each individual’s observed choices. This no moral hazard assumption is common in Part D plan demand models.³¹ Second, we assume that the rebate for all branded nonstatin drugs is 13.8%.³² With these two assumptions and the institutional accounting details in Appendix B, we calculate plan costs as a function of selection.

In order to focus attention on the role of formularies and rebates, it is helpful to rewrite our profit measure for plan j in Equation (7) as follows:

$$\hat{\Pi}_j(f_j, p_j; r_{jk}) = A_j(f_j, p_j; f_{-j}, p_{-j}) + \sum_{k \in K_j^b} r_{jk}(f_j) L_{jk}(f_j, p_j; f_{-j}, p_{-j}) \quad (8)$$

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.³³ This representation of profits makes clear two important facts: first, profits are increasing in rebates; second, profits are linear in rebates conditional on demand (for both plans and statins) because rebates are paid as per unit discounts off list price.

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

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

³¹Abaluck and Gruber (2011), Abaluck and Gruber (2016), Ketcham, Kuminoff and Powers (2016) all use this assumption to calculate the out-of-pocket costs that Part D beneficiaries would have spent on plans that they did not choose. If a beneficiary buys a drug on their chosen plan that is not on the formulary of another plan in their region, then we assume that they would have replaced the drug with a different drug that had the same cost.

³²In 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% base on the Medicare Trustees Reports. We assume that the mean nonstatin branded drug rebate in 2010 is 13.8% (calculated from $.175 \times .113/.143$).

³³An institutional detail that is relevant to correctly accounting for the effect of rebates on insurer profits concerns federal reinsurance for beneficiaries who pass the catastrophic threshold for drug costs; the government pays 80% of catastrophic coverage region costs net of manufacturer rebates. We account for this when we calculate our profit functions.

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, capturing unobserved heterogeneity. This heterogeneity could reflect the fact that insurers use different PBMs and, as a consequence, obtain different rebates. Given this motivation, rebate heterogeneity is constant across plans within an insurer and mean zero conditional on the insurer's information set. Let $h(j)$ denote the insurer that owns plan j . Then

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

and

$$\mathbb{E}[\nu_{2,h(j)}|\mathcal{I}_h(j)] = 0$$

where \mathcal{I}_h denotes the information set of insurer h and $\nu_{2,h}$ denotes the rebate offered to insurer h . We assume that insurers observe $\nu_{2,h}$ before they design their formularies. As a consequence, the formulary choices that insurers make generate a selection issue:

$$\mathbb{E}[\nu_{2,h(j)}|\mathcal{I}_h, f_1, \dots, f_J] \neq 0.$$

This selection issue frequently arises in moment inequality models and is discussed in [Pakes et al. \(2015\)](#). 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 $\nu_{1,j}(f_j)$ that is mean zero even conditional on formulary choices; $\mathbb{E}(\nu_{1,j,f_j}|\mathcal{I}_{h(j)}, f_1, \dots, f_J) = 0$. Measurement error captures the difference between insurer j 's expectation of its profits and our profit measure:

$$\mathcal{E}[\Pi_j(f_j, p_j; \gamma)|\mathcal{I}_{h(j)}] = \hat{\Pi}_j(f_j, p_j; \gamma) + \nu_{1,j}(f_j). \quad (10)$$

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 , $J_h = \{j = 1, \dots, J : h(j) = h\}$. Let f_h, p_h be vectors that collect the formularies and premiums for insurer h 's plans. Let f_{-h} and p_{-h} be vectors collecting the formularies and premiums of other insurers. Thus, insurer h 's expectation of its profits is

$$\mathcal{E}[\Pi_h(f_h, p_h; \gamma, \nu_{2,h})|\mathcal{I}_h] = \sum_{j \in J_h} \mathcal{E}[\Pi_j(f_j, p_j; \gamma, \nu_{2,h})|\mathcal{I}_{h(j)}]. \quad (11)$$

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

$$\mathcal{E}(\Pi_h(f_h, p_h, f_{-h}, p_{-h}; \gamma, \nu_{2,h}) | \mathcal{I}_h) \geq \mathcal{E}(\Pi_h(f'_h, p_h, f_{-h}, p_{-h}; \gamma, \nu_{2,h}) | \mathcal{I}_h) \quad \forall f'_h. \quad (12)$$

Inequality (12) 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.³⁴ 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

This section provides details on how we estimate the models presented in Section 4.

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

$$s_{ikt}(\theta^j, \theta^k) = \sum_{j=1}^J s_{ijt}(\theta^j, \theta^k) s_{ikt|j}(\theta^k). \quad (13)$$

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

$$E[(y_{ikt} - s_{ikt}(\theta^j, \theta^k)) z_{it}^k] = 0 \quad k \in \{1, \dots, K\} \quad (14)$$

³⁴For example, insurer profits depend on plan deductibles, gap coverage, and the formulary treatment of nonstatin drugs.

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. 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 (14).

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

$$E[\zeta_{jt}(\theta^j, \theta^k)z_j^j] = 0, \quad (15)$$

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 (15), so we have 54 moments in total.³⁵ 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. Decarolis, Polyakova and Ryan (2020) justify this Hausman instrument by arguing that it captures variation in prices that come from sources such as an “insurer’s price negotiations with pharmaceutical producers”, but is not correlated with unobserved market-specific plan quality.

In order to calculate sample moments based on Equations (14) and (15) at a candidate parameter vector (θ^j, θ^k) , we need to calculate the statin and plan choice probabilities implied by the model. However, due to the simultaneous estimation of statin and plan demand, there is no closed-form solution for $s_{ijt}(\theta^j, \theta^k)$ and thus we simulate it. Specifically, in simulation r , we take draws of ε_{ikt}^r (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 solve for a simulated version of v_{ijt}^* from Equation (2). We replace v_{ijt}^* in Equation (3) with its simulated version v_{ijt}^{*r} . The simulated plan utility is given by

$$u_{ijt}^r = \delta_{jt} + \beta_t^{v*} v_{ijt}^{*r} + \tau_{ijt}, \quad (16)$$

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

$$s_{ijt}^{sim}(\theta^j, \theta^k) = \frac{1}{R} \sum_{r=1}^R \frac{\exp(\delta_{jt} + \beta_t^{v*} v_{ijt}^{*r})}{\sum_{j'=1}^J \exp(\delta_{j't} + \beta_t^{v*} v_{ij't}^{*r})}, \quad (17)$$

³⁵Out of the 39 moments that we obtain from Equation (15), 29 correspond to region fixed effects.

where R is the total number of simulation draws per beneficiary. The simulated probability that beneficiary i chooses statin k substitutes s_{ijt}^{sim} into Equation (13):

$$s_{ikt}^{sim}(\theta^j, \theta^k) = \sum_{j=1}^J s_{ijt}^{sim}(\theta^j, \theta^k) s_{ikt|j}(\theta^k). \quad (18)$$

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 . The sample analogs of Equations (14) and (15) are given by

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

To obtain ζ_{jt} we first calculate s_{ijt}^{sim} as described above and then use the BLP contraction. We estimate the parameters by minimizing the following objective function

$$Q(\theta^j, \theta^k) = g_t(\theta^j, \theta^k)' W_t g_t(\theta^j, \theta^k) \quad (19)$$

Here $g_t(\theta^j, \theta^k)$ is a $(3 \times J + M^j) \times 1$ vector and W_t is a $(3 \times J + M^j) \times (3 \times J + M^j)$ 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.

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 (12) 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 (12) is the basis for our moment inequality approach. However, as stated in Equation (10), we measure profits with error. After substituting Equations (10) and (11) into Inequality (12) we obtain

$$\sum_{j \in J_h} [\hat{\Pi}_j(f_j, p_j, \gamma, \nu_{2,h}) + \nu_{1,j}(f_j)] \geq \sum_{j \in J_h} [\hat{\Pi}_j(f'_j, p_j, \gamma, \nu_{2,h}) + \nu_{1,j}(f_j)] \quad \forall f'_h \quad (20)$$

Inequality (20) 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 chose formulary f_j for plan j instead of f'_j . Then substituting Equations (8) and (9) into Inequality (20), we have

$$\begin{aligned} \sum_{j \in J_h} \Delta A_j(f_j, f'_j) + \sum_{j \in J_h} \sum_{k \in K_j^b} \gamma_k(f_j) \Delta L_{jk}(f_j, f'_j) + \sum_{k \in K_j^b} (\gamma_k(f_j) - \gamma_k(f'_j)) L_{jk}(f'_j) \geq \\ - \sum_{j \in J_h} \sum_{k \in K_j^b} \Delta L_{jk}(f_j, f'_j) \nu_{2,h} + \sum_{j \in J_h} \Delta \nu_{1,j}(f_j, f'_j). \end{aligned} \quad (21)$$

where the Δ operator is defined in terms of formulary differences, e.g., $\Delta A_j(f_j, f'_j) = A_j(f_j) - A_j(f'_j)$ and we assume that $\Delta L_{jk}(f_j, f'_j) \in \mathcal{I}_h$.

Inequality (21) can be rearranged to provide a bound on $\nu_{2,h(j)}$. When we take sample averages across insurers, the measurement error term $\Delta \nu_{1,j}(f_j, f'_j)$ averages out. Thus, the direction of the bound depends on the sign of

$$\sum_{j \in J_h} \sum_{k \in K_j^b} \Delta L_{jk}(f_j, f'_j). \quad (22)$$

To build intuition further, we show that with a single-plan insurer Inequality (21) can be simplified and rearranged to give a bound on formulary-contingent rebates. For a single plan insurer, we can identify the plan with the insurer (thus j subscripts denote both the

plan and the insurer). Suppose that insurer j chooses f_j to cover Crestor on the preferred tier and exclude Lipitor. Compare profits with the case where f'_j excludes both branded statins. We show in Appendix D that Inequality (21) can be rearranged as

$$-\mathcal{E}\left(\sum_{k \in K_h^b} L_{jk}(f_j) | \mathcal{I}_j, f_j\right)^{-1} \mathcal{E}[\Delta A_j(f_j, f'_j) | \mathcal{I}_j, f_j] \leq r_{jk}(f_j). \quad (23)$$

This Inequality provides a lower bound on the rebate for having Crestor on the preferred tier and is much simpler than Inequality (21) because it considers a single plan and also because insurers do not cover the cost of excluded drugs, so many terms are zero. There is a simple intuition for why the comparison between f_j and f'_j provides a lower bound on the rebate for having Crestor on the preferred tier. Insurer j chose to cover Crestor on f_j , but could have instead excluded Crestor on f'_j . If there rebate for covering Crestor on the preferred tier were very low, for example if there were no rebate, then excluding Crestor look more enticing because the insurer is paying the full cost of Crestor. Since the insurer infact covered Crestor, we infer that the rebate cannot have been too small, hence we obtain a lower bound.

More generally, our estimation approach combines both Equation (4.2) and Inequality (21) and as such we focus on bounds for $\nu_{2,h(j)}$. 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 $\nu_{2,h(j)}$ when the coverage of branded statins is reduced (e.g, moving from preferred to excluded) and provides an upper bound on $\nu_{2,h(j)}$ 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 (21), for any vector of mean rebates γ , define the following quantity

$$B_j(f_j, f'_j; \gamma) = -\left(\sum_{j \in J_h} \sum_{k \in K_j^b} \Delta L_{jk}(f_j, f'_j)\right)^{-1} \times \quad (24)$$

$$\left(\sum_{j \in J_h} \Delta A_j(f_j, f'_j) + \sum_{j \in J_h} \sum_{k \in K_j^b} \gamma(f_j) \Delta L_{jk}(f_j, f'_j) + \sum_{k \in K_j^b} (\gamma_k(f_j) - \gamma_k(f'_j)) L_{jk}(f'_j)\right)$$

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 (off 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:

$$-\min_{k \in K_j^b} \{\gamma_k(f_j)\} \leq \nu_{2,h(j)} \leq 1 - \max_{k \in K_j^b} \{\gamma_k(f_j)\}. \quad (25)$$

We combine the bounds from the data in Equation (24) with the support bounds in Inequality (25) for estimation.

The lower bound function is defined as follows:

$$\mathcal{L}_j(f_j, f'_j, \gamma) = \begin{cases} B_j(f_j, f'_j, \gamma) & \text{if } f_j \text{ does not exclude both Crestor and Lipitor} \\ -\min_{k \in K_j^b} \{\gamma^k(f_j)\} & \text{else} \end{cases} \quad (26)$$

The upper bound function is defined similarly:

$$\mathcal{U}_j(f_j, f'_j, \gamma) = \begin{cases} B_j(f_j, f'_j, \gamma) & \text{if } f_j \text{ does not make both Crestor and Lipitor preferred} \\ 1 - \max_{k \in K_j^b} \{\gamma^k(f_j)\} & \text{else} \end{cases} \quad (27)$$

Then, for every plan j , at the true vector of rebates γ_0 , we have

$$\mathcal{L}_j(f_j, f'_j, \gamma_0) + \nu_{1,j,f_j} \leq \nu_{2,h} \leq \mathcal{U}_j(f_j, f'_j, \gamma_0) + \nu_{1,j,f_j}. \quad (28)$$

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 (4.2), at the true rebate parameter vector γ_0^k , we have

$$\text{plim}_{h \rightarrow \infty} \frac{1}{H} \sum_{h=1}^H \frac{1}{J_h} \sum_{j \in J_h} \mathcal{L}_j(f_j, f'_j, \gamma_0) \leq \mathbb{E}[\nu_{2,h} | \mathcal{I}_h] = 0. \quad (29)$$

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

$$\text{plim}_{h \rightarrow \infty} \sum_{h=1}^H \frac{1}{J_h} \sum_{j \in J_h} \mathcal{L}_j(f_j, f'_j, \gamma_0) w(z_j) \leq 0. \quad (30)$$

With $m = 1, \dots, M^r$ instruments z_j^m , we have M^r sample moments corresponding to the left-hand side of Inequality (30). For all m , and any rebate vector γ , we define

$$Q_m^{\mathcal{L}}(\gamma) = \max \left\{ \frac{1}{H} \sum_{h=1}^H \frac{1}{J_h} \sum_{j \in J_h} \mathcal{L}_j(f_j, f'_j, \gamma) w(z_j^m), 0 \right\} \quad (31)$$

$$\hat{Q}_m^{\mathcal{L}}(\gamma) = \max \left\{ \frac{1}{H} \sum_{h=1}^H \frac{1}{J_h} \sum_{j \in J_h} \mathcal{L}_j(f_j, f'_j, \gamma) w(z_j^m), 0 \right\} \quad (32)$$

which measure the extent to which sample analog of Inequality (30) 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

$$R^I = \{\theta : Q_m^{\mathcal{L}}(\theta) = 0 \text{ and } Q_m^{\mathcal{U}}(\theta) = 0, m = 1, \dots, M^r\}. \quad (33)$$

To use Equation (32) 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. [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, 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 (32). 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.³⁶ After defining the set of moment inequalities from these instruments, we follow [Chernozhukov, Chetverikov and Kato \(2019\)](#) to construct

³⁶Our results are robust to constructing instrument functions in different ways.

a 90% percent confidence set for the true parameter values. The details of the estimation procedure are given in Appendix D.2.

In terms of the approach to supply-side estimation, Eizenberg (2014) and Wollmann (2018) are closest to ours. Relative to those papers, we study a setting where firms have many options for each decision and, due to the institutions, the parameters that we recover a per unit rebates as opposed to fixed costs. Both of these differences play important roles in our approach. The fact that there are many formulary configurations allows us to reduce our reliance on the support bounds used in Eizenberg (2014). The fact that we estimate 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

In this section, we report our estimation results.

6.1 Demand

Table 4 reports estimates from minimizing the simultaneous demand model objective given in Equation (19). 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, α_t^{OOP} decreases by risk score tercile. Our estimates of mean drug quality show that Lipitor is preferred to Crestor by all risk types with LIS and the highest risk score tercile beneficiaries having the smallest difference in their preferences between Crestor and Lipitor. 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 the fact that higher income LIS beneficiaries must pay a larger share of drug costs.

Turning to Panel B, for all risk types, we find a positive coefficient on maximized statin

Table 4: Simultaneous Demand Estimates

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

Notes: This table reports estimates from the simultaneous demand model described in Section 4.1. In particular, we minimize the objective in Equation (19) 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 tier 1, and the number of drugs on tier 2.

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 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.³⁷ 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.³⁸ 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.

6.2 Supply

Figure 1 plots our set estimate of the mean rebate 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.

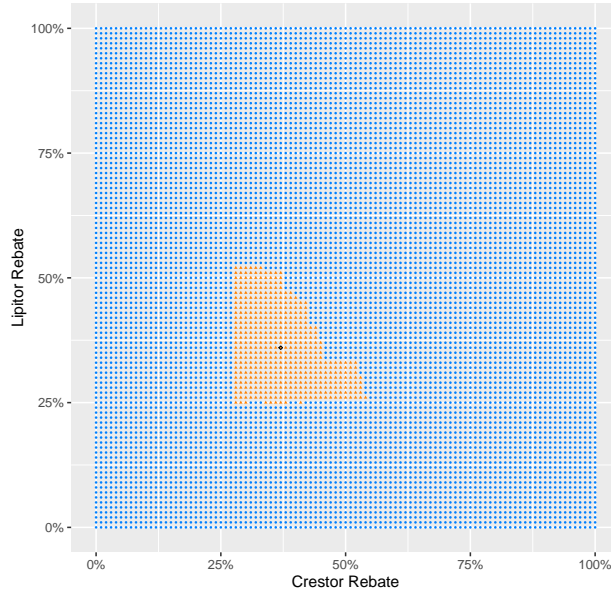
Table 5 reports the 90% confidence set for our mean branded statin rebate estimates. The confidence set for AstraZeneca’s Crestor is [28%, 54%] while the confidence set for Pfizer’s Lipitor is [25%, 52%]. Despite the fact that Lipitor was the incumbent branded statin with a big market share advantage (21% compared to 9% for Crestor), the confidence sets are remarkably symmetric. However, we cannot rule out asymmetric rebates either, e.g., we do not reject the Crestor–Lipitor rebate pairs (54%, 25%) or (28%, 52%).

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

³⁷The elasticities for LIS beneficiaries are very small because LIS beneficiaries have highly subsidized OOP costs and premiums.

³⁸We focus on conditional elasticities (i.e., elasticities of $s_{ikt|j}$) because they have closed-form expressions in our model, while calculating unconditional statin demand elasticities requires calculating numerical derivatives and is computationally expensive. The unconditional elasticities must be smaller than the conditional elasticities, because if people can change plans in response to an increase in the annual OOP cost of Crestor, then they may continue to buy Crestor on a different plan.

Figure 1: Estimates of Branded Statin Rebates on Preferred Tier



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

on the aggregate level annually. In 2010, the average annual Part D rebate was 11.3%.³⁹ 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 2014.⁴⁰ 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.

³⁹Table IV.B8 of 2018 Trustees of Medicare Annual Report.

⁴⁰CMS 2014 Manufacturer Rebate Summary Report.

Table 5: Branded Statin Rebate Estimates

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

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

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 have 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 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.

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

In this section, we quantify how the market equilibrium would change under counterfactual branded statin rebates. These counterfactuals are relevant to any evaluation of government policy that targets rebates or drug prices. For a large range of rebates, we answer the question: if the government could negotiate a certain level of rebates (or prices), what would happen to consumer surplus, formularies, and profits. We then compare the status quo equilibrium to a set of equilibria that reflect branded statin prices obtained by the Canadian

government.

Increasing Crestor rebates could, theoretically, make Lipitor users worse off. Consider an insurer that initially places both Crestor and Lipitor on the preferred tier. Increasing Crestor rebates reduces the insurer’s cost when beneficiaries purchase Crestor. As a consequence, the insurer would like its beneficiaries to buy Crestor instead of Lipitor. Crestor is already on the preferred tier, but the insurer could try to steer beneficiaries towards Crestor, away from Lipitor, by moving Lipitor to the nonpreferred tier or excluding Lipitor altogether. However, moving Lipitor off the preferred tier reduces plan demand among statin users and the loss of premium revenue associated with lower plan demand must be balanced against the cost savings from steering beneficiaries to Crestor. Moreover, these distributional effects (where one group of consumers benefits, but another group is harmed) can even occur if both Crestor and Lipitor rebates increase. The incentive for insurers to steer beneficiaries towards one branded statin or the other depends on the difference between the branded statin rebates among other factors. Ultimately, understanding how changing branded drug rebates affect consumer surplus is an empirical question that depends upon drug demand, plan demand, and the initial level of rebates.

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

Our counterfactuals evaluate the effects of changing branded statin rebates. What would happen if the government prohibited manufacturers from paying insurers rebates in Part D? Alternatively, what would happen if the government negotiated rebates on behalf of all insurers? 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 insurer profits. Given tiered formularies are pervasive in drug insurance, understanding how changes in branded drug rebates affect formulary design is important.

In our counterfactuals, 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 study counterfactuals that only allow premiums to

change, while holding fixed the formulary (and all other plan characteristics).

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. Even statins, which were the largest therapeutic class of drugs by fills in 2010, only comprise around 5% of insurer costs.⁴¹ 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. In Appendix E, we outline a back-of-the-envelope approach to calculating the premium effect of branded statin rebates. Using premium elasticities for non-statin users taken from other studies, we calculate small premium effects. A policy that changed all branded drug rebates could have considerable effects on premiums; however it would also have important effects on all branded drug formulary placements and this paper is the first, that we are aware of, that provides an analysis that speaks to these formulary placement effects.

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 (11), a Nash equilibrium obtains if every insurer h solves

$$\max_{f_h} \mathcal{E}[\Pi_h(f_h, p_h, f_{-h}, p_{-h}, \gamma, \nu_{2,h}) | \mathcal{I}_h], \quad (34)$$

Since we are interested in policies where the government negotiates rebates on behalf of insurers, we model counterfactuals where all insurers receive the same rebate. I.e., we are specifically interested in counterfactuals where there is no rebate heterogeneity ($\nu_{2,h} = 0$). Our interest in counterfactuals without rebate heterogeneity is motivated by policy questions.⁴²

Because of the large number of market configurations, calculating the Nash equilibrium for all plans is computationally intractable.⁴³ Thus, we assume that the formulary choice for

⁴¹To calculate this number, we applied an average branded rebate of 13.8% to all branded drugs (based off calculations in Section 6.2).

⁴²It also allows us to sidestep issues that arise when evaluating counterfactuals due to the fact that $\nu_{2,h}$ is not recovered by our moment inequality estimation procedure, e.g., Eizenberg (2014) and Wollmann (2018).

⁴³The mean number of plans per region (after our sample restrictions) is 14. This implies that there are on the order of 9^{14} possible market configurations per region, thus simulating demand for every possible market configuration is not possible.

all small plans is fixed. A similar assumption is made [Eizenberg \(2014\)](#).⁴⁴ 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 choices of large plans, we account for the demand responses of 62% of beneficiaries on average (across markets) while keeping the number of formulary configurations that we need to simulate tractable.⁴⁵

Thus in our counterfactuals, for any vector of rebates γ , we set $\nu_{2,h} = 0$ and solve for the branded statin formulary placement of the 4 largest plans in each Part D region using Equation (34). When plans choose their formularies they take into account endogenous plan selection and its consequences for the cost distribution of their enrollees based off our demand estimates. After plans set formularies, beneficiaries choose plans and statins optimally. Our measure of consumer surplus is calculated using Equations (1) and (2) and the demand estimates from Table 4. Insurer profits are calculated using Equation (11).

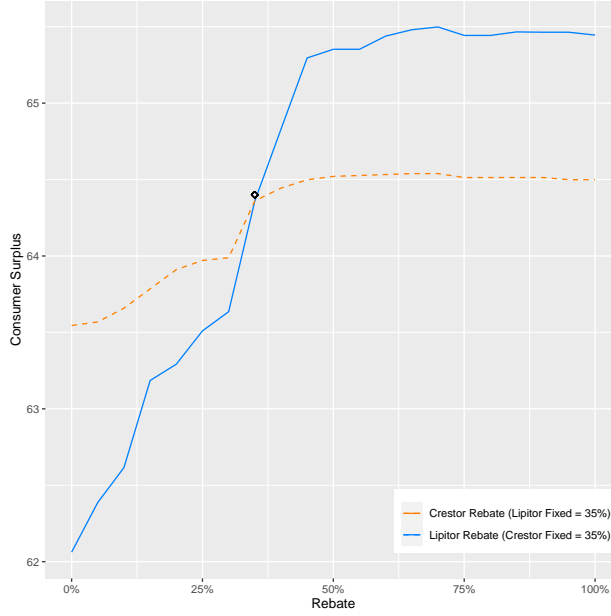
We quantify the effect that counterfactual branded statin rebates would have on formularies, consumer surplus, and insurer profit consider all possible rebates (from 0% to 100%) for placing branded statins on the preferred formulary tier (while keeping the rebate for being on the non-preferred tier fixed at 0%). This approach allows us to quantify how a policy that sets rebates to a certain level would affect outcomes without requiring us to take a stand on any specific model of bargaining between the government and drug manufacturer. I.e., our counterfactuals model the consequences of any level of rebates, but do not model how rebates are determined.

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 our counterfactuals. For the remaining 12 cases, we do not find any pure strategy equilibria and use linear interpolation to quantify these

⁴⁴[Eizenberg \(2014\)](#) fixes the product entry decisions of all laptop lines except the 4 largest.

⁴⁵Appendix 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 and hold fixed the remaining plans in each region. Since there are 30 regions in our analysis, we allow 120 plans to change their formularies in response to rebates. The 4 largest plans in each market capture 62% of each market’s beneficiaries on average (unweighted). In the smallest region, we capture 91% of beneficiaries, while in the largest region we capture 44% of beneficiaries.

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



Notes: This figure plots the effect of increasing the rebate for placing either Crestor or the Lipitor on the preferred tier rebate (holding fixed the other branded rebate near its mean value in our estimated set shown Figure 1). The black diamond corresponds to our counterfactual that sets rebates nearest to the mean of our estimated set.

counterfactuals.⁴⁶

7.2 Counterfactual Results

Figure 2 shows one of our main results; increasing the Crestor rebate, relative to the mean rebate in our estimated set, has no effect on consumer surplus, but increasing the Lipitor rebate has a substantial effect on consumer surplus. Consumer surplus is on the y -axis, and the level of rebates is on the x -axis. The solid blue line shows the effect of increasing the Crestor rebate holding the Lipitor rebate fixed at 35% (the mean of our estimate set is 37%). The dashed orange line shows the effect of increasing the Crestor rebate holding the Lipitor rebate at 35% (the mean of our estimate set is 36%). The black diamond plots the consumer surplus near the mean of our estimated set of rebates. Starting from the black diamond on the Crestor line (dashed orange), we see that there is no effect on consumer surplus to

⁴⁶Given the game that we analyze has a finite number of players and a finite strategy space, there exists a mixed strategy equilibrium.

further increasing the Crestor rebate. In contrast, the Lipitor line is relatively steep near the black diamond. Overall there are two takeaways from this graph: first, the consumer surplus effect of increasing rebates is heterogeneous across drugs and can even be close to zero for some drugs; second, the initial level of rebates can matter substantively.

Figure 3 extends Figure 2 by allowing for any combination of changes in Crestor and Lipitor rebates. The figure shows level curves of consumer surplus in rebate space where rebates vary between 0% and 100%. Crestor rebates are shown on the y -axis and Lipitor rebates are shown on the x -axis. The black diamond is a reference point that is near the mean rebates of our estimated set. The black line shows the level curve of all points that have the same consumer surplus as the counterfactual with the black diamond. Figure 2 showed lines corresponding to vertical and horizontal cross sections of Figure 3 that pass through the black diamond. The orange dashed line plots a set of rebates that are consistent with the prices that branded statin manufacturers receive in Canada where provincial governments and drug manufacturers negotiate over prices; the dashed orange line provides a useful comparison because it provides a benchmark for what Part D rebate policy reform might achieve relative to the current system, where private insurers negotiate branded statin rebates (typically through PBMs). In order to calculate the dashed orange line, we use data on the mean price of all branded statins in Canada from [Dubois, Gandhi and Vasserman \(2019\)](#) to convert Canadian prices into rebates (relative to U.S. list prices). 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 cost as the Canadian government. The dashed orange line shows the set of rebates consistent with an average rebate of 48.4%. Further details of the Canadian price calculations are in [Appendix C](#).

Figure 3 shows that consumer surplus is higher for many rebate vectors that are consistent with Canadian prices because most of the points on the dashed orange line lie on higher consumer surplus isocurves than the black diamond. Thus, if the U.S. government could negotiated branded statin rebates and could obtain rebates at least as good as those obtained by provincial Canadian governments, then consumer surplus would likely increase. Specifically, comparing the consumer surplus near the mean of our estimated rebates (the black diamond) to the intersection of the dashed orange line and the 45 degree line increases consumer surplus by 1.9%. If we consider the minimum of our estimated rebate set, then con-

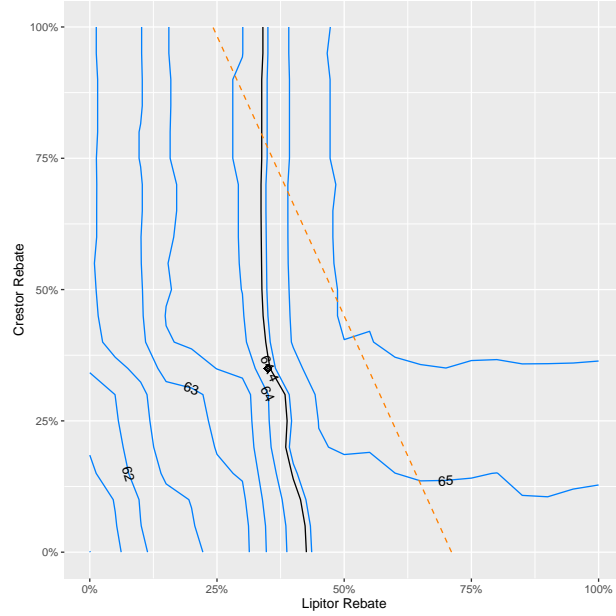
sumer surplus increases by 3.1%. This suggests that there is room for government negotiated rebates to increase consumer surplus in Part D.

Figure 3 also provides a detailed description of how branded statin rebates for preferred tier status affect consumer surplus (through formulary design). First, as in Figure 2, increasing the Crestor rebate relative to the black diamond moves parallel to the consumer surplus isocurves and so does not increase consumer surplus, while increasing the Lipitor rebate moves (almost) perpendicular to the isocurves and hence increases consumer surplus most quickly (i.e., it is in the direction of the gradient of the consumer surplus function). Second, the effect of changing rebates is nonlinear and depends on the initial level of rebates. There is little effect on consumer surplus from increasing Crestor rebates beyond 35%, however increasing Lipitor rebates increases consumer surplus as long as rebates are less than 50%. Once rebates exceed 40%, the level curves exhibit a Leontieff pattern. Last, the isocurves make it clear that in the case of branded statins, Lipitor rebates are more important than Crestor rebates for consumer surplus. For example, relative to a Lipitor rebate of 45% and a Crestor rebate of 0%, consumer surplus is roughly the same if the Crestor rebate increases to 100%, but the Lipitor rebate falls to 35%. As a consequence, a government policy that results in uniform rebates across branded drugs may be far from optimal from the perspective of maximizing consumer surplus; more generally, the value of increasing rebates for any specific branded drug is a complicated function of demand and the initial level of rebates for all substitute drugs.

To understand what drives the effects of rebates on consumer surplus, we examine the effect of rebates on branded statin formulary placement. Figure 4 show the effect of rebates on the distribution of equilibrium branded statin formulary placement. To summarize the effects of rebates on formularies, we collect plans into four groups based on their placement of branded statins: 1) both preferred; 2) both non-preferred or both excluded; 3) Crestor advantaged, i.e., Crestor preferred and Lipitor not preferred or Crestor non-preferred and Lipitor excluded; 4) Lipitor advantaged, i.e., Lipitor preferred and Crestor not preferred or Lipitor non-preferred and Crestor excluded. After grouping these tiers, we have four possible formulary structures that are shown in each of the panels of Figure 4.⁴⁷

⁴⁷Appendix Figure 2 isolates the effect of branded statin rebates on the equilibrium share of plans that place either Crestor or Lipitor on the preferred tier, however a complete branded formulary description must

Figure 3: The Effect of Statin Rebates on Consumer Surplus

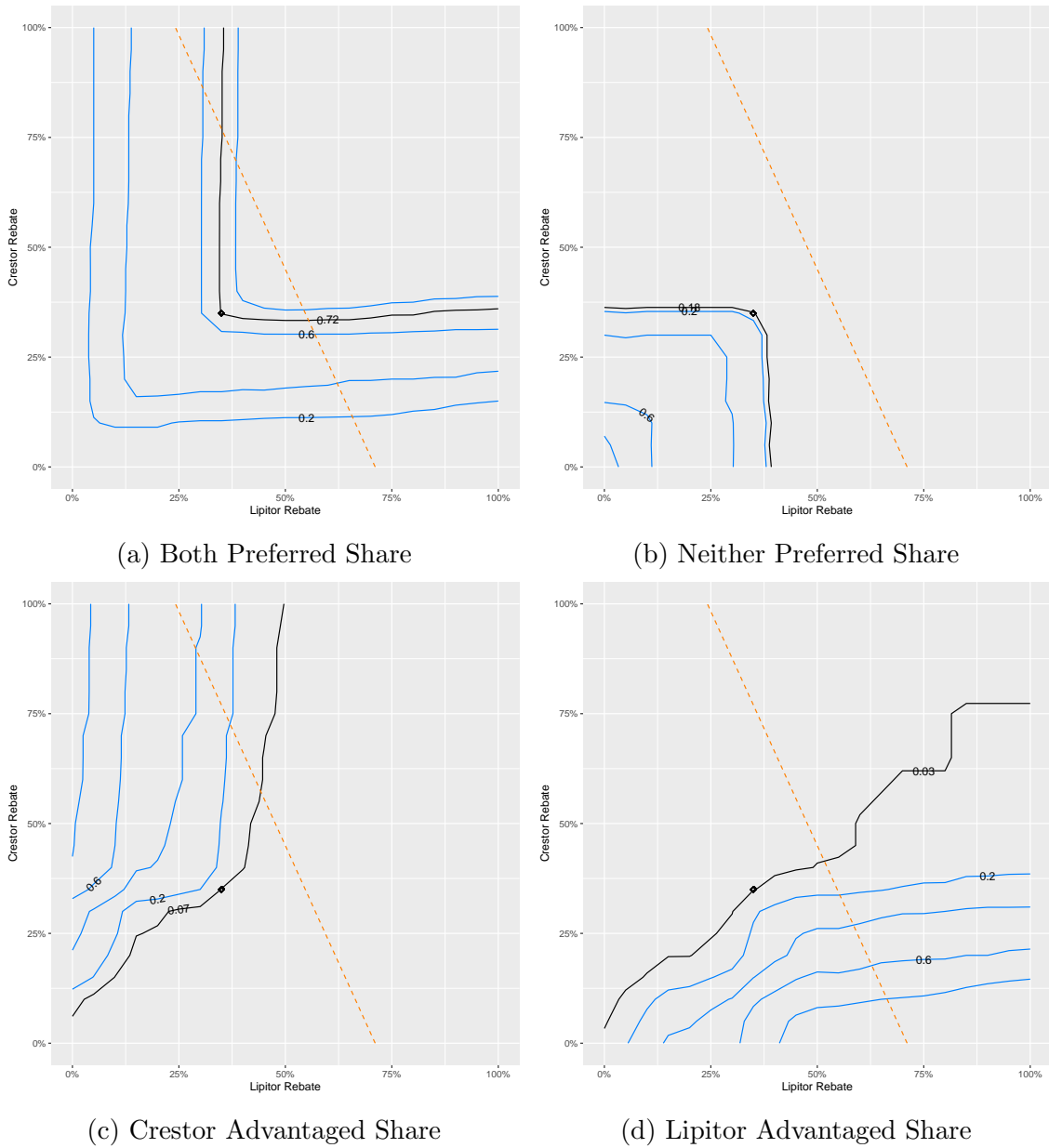


Notes: This figure plots level curves of consumer surplus as a function of the rebates for placing Crestor and Lipitor on the preferred tier.

Panels (a) and (b) both have a Leontieff pattern. As a consequence, increasing only the Crestor rebate or only the Lipitor rebate does not affect the share of plans that treat branded statins symmetrically on the formulary. Thus, all of the formulary effects that are induced by increasing a single branded statin rebate come from changing the share of plans that advantage one branded statin or the other. Panels (c) and (d) show that increasing Crestor rebates (holding the Lipitor rebate fixed) induces some insurers to give Crestor an advantageous formulary position instead of Lipitor. From the perspective of insurers, this can be profitable because it induces selection among beneficiaries who want Crestor (which is cheaper due to the increased rebate) and because the altered formulary can steer beneficiaries to Crestor. However, advantaging Crestor instead of Lipitor creates winners (beneficiaries who prefer Crestor) and losers (beneficiaires who prefer Lipitor). Figure 3 shows that if only the Crestor rebate is increased, then the consumer surplus effects happen to average out while when only the Lipitor rebate is increased, the benefit to winners exceeds the losses to losers.

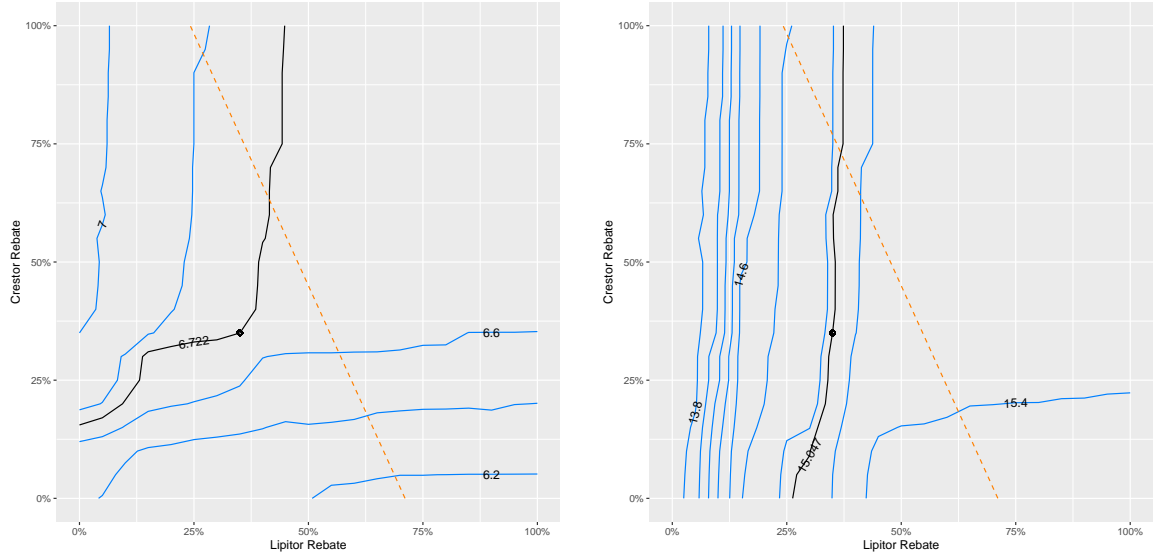
specify the formulary treatment of both branded statins and hence cannot be inferred from Appendix Figure 2.

Figure 4: The Effect of Statin Rebates on Formulary Placement



Notes: This figure plots the effect of branded statin rebates on the distribution of branded statin formulary placement. Each panel plots level curves of the market share of (large) plans with the corresponding formulary type. Panel (a) plots the share of plans that place both Crestor and Lipitor on the preferred tier. Panel (b) plots the share of plans that place neither Crestor nor Lipitor on the preferred tier. Panel (c) plots the share of plans that have Crestor advantaged, so that Crestor is on the preferred tier, but Lipitor is not on the preferred tier. Finally Panel (d) plots the share of plans that have Lipitor advantaged.

Figure 5: The Effect of Statin Rebates on Statin Demand



(a) Crestor Demand (10,000s beneficiaries) (b) Lipitor Demand (10,000s beneficiaries)

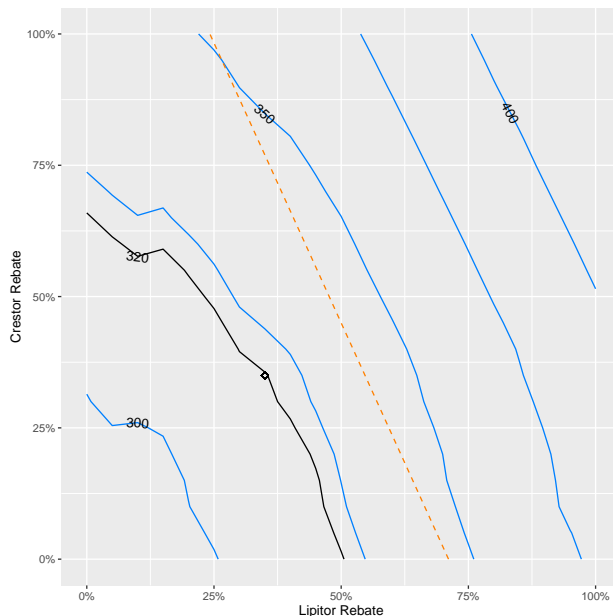
Notes: This figure plots the effect of branded statin rebates on the demand of branded statins. Panel (a) plots the demand of Crestor and Panel (b) plots the demand of Lipitor.

Figure 5 shows how equilibrium formulary design translates into demand for branded statins. The demand isocurves are equally spaced in both panels. The fact that there are far fewer lines in Panel (a) than in Panel (b) indicates that rebates have less effect on the total quantity demanded for Crestor than for Lipitor. This is also related to the result that increasing only Crestor rebates does not increase consumer surplus. Since Crestor the total quantity of Crestor is less responsive to rebates than the total quantity of Lipitor, inducing plans to advantage Crestor instead of Lipitor benefits relatively few statin users and harms relatively more.

Together, the results from Figures 2, 3, 4, and 5 suggest challenges to increasing consumer surplus through government negotiated rebates: when insurers are free to design their formularies, the marginal effect of increasing the rebate on a single branded drug depends on the initial level of both rebates. Moreover, increasing a single branded drug rebate can have very asymmetric effects. In our setting, three effects mute the consumer surplus effect of increasing only the Crestor rebate. First, starting from the mean rebates in our estimated set, increasing the Crestor rebate has modest effects on formularies because the Crestor rebate was already large to begin with. Second, as the Crestor rebate increases, some formularies

advantage Crestor, which benefits Crestor users and harms Lipitor users. Third, beneficiaries can change plans in response to changing formularies and this mitigates the harm to Lipitor users whose plans begin to favor Crestor.

Figure 6: The Effect of Statin Rebates on Total Insurer Profits



Notes: This figure plots level curves of total insurer profits, which is calculated using Equation (11). We ignore administrative costs when calculating insurer profits and assume that they are fixed across all equilibria.

While the consumer surplus effects, that are mediated through equilibrium formulary placement, are nuanced, the effects on insurer profits are straightforward. Figure 6 shows the effects of branded statin rebates on insurer profits. Increasing either rebate reduces insurer marginal costs. Moreover (large) insurers can further adjust their formularies in response to lower marginal costs. These formulary adjustments can only further increase profits beyond the first-order effect of lower marginal costs. The profit isocurves indicate that the profit function is steeper in the direction of Lipitor rebates (since the gradient, which is perpendicular to the level curves and is not shown, is typically flatter than the 45 degree line). This makes sense because Lipitor has a much larger market share than Crestor and so reductions in its cost have larger effects on insurer profits.

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 estimate that Medicare Part D insurers receive large rebates for branded statins. We use revealed preference arguments operationalized with moment inequalities to partially identify unobserved formulary-contingent rebates. We estimate that rebates from branded statins are at least 25% and could be as large as 54%. Increasing rebates can create winners and losers due to endogenous formulary design. Indeed, 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. As a consequence there are winners (Crestor users) and losers (Lipitor users) and no net effect on consumer surplus. On the other hand, increasing only Lipitor rebates does increase consumer surplus. More generally, the consumer surplus effects of increasing branded statin rebates are nonlinear and depend on the initial level of rebates. 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. There is considerable interest in U.S. rebate policy as a consequence of high drug prices. Changing rebates has first-order implications for insurers costs of covering branded drugs and, as we show here, has important, but subtle effects on formulary design.

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Appendix A Variation in Annual OOP Costs

We assume that beneficiaries consider the effect of statin brand choice on their total annual drug spending, i.e., the price for Crestor is 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 Standard Benefit Schedule 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 on the SBS (given by the slope of the function in Figure 1) is a piecewise constant function. 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, 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; some plans remove the deductible or provide some gap coverage.

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 c_{ijk} for beneficiary i choosing statin j on plan k can be written as

$$OOP_{ijk}(f_j) = oop_k(g_{ik}^{ns}(h_i, \eta_i), f_j).$$

g_{ik}^{ns} is an unknown function that maps health h_i and preferences η_i into spending on nonstatin drugs; oop_k is a known function that maps spending on nonstatin drugs g_{ik}^{ns} and the formulary f_k (which, in this section refers to the tier placement of all drugs and the associated copays and coinsurance rates) into annual OOP costs for statins c_{ijk} .⁴⁸ The fact that g_{ik}^{ns} is unknown means that we need to make an assumption in order to calculate c_{ijk} . The assumption that

⁴⁸We assume that beneficiaries would not change the timing of their drug purchases if they changed statins otherwise the function translating non-statin spending and cost-sharing rules in statin prices would vary by statin and we would not be able to calculate statin prices for unobserved choices.

we use has been used many times in the literature on plan choice: We assume no moral hazard on nonstatin drugs. This means that we calculate the cost of statins on each plan, we hold fixed the nonstatin drug decisions 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 the source of beneficiary variation in prices in the context of the standard benefit schedule described in Section 2. The figure shows the relationship between the annual 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. Changes in non-statin drug spending shift the nonlinear schedule to the left by an amount determined from the known function oop_k . The solid line shows the schedule corresponding to no spending on other drugs; the dashed lines show the schedules when annual spending on other drugs is \$250 or \$1,000. A simplification in the context of the standard benefit schedule is that the function oop_k is particularly simple. In tiered plans with copays, oop_k is high-dimensional, but still known; and I can still compute the effect of changes in non-statin drug spending on oop_k .

Annual OOP costs c_{ijk} raise endogeneity concerns in our model if the preferences that determine nonstatin drug spending η_i are correlated with preferences for statins ε_{ij} 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_i that is correlated with ε_{ij} .

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

$$R_{ij}(p_j) = p_j + p_j^{LIPSA} + SUB_{ij} + RE_{ij} \quad (35)$$

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.⁴⁹

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. Thus, we observe the premium that each LIS beneficiary would face for any counterfactual set of plan choices.
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):

$$SUB_{ij} = CCS_i \cdot BID_j - (p_j + p_j^{LIPSA}). \quad (36)$$

We use the CMS risk score software to calculate each beneficiary’s risk score based off their claims data. We recover plan bids from their premiums and public data on the national average bid amount and the base premium.

⁴⁹The catastrophic coverage region started once beneficiaries spent more than \$4,880 in annual out-of-pocket costs in 2010

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 ($d \in \mathcal{D} = \{F_j, \mathcal{G}, \mathcal{B}\}$ where F_j are the statins on plan j , \mathcal{G} are non-statin generics, and \mathcal{B} are branded non-statin drugs).

$$\begin{aligned}
RE_{ij}(f_j, \theta^k, \gamma) &= .8 \cdot \sum_{k \in F_j^b} (1 - \gamma) \cdot CC_{ikj} \cdot s_{ik|j}(f_j, \theta^k) \\
&+ .8 \cdot CC_{i\mathcal{G}j} \\
&+ .8 \cdot (1 - \gamma^{\mathcal{B}}) \cdot CC_{i\mathcal{B}j}.
\end{aligned} \tag{37}$$

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%.⁵⁰ 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. The bid for plan j , BID_j , specifies a monthly revenue requirement that the plan needs to cover its costs (for basic coverage) and a profit margin. The premium for basic drug coverage is equal to the bid minus the base premium. 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

Let Crestor and Lipitor rebates (which are formulary contingent and hence are functions of f_k) be given by $r_C(f_k)$ and $r_L(f_k)$ respectively. The expected cost to plan k from enrolling

⁵⁰In 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.

beneficiary i is

$$\begin{aligned}
C_{ik}(f_k, \theta^s, r_C, r_L) &= \sum_{j \in \mathcal{J}_k} s_{ij|k}(f_k, \theta^s) \cdot ([1 - r_j(f_k)] \cdot tc_{jk} - c_{ijk} - licsa_{ijk}) + C_i^{NS} \\
&= \sum_{j \in \mathcal{J}_k} s_{ij|k}(f_k, \theta^s) \cdot C_{ij}(r_j(f_k)) + C_i^{NS}
\end{aligned} \tag{38}$$

where $r_j(f_k)$ is the rebate for statin j when plan k chooses formulary f_k ⁵¹, C_{ij} is the cost to plan k from beneficiary i 's purchase of statin j , C_i^{NS} is the cost that plan k incurs to cover beneficiary i 's nonstatin drugs and $s_{i|k}(f_k, \theta^s)$ is the vector conditional statin choice probabilities. The second line simply defines C_{ij} as total costs, net of rebates, less annual OOP contributions, and LICSA payments for statin j .

The expected costs for plan k are given by the sum of the costs of the enrollees that endogenously select into plan k . Plan k 's expected costs depend on demand for the plan as well as per enrollee costs. Critically, these costs depend on branded formulary placement f_k as well as rebates $r_j(f_k)$. The rebates affect the marginal costs of branded statins and the formularies affect the extent to which enrollees are steered to different branded statins. The set of formularies available in the market (f_k, f_{-k}) is important because it determines the degree to which beneficiaries adversely select into plan k .

Most of the quantities that we require to calculate $C_{ik}(f_k, \theta^s)$ were described in the section on Federal Reinsurance revenues. The only extra quantities that we need are beneficiary out-of-pocket payments and LICSA payments, which are observed functions of plan cost-sharing rules, beneficiary cost-sharing groups (for LIS enrollees), and branded statin formularies.⁵²

Appendix C Canadian Prices

In this section, we describe how we calculate the Canadian prices that we compare to Part D status quo rebates in our counterfactual section.

We use data on the prices that branded statin manufacturers are paid per pill from [Dubois, Gandhi and Vasserman \(2019\)](#).⁵³ We calculate mean branded statin rebate that

⁵¹We assume that no rebates are paid for generic statins.

⁵²Because we assume no moral hazard on non-statin drugs, only branded statin out-of-pocket payments and LICSA payments depend on f_k . Thus, $oop_{ikG}(f_k)$ and $oop_{ikB}(f_k)$ are constant (or trivial functions of f_k).

⁵³This statin price data comes from a hospital setting, however because statins are taken orally, we believe

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 \(2019\)](#). In particular, 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. insurers would pay the same mean price for branded statins as provincial Canadian government if the mean rebate were $48.4\% = 1 - 1.77/3.43$.

If both Crestor and Lipitor had rebates of 48.4%, then the mean rebate would be 48.4%. However, in Part D, in Section 6.2 we estimate that the rebates for Crestor and Lipitor to be very different. Ideally, we would have data on both Crestor prices and Lipitor prices in Canada. However, we only observe a mean rebate. Thus we assume that Canadian market shares for 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%.

Recall that 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. The pairs of Crestor and Lipitor rebates that are consistent with a 48.4% rebate solve the following linear equation:

$$1 - \frac{1}{3.97} \left[(1 - r_C) \frac{.095}{.095 + .211} 4.08 + (1 - r_L) \frac{.211}{.095 + .211} 3.92 \right] = 1 - \frac{1.77}{3.43}. \quad (39)$$

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.

Appendix D Details on Moment Inequalities

D.1 Calculating Bounds

Let $f_{j_k} = (x, 3) \neq (3, 3)$; Crestor is not excluded, but Lipitor is excluded. Consider $f'_{j_k} = (3, 3)$. Since Crestor's copay on j_1 increased, demand for Crestor on j_k falls, so that pharmacy prices were similar.

$\Delta P_{j_k}^C(f_{j_k}; f'_{j_k}) > 0$. The remaining terms in Expression (22) capture the change in the insurer's branded statin costs across all its plans when the formulary on j_1 changes from f_{j_k} to f'_{j_k} . Since branded statins on other plans substitute for Crestor on j_k , these terms are all negative (demand is higher under f'_{j_k}). Since some people substitute to different insurers, Expression (22) is positive. Thus dividing both sides of Inequality (21) by the negative of Expression (22), we get a lower bound for $\nu_{2,h}$.

Upper bounds on $\nu_{2,h}$ are obtained by comparing f_{j_k} to a formulary f'_{j_k} that decreases copays for either (or both) branded statins. This works for all plans with $f_{j_k} \neq (1, 1)$. For example, if $f_{j_k} = (x, 1) \neq (1, 1)$ and $f'_{j_k} = (1, 1)$, then the Expression (22) is negative (the argument is the exact reverse of the lower bounds case) and thus dividing both sides of Inequality (21) by the negative of Expression (22) gives an upper bound on $\nu_{2,h}$.

D.2 Estimation

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

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

against the alternative

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

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

follows:

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

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

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 $(1-\alpha)\%$ 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 Endogenizing Premiums

Insurer h 's profits are the sum of the profits of all its plans:

$$\Pi_h(F_h, P_h; F_{-h}, P_{-h}) = \sum_{k=h_1}^{h_K} \Pi_{j_k}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k}) \quad (44)$$

where $Z_h = (z_{j_{h_1}}, \dots, z_{j_{h_K}})$ is a vector containing insurer h 's plans and Z_{-h} contains insurer h 's competitors plans.

We assume that insurers simultaneously choose their premiums and formularies. A Nash Equilibrium is a vector of premium–formulary pairs (one per insurer) such that each insurer is best responding to all the other insurers:

$$(F_h^*, P_h^*) = \max_{(F_h, P_h)} \Pi_h(F_h, P_h; F_{-h}^*, P_{-h}^*) \quad \forall h. \quad (45)$$

Our model has two types of selection: *formulary selection* where enrollees with different insurance costs choose plans based on formulary design; *premium selection* where enrollees with different insurance cost choose plans based on premiums. There are computational challenges in addressing each of these sources of selection.

The mean number of plans per region is 14, thus there are on the order of 9^{14} formulary configurations per region. Calculating each insurer’s profit for each formulary configuration is infeasible. Thus, in our rebate counterfactuals, we follow Eizenberg (2014) and only allow the largest plans to change their formularies.

Fix a formulary configuration $(\bar{F}_h, \bar{F}_{-h})$. For $(\bar{F}_h, \bar{F}_{-h})$ to be a Nash Equilibrium, we need $(\bar{P}_h, \bar{P}_{-h})$ such that

$$(\bar{F}_h, \bar{P}_h) = \max_{(F_h, P_h)} \Pi_h(F_h, P_h; \bar{F}_{-h}, \bar{P}_{-h}) \quad \forall h. \quad (46)$$

In our setting, solving Equation (46) for premiums $(\bar{P}_h, \bar{P}_{-h})$ is much more difficult than typical Nash–Bertrand price counterfactuals because we do not assume constant marginal costs. To see this, rewrite profits:

$$\Pi_h(F_h, P_h; F_{-h}, P_{-h}) = \sum_{k=h_1}^{h_K} q_{j_k}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k}) p_{j_k} - c_{j_k}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k}) \quad (47)$$

where q_{j_k} is demand for plan j_k and c_{j_k} is the cost function for plan j_k , which depends on formularies and premiums. Instead, we calculate both statin and non–statin costs as a function of enrollee selection into each plans.

Thus in order to find premiums that solve Equation (46), we need to know two derivatives:

$$\frac{\partial q_{j_k}}{\partial p_{j_k}}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k}) \quad (48)$$

and

$$\frac{\partial c_{j_k}}{\partial p_{j_k}}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k}). \quad (49)$$

The first derivative, in Equation (48) is the standard derivative used in Nash–Bertrand price setting counterfactuals. However, the second derivative, in Equation (49) is needed because we do not assume constant marginal costs.

In order to endogenize premiums in our counterfactuals, we assume that, mean plan costs per enrollee depend on *formulary selection*, but not *premium selection*. I.e., we assume that if premiums change from (p_{j_k}, p_{-j_k}) to (p'_{j_k}, p'_{-j_k}) , but formularies are held fixed, then mean plan costs per enrollee do not change:

$$\bar{c}_{j_k}(f_{j_k}, f_{-j_k}) := \frac{c_{j_k}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k})}{q_{j_k}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k})} = \frac{c_{j_k}(f_{j_k}, p'_{j_k}; f_{-j_k}, p'_{-j_k})}{q_{j_k}(f_{j_k}, p'_{j_k}; f_{-j_k}, p'_{-j_k})} \quad \forall j_k.$$

Under this assumption, we can rewrite Equation (47) as

$$\Pi_h(F_h, P_h; F_{-h}, P_{-h}) = \sum_{k=h_1}^{h_K} q_{j_k}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k}) [p_{j_k} - \bar{c}_{j_k}(f_{j_k}, f_{-j_k})]$$

and we can endogenize premiums by solving for the premium configuration that would rationalize each formulary configuration and then find the Nash equilibrium by searching for the formulary configuration that makes all insurers best respond.

The goal is to endogenize premiums using the simulated demand functions for the current counterfactuals. Recall that we split statin users into four types indexed by t . Thus the data that we have is the following:

- Status quo observed premiums p_{j_k} for all plans;
- Plan market shares for all types *statin users* $q_{j_k,t}$ and for *non-statin users* $q_{j_k,n}$ at the observed premiums for each formulary configuration for all plans;
- Profits for *statin users* at observed premiums $\Pi_{j_k,t}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k})$ for each formulary configuration for all plans and types.
- Coefficient on premiums in plan utility for all types *statin users* β_t^p and for *non-statin users* β_n^p

Profit maximizing premiums set the premium first-order condition to zero:

$$\beta_n^p q_{j_k,n} (1 - q_{j_k,n}) [p_{j_k}^* - \bar{c}_n] + q_{j_k,n} + \sum_t \beta_t^p q_{j_k,t} (1 - q_{j_k,t}) [p_{j_k}^* - \bar{c}_{j_k,t}(f_{j_k}, f_{-j_k})] + \sum_t q_{j_k,t} = 0.$$

Alternatively, profit maximizing premiums solve

$$p_{j_k}^* = \frac{-q_{j_k,n} - \sum_t q_{j_k,t} + \sum_t \beta_t^p q_{j_k,t} (1 - q_{j_k,t}) \bar{c}_{j_k,t}(f_{j_k}, f_{-j_k}) + \beta_n^p q_{j_k,n} (1 - q_{j_k,n}) \bar{c}_n}{\beta_n^p q_{j_k,n} (1 - q_{j_k,n}) + \sum_t \beta_t^p q_{j_k,t} (1 - q_{j_k,t})}.$$

A good approximation to the change in profits accounting for endogenous premiums is

$$\underbrace{\beta_n^p q_{j_k,n} (1 - q_{j_k,n}) (p_{j_k}^* - p_{j_k}) (p_{j_k}^* - \bar{c}_n)}_{\text{Change in non-statin plan share times markup}} + \underbrace{\sum_t \beta_t^p q_{j_k,t} (1 - q_{j_k,t}) (p_{j_k}^* - p_{j_k}) [p_{j_k}^* - \bar{c}_{j_k,t}(f_{j_k}, f_{-j_k})]}_{\text{Change in statin plan share times markup}} + \underbrace{\left(q_{j_k,n} + \sum_t q_{j_k,t} \right) (p_{j_k}^* - p_{j_k})}_{\text{Change in markup on old share}}. \quad (50)$$

To approximate $\bar{c}_{j_k,t}(f_{j_k}, f_{-j_k})$ we use

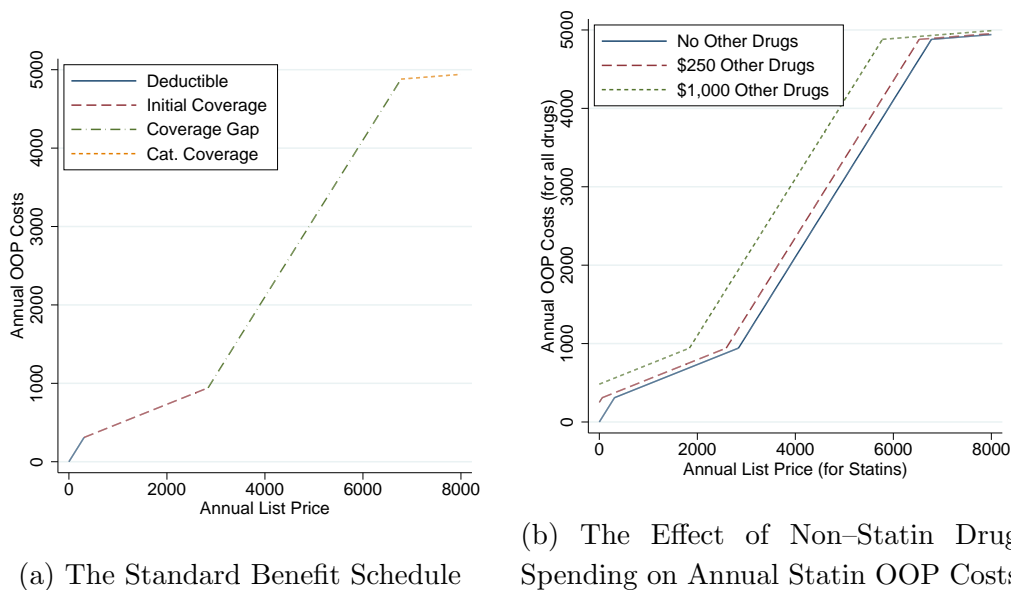
$$p_{j_k} - \frac{\Pi_{j_k}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k})}{\sum_t q_{j_k,t}(f_{j_k}, p_{j_k}; f_{-j_k}, p_{-j_k})}.$$

To approximate \bar{c}_n we could calculate the profit of non-statin users and analogously use

$$p_{j_k} - \frac{\Pi_{j_k,n}(p_{j_k}; p_{-j_k})}{q_{j_k,n}(p_{j_k}; p_{-j_k})}.$$

Appendix F Extra Figures and Tables

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

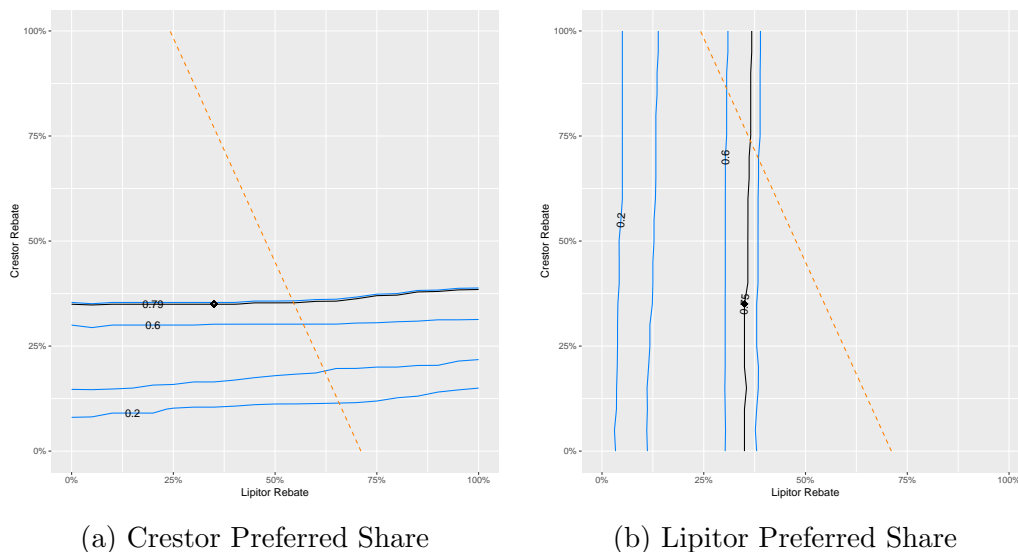


(a) The Standard Benefit Schedule

(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) Crestor Preferred Share

(b) Lipitor Preferred Share

Notes: This figure plots the effect of branded statin rebates on the share of formularies that place each branded statin on the preferred tier. Panel (a) plots the share of plans that place Crestor on the preferred tier and Panel (b) plots the share of plans that place Lipitor on the preferred tier.

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 Tier 2 Drugs	642	121	48	821
Number of Tier 3 Drugs	330	122	145	769
Tier 2 Copay (\$)	34.4	9.3	4.0	45.0
Tier 3 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.