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

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Abstract

In contrast to many countries and other government programs, drug prices in Medicare Part D are determined by privately negotiated rebates between insurance plans and drug manufacturers. How big are these rebates? What would happen in equilibrium if the government increased the rebates of a blockbuster drug? We use moment inequalities to estimate formulary–contingent rebates between 25% and 54% for branded statins in 2010. In counterfactuals, we show that rebates have large effects on formulary design and heterogeneous effects on consumer surplus. If rebates reduced U.S. prices to match those in Canada, consumer surplus would increase by up to 3.7%.

1 Introduction

A controversial aspect of the Medicare Part D program, which provides drug insurance to the vast majority of Americans older than 65, is that drug prices are determined by rebates that are negotiated by private insurance companies

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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 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 Part D plans use tiered formularies, which place each covered drug on a tier, and enrollees have to pay larger out–of–pocket costs for drugs on higher tiers. If an insurer places a branded drug on the "preferred" tier of their formulary, copays for the drug are lower, and demand is higher. Alternatively, for drug on the "non–preferred" tier, copays are higher, and demand is lower. Finally, for drugs excluded from the formulary, enrollees on

the plan must pay list price. Institutionally, drug manufacturers offer insurers (typically through intermediaries called Pharmacy Benefit Managers) rebates for branded drugs that are per unit discounts off of list price and are contingent on the tier their drug is placed on. The rebates that result from this process, however, are not publicly known.

We focus on branded statins in 2010. Statins comprised 6% of all prescriptions filled on Part D in 2010, which is the most recent year for which Lipitor (a blockbuster statin produced by Pfizer) and Crestor (a newer and more potent statin produced by AstraZeneca) were both on patent. These two branded drugs also faced competition from three main generic alternatives: Lovastatin, Pravastatin, and Simvastatin.

We 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), which is a key dimension of Part D plan differentiation. Second, we simultaneously model both plan demand and statin demand to capture selection in plan choice due to statin preferences. This is important because statins treat chronic underlying health conditions, and thus when consumers choose their plans, they are 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; (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 plan characteristics) 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.

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 observed in the data. A key advantage of estimating rebates using insurers' formulary choices is that it allows us to be agnostic about the particular form of bargaining between insurers and drug manufacturers. For example, with our moment inequalities approach, we can consistently estimate mean rebates even if AstraZeneca offers extra rebates on Crestor to insurers who place other AstraZeneca drugs on the preferred tier.

Our model captures an important institutional aspect of the structure of rebates in Part D; rebates are formulary–contingent. Drug manufacturers are willing to pay larger rebates to have their branded drugs placed on the preferred tier of the formulary.

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

There is substantial interest in rebate policy reform.[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 incur. 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 paid by Canadian provincial governments. Insurers need a 48.4% rebate for preferred placement of both Crestor and Lipitor in order to match the prices paid in Canada. However, we reject such high rebates with our model.

We use our rebate estimates to quantify how changing rebates would affect formulary design, insurer profits, and consumer surplus. Increasing Lipitor rebates from 35% to 50% (in line with Canadian prices) increases consumer surplus by 1.5% and increases insurer profits by 4.1%. In contrast, increasing Crestor rebates from 35% to 50% has no effect on consumer surplus and mainly affects insurer profits, which rise by 2.8%.

The effect of rebates on consumer surplus depends on how insurers redesign their formularies and how demand changes. Increasing Lipitor rebates from 35% to 50% results in an 18 percentage point increase in the share of large plans that place Lipitor on the preferred tier (from a base of 75%). In contrast, increasing the Crestor rebate from 35% to 50% increases the Crestor preferred–share by 11 percentage points and *decreases* the Lipitor preferred–share by 2 percentage points; this reduction in the Lipitor preferred–share (that occurs despite holding Lipitor rebates fixed) results in some beneficiaries being hurt as insurers try to steer statin users towards Crestor and partially explains why increasing only Crestor rebates does not increase consumer surplus.

Policy reform that increased rebates so that Part D insurer prices matched

[1]For example, on the 20th of November 2020, the Trump administration announced a new rule prohibiting drug manufacturers from paying insurers rebates in Medicare Part D.

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 3.7% if Part D insurers could match Canadian government prices. However, our results also suggest a complication for rebate policy reform: 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.

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

This paper also contributes to the endogenous product positioning literature. We use moment inequalities to estimate unobserved per unit rebates and model formulary design. A common methodological challenge in the applica-

[2]Carey (2017) studies the effect of incomplete risk adjustment on plan design. Decarolis and Guglielmo (2017) study enrollment reform and plan design. Feng (2019) and Kakani, Chernew and Chandra (2020) both study rebates using data on average net prices, which are not equal to the prices that insurers face: first, they are not formulary contingent; second, they are net anything that pharmaceutical companies can legally use to reduce their revenues when they file their 10-K (for example point–of–sale coupons and payments to wholesalers).

tion of moment inequalities is selection (Pakes 2010), which, in our setting, arises because firms choose formularies based on unobserved heterogeneity in rebates. We address this by imposing a restricted form of rebate heterogeneity that is a natural fit for our institutional setting: unobserved rebate heterogeneity varies across insurers, but is constant within insurer. With insurer–specific structural errors, we address selection by combining the approaches in Eizenberg (2014) and Wollmann (2018) and using support bounds and reweighting. Our paper also provides a nice setting in which to study endogenous product positioning because the cost of changing formularies is low and, as a consequence, they are frequently changed every year. Thus, we study endogenous product positioning without the dynamic concerns present in settings with large fixed costs of entry.

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

2 Institutional Background

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

2.1 Medicare Part D

Medicare Part D is a voluntary, prescription-drug insurance program. All Medicare beneficiaries are eligible to enroll in Part D, and enrolling is typically

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

Medicare beneficiaries can enroll in Part D plans between October 15 and December 7 each year with coverage starting on January 1 the following year. Beneficiaries who are on Medicaid or have incomes less than 150% of the poverty level receive the Low Income 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.[4] Each Medicare beneficiary is assigned to one of 34 geographical regions (based on their state of residence) and can enroll in PDPs from their region. To facilitate plan choice, the government runs a website that allows beneficiaries to compare plans.[5]

Part D insurance plans are divided into two types: stand–alone Prescription Drug Plans (PDPs) and Medicare Advantage Prescription Drug Plans (MAPDs). We restrict our analysis to the PDP market. MAPDs cover hospi-

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

[4]Each 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 the regional benchmark plus a *de minimis* threshold of $1 or $2. The *de minimis* rule reduces the number of plans that change benchmark status from year to year. Plans can change below benchmark status from year to year, and LIS beneficiaries in a plan that loses below benchmark status are randomized into new below benchmark plans unless they opt out and pay the premium difference.

[5]https://www.medicare.gov/find-a-plan/questions/home.aspx.

tal care in addition to drug insurance and face complicated incentives, which would distract from the focus of this paper and has been studied in depth elsewhere (Lavetti and Simon 2018 and Starc and Town 2020).

Plans compete on financial characteristics (copays, coinsurance, and premiums) as well as formularies (the list of covered drugs and their associated tiers). In 2010, more than 90% of plans used tiered formularies where each drug is put on a tier, e.g., generic, preferred branded, non–preferred branded, specialty, or excluded. Most plans cover thousands of drugs. As a consequence, formularies are high-dimensional objects. 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.[6] Beyond these two rules, plans have substantial freedom to design their formularies and, as we document below, the variation in observed formularies generates large variation in annual OOP costs for the same beneficiary in different plans. In addition to formulary requirements, CMS also imposes actuarial requirements on PDPs. Plans must be at least as generous as the Standard Benefit Schedule (SBS), which is not tiered, unlike the vast majority of PDPs. Appendix A has further details on the SBS.

2.2 Statins

To estimate our drug–demand model, we focus on the therapeutic class of HMG-CoA Reductase Inhibitors (statins), which are lipid-lowering drugs that are taken daily as a preventative for cardiovascular disease.[7] In 2010, statins

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

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

were the largest therapeutic class of drugs in Part D by fills. Moreover, in 2010, five statins comprised more than 98% of the market: from newest to oldest, they are Crestor, Lipitor, Simvastatin, Lovastatin, and Pravastatin. In 2010, Crestor, manufactured by AstraZeneca, and Lipitor, manufactured by Pfizer, were both on–patent branded drugs. Plans place these branded statins on the preferred branded or non–preferred branded tiers of their formularies or exclude them from the formulary altogether. Lovastatin, Pravastatin, and Simvastatin are all generic statins and as such are always on the generic tier of formularies. We focus on Crestor and Lipitor because we model the formulary placement of branded drugs and how it responds to changes in rebates.

2.3 Rebate Setting

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

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.

hydrophilic, while Lipitor, Simvastatin, and Lovastatin are lipophilic.

3 Data

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

3.1 Beneficiary Data

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

We impose similar sample restrictions to prior papers studying Medicare Part D; we exclude beneficiaries who are younger than 65, who do not have full–year coverage on Part A and B, who enroll in a Part C plan for any month, who do not enroll in Part D for any month, who switch PDPs or LIS status mid-year, or who die mid-year. There are two main differences between our sample restrictions and those of prior papers. First, we do not exclude LIS beneficiaries because they account for 32.1% of our sample and thus their demand is important for formulary design. Second, we restrict to statin users because we do not think that anticipated statin utility is likely to be a significant determinant of plan choices for people who do not yet need statins.[8] After imposing all of these sample restrictions, we are left with 737,057 beneficiaries. Appendix Table 1 reports summary statistics for the beneficiaries that survive our sample restrictions.[9]

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

[9] The mean age is 76.0 years. The sample is majority white (86.6%) and female (61.3%). Just

3.2 Plan Data

We restrict our sample to plans with at least 1,000 enrollees (after beneficiary sample restrictions) to ensure we have enough observations in each plan to estimate our model.[10] In our resulting sample, each region has between 5 and 26 plans. For each plan, we observe enrollment and the financial characteristics relevant to beneficiary plan choice (along with formulary design, which is described in the next subsection). We exclude Employer Group Waiver Plans because they are not open to general enrollment. This reduces the number of plans in our data from 1,542 to 431, which account for 86% of total enrollment across Part D regions. Appendix Table 2 reports summary statistics relating to the formulary design of the plans in our data. 90.0% of the plans in our data are tiered.[11]

3.3 Formulary Data

In 2010, the typical tiered formulary had separate tiers for generic drugs, preferred branded drugs, non–preferred branded drugs, and specialty drugs.[12]

over a quarter (28.2%) of the sample are eligible for Medicaid, and almost a third (32.1%) of the sample are LIS beneficiaries.

[10] 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.

[11] 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 preferred tier and 330 drugs on the non–preferred tier. 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.

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

Table 1: Formulary Design for Branded Statins

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

Table 2: Branded Statins Market Shares by Formulary Design

	Lipitor Tier		
Crestor Tier	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.

Table 1 enumerates the combinations of tier placement for Crestor and Lipitor for the plans in our data. Just over half (53.2%) of plans have both Crestor and Lipitor on the preferred branded tier. 11.3% of plans have both drugs on the non–preferred branded tier. There is a clear asymmetry between the two branded statins with Crestor generally getting preferential formulary treatment; Crestor is in a favored position on 26.6% of plans while Lipitor is only in a favored position on 5.2% of plans.

Table 2 shows that branded statin formulary placement is strongly related to statin demand. For example, on plans that place both Crestor and Lipitor on the preferred tier, 9.4% of enrollees buy Crestor, and 24.8% of enrollees buy

Lipitor. In contrast, on plans that place Crestor on the preferred tier and Lipitor on the non–preferred tier 14.7% of enrollees buy Crestor, and only 4.8% of enrollees buy Lipitor. These drastic changes in demand may reflect both adverse selection and moral hazard. For example, beneficiaries who know that they prefer Lipitor may choose a plan where Lipitor is preferred (and these beneficiaries are high–cost in terms of statins because they do not use generics). However, even absent this plan selection channel, copay differences can induce differential statin choice with implications for plan costs, for example beneficiaries who are in plans that place Crestor on the preferred tier and Lipitor on the non–preferred tier will face a copay differential that may induce them to not to purchase Crestor. The model of demand that we present in the next section accounts for both of these effects.

3.4 Drug Claims Data

We observe claim–level data for all Part D fills for all beneficiaries in our sample. For each fill, we observe the specific drug, the date of the fill, the quantity supplied, and the OOP cost that the beneficiary has to pay. We also observe the list price associated with each claim.[13] The mean list price per pill for Crestor and Lipitor are $4.08 and $3.92 per pill respectively. This list price determines beneficiaries' OOP costs in the deductible region as well as for plans that use coinsurance.[14]

We use the change in annual OOP costs as the price that statin users consider when they make their statin and plan choices: we think of this as modeling a situation where beneficiaries use the CMS calculator to determine their annual costs of each statin under various plans. The calculator takes into

[13]The list price does not reflect the true cost to either Medicare or the PDP because it does not account for rebates.

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

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, consider non–LIS beneficiaries. The mean annual OOP costs from buying Crestor (instead of no statin) is \$568. Lipitor is slightly more expensive with a mean annual OOP cost of \$586. The standard deviations show substantial variation in the annual OOP cost of branded statins across beneficiaries.[15] LIS beneficiaries annual

[15]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

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.

4 Model

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

4.1 Demand

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

For each statin user enrolled in a stand-alone Part D Plan, we estimate a simultaneous demand model; statin users make their decisions over plans and statins at the same time.[16] A key advantage of a simultaneous model

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.

[16] As in Abaluck and Gruber (2011), we only model the choices of beneficiaries who enroll in a

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. [17] We first specify the statin–demand component of the model. We then use the indirect utility from statins to specify the plan–demand component of the model.

In each Medicare Part D regional market $r = 1, ..., R$, plan $j = 1, ..., J_r$ covers a subset of statins K_j.[18] 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 $i = 1, ..., N$ 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.[19] The utility from choosing statin k on plan j is given by

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

where OOP_{ijtk} is the annual out-of-pocket (OOP) costs for statin k, x_{ikt} are

stand-alone Part D Plan. Thus, we normalize the mean utility of an arbitrary plan in each region.

[17] 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). Several papers have used a sequential approach to estimating demand in settings with a similar structure, e.g., Ho (2006), Gowrisankaran, Nevo and Town (2015), and Ho and Lee (2017).

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

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

observed enrollee characteristics, and ξ_{kt} is a statin fixed effect. The error term, ε_{ijt}, is assumed to be IID and Type 1 Extreme Value. It is individual and brand–specific, so unobserved preferences for branded statins do not depend on the identity of the plan in which the user is enrolled.

Annual OOP costs, OOP_{ijkt}, depend on the formulary placement of branded statins f_j as well as other cost–sharing rules of the plan (e.g., the rest of the formulary, copays, and the deductible) and non–statin drug purchases. We calculate OOP_{ijkt} for any statin choice on every plan using the cost–calculator approach that has been used in many Part D papers.[20] This approach uses data on observed formularies, plan cost–sharing rules, and the assumption that non–statin drug choices are unaffected by plan choice (i.e., no moral hazard on non–statin drug choices).[21] Implementation details for our cost calculator are in Appendix A. Importantly, we explicitly model how statin choice is affected by plan characteristics and especially branded statin formulary placement.

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

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

[21] An 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.

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

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

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

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

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

$$u_{ijt} = \beta_t^{v^*} v^*_{ijt} - \beta_t^p p_j + \beta_t^x x_j + \zeta_{jt} + \tau_{ijt}, \tag{3}$$

where p_j is the plan premium, which does not vary across types,[22] 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 and Type 1 Extreme Value.

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

The v^*_{ijt} term, which captures statin utility, adds an important dimension to the specification. The v^*_{ijt} implies that beneficiaries know their statin preferences when they choose their plan and that beneficiaries who have strong preferences for a specific statin prefer plans where that statin is cheap. The plan covariates, x_j, are standard and include the annual deductible, the presence of gap coverage, enhanced plan status, and formulary generosity summary statistics such as the number of drugs covered on the plan, the number of drugs on each tier, and cost sharing on each tier (copay or average value of coinsurance), insurer (e.g., United Healthcare) fixed effects, Part D market fixed effects and plan age.[23] Unobserved plan quality is captured by ζ_{jt} and induces 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.[24]

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

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

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

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

Our model has two sets of demand–side parameters: Let $\theta_t^k = (\alpha_t^{OOP}, \alpha_t^x, \xi_{kt})$ and $\theta_t^j = (\beta_t^{v^*}, \beta_t^p, \beta_t^x)$ denote vectors that collect the parameters from the

[23] We 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).

[24] Equation (2) shows that v^*_{ijt} includes the contributions of unobserved statin taste shocks ε_{ijkt}.

statin utility component of demand in Equation (1) and the plan utility component of demand in Equation (3) respectively. We write choice probabilities as explicit functions of the formulary placement of branded statins, which is critical to our model of supply.

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

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

As the choice probabilities make clear, we model statin demand as a static choice. There are two reasons behind our decision to use a static model of statin demand. First, statins are used as a prophylactic for a chronic underlying condition: hyperlipidemia (high cholestrol). As such most statin users take statins every day of the year. Moreover, in our data, statin users typically buy a single type of statin, e.g., Crestor or Simvastatin.[25] 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.[26]

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

[25] 94.7% of statin users in our data buy a single type of statin.

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

probabilities are

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

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

4.2 Supply

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.

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:

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

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

We account for all types of plan revenue using the same definitions as the CMS Medical Loss Ratio (MLR) reports. Specifically we account for the following four components: beneficiary premiums, direct subsidies, federal reinsurance, and Low Income Premium Subsidy Amounts (LIPSA).[27] Appendix B provides the details as to how we calculate each source of revenue.[28]

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

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

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

Appendix B contains a detailed description of the different components of cost.

We impose two important assumptions that allow us to calculate costs. The assumptions relate to how we calculate non–statin costs and are necessary because we do not estimate demand for non–statin drugs. First, we assume no moral hazard on non–statin drugs, so that we can calculate non–statin drug costs on any plan for each individual's observed choices. This no moral hazard assumption is common in Part D plan demand models.[29] Second, we assume that the rebate for all branded non–statin drugs is 13.8%.[30] 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:

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

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.[31] This representation of profits makes clear two important facts: first, profits are increasing in rebates; second, profits are linear in rebates conditional on demand

[29] Abaluck 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. When beneficiaries buy non–statin drugs that are excluded from the formulary of other plans in their region, we assume they would have replaced the drug with a different drug of the same cost.

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

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

(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:

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

where $\gamma_k(f_j)$ is the mean rebate for drug k under formulary f_j and ν_{2j} is the deviation from the mean, capturing unobserved heterogeneity. This heterogeneity could reflect the fact that insurers use different PBMs and, as a consequence, obtain different rebates. Given this motivation, we will assume that rebate heterogeneity is constant across plans within an insurer and mean zero conditional on the insurer's information set. Specifically, let $h(j)$ denote the insurer that owns plan j. Then

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

and

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

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. Let f_h be a vector that collects the formularies of insurer h's plans. Then

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

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

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

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

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

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

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

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

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

Inequality (13) is a direct implication of insurers' revealed preferences. We have suppressed many arguments of the profit function because they are held fixed on both sides of the inequality.[32] The key point is that given all of

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

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

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

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

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

where y_{ikt} is an indicator that is one if beneficiary i of type t chooses statin k, $z_{it}^k = (1, a_{it}, i_{it})'$ is the vector of instruments. a_{it} denotes the age of beneficiary i, and i_{it} denotes the median income of beneficiary i (based on 5–digit ZIP codes). The second and third sets of moments equate the average age and

income of beneficiaries who buy each type of statin in the data and the model. For each type, we obtain 15 moments from Equation (15).

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

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

where z_j^j is an $M^j \times 1$ vector consisting of the exogenous plan characteristics and the premium instrument for plan j. For each type, we obtain 39 moments from Equation (16), so we have 54 moments in total.[33] To account for premium endogeneity we follow the approach in Decarolis, Polyakova and Ryan (2020) and Starc and Town (2020), and use a Hausman instrument, which measures the premium of similar plans offered by the same insurer in other Part D markets. This Hausman instrument is valid under the assumption that the difference in premiums for similar plans across Part D markets captures national–level costs, but is unrelated to market specific demand.

In order to calculate sample moments based on Equations (15) and (16) at a candidate parameter vector (θ^j, θ^k), we need to calculate the statin and plan choice probabilities implied by the model. 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 b, we take draws of ε_{ikt}^b (we hold these draws fixed for every candidate parameter vector to prevent chatter from causing problems with our simulated estimator). Given these random draws, we calculate and use the simulated quantity v_{ijt}^{*b} instead of v_{ijt}^*. The simulated plan utility is given by

$$u_{ijt}^b = \delta_{jt} + \beta_t^{v^*} v_{ijt}^{*b} + \tau_{ijt}, \tag{17}$$

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

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

$$s_{ijt}^{sim}(\theta^j, \theta^k) = \frac{1}{B}\sum_{b=1}^{B} \frac{\exp(\delta_{jt} + \beta_t^{v^*} v_{ijt}^{*b})}{\sum_{j'=1}^{J_r} \exp(\delta_{j't}' + \beta_t^{v^*} v_{ij't}^{*b})}, \tag{18}$$

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

$$s_{ikt}^{sim}(\theta^j, \theta^k) = \sum_{j=1}^{J_r} s_{ijt}^{sim}(\theta^j, \theta^k) s_{ikt|j}(\theta^k). \tag{19}$$

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 (15) and (16) are given by

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

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

$$Q(\theta^j, \theta^k) = g_t(\theta^j, \theta^k)' W_t g_t(\theta^j, \theta^k) \tag{20}$$

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

5.2 Supply

We use necessary conditions implied by insurers' profit-maximizing branded statin formulary placement to construct a moment inequality estimator, which we use to recover unobserved rebates.

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

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

$$\sum_{j \in J_h} \left[\hat{\Pi}_j(f_j, p_j, f_{-j}, p_{-j}, r_j) + \nu_{1j}(f_j)\right] \geq \sum_{j \in J_h} \left[\hat{\Pi}_j(f'_j, p_j, f_{-j}, p_{-j}, r_j) + \nu_{1j}(f'_j)\right] \quad \forall f'_h \tag{21}$$

Inequality (21) holds for any vector of branded statin formularies f'_h that was not chosen, however we restrict attention to comparisons that change one plan formulary at a time. Suppose that insurer h chooses formulary f_j for plan j instead of f'_j. Then substituting Equations (8) and (9) into Inequality (21),

and suppressing many function arguments, we have

$$\sum_{j\in J_h} \Delta A_j(f_j, f_j') + \sum_{j\in J_h}\sum_{k\in K_j^b} \gamma_k(f_j)\Delta L_{jk}(f_j, f_j') + \sum_{k\in K_j^b} (\gamma_k(f_j) - \gamma_k(f_j'))L_{jk}(f_j') \geq$$
$$- \sum_{j\in J_h}\sum_{k\in K_j^b} \Delta L_{jk}(f_j, f_j')\nu_{2,h} - \sum_{j\in J_h} \Delta\nu_{1j}(f_j, f_j'). \tag{22}$$

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

Inequality (22) can be rearranged to provide a bound on $\nu_{2,h}$. When we take sample averages across insurers, the measurement error term $\Delta\nu_{1j}(f_j, f_j')$ averages out. Thus, the direction of the bound depends on the sign of

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

Inequality (22) can be simplified and rearranged to give an intuitive bound on formulary–contingent rebates for single–plan insurers. Suppose that single–plan insurer h chooses f_h to cover Crestor on the preferred tier and exclude Lipitor. Compare profits with the case where f_h' excludes both branded statins. Then, ignoring measurement error, which averages to zero across insurers, Inequality (22) can be rearranged as

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

where L_{hc} is the cost of Crestor for insurer h at list price and r_{hc} is the rebate for placing Crestor on the preferred tier. This Inequality is much simpler than Inequality (22) because it considers a single plan and also because insurers do not cover the cost of excluded drugs, so many terms are zero. The left–hand side of the inequality is the change in all non–rebate components of profits on plan h between formularies f_h and f_h'. The right–hand side of the inequality is the rebate payment. The inequality can be further rearranged to provide an intuitive lower bound on the Crestor rebate. If the Crestor rebate were very

low, for example if there were no rebate, then excluding Crestor would look more enticing because the insurer would pay the full cost of Crestor. Since the insurer covered Crestor, we infer that the rebate cannot have been too small, hence we obtain a lower bound.

More generally, our estimation approach combines both Equation (10) and Inequality (22) and as such we focus on bounds for $\nu_{2,h}$. The intuition from the single plan insurer extends generally. Specifically, comparing a plan with branded statin formulary f_j to f'_j provides a lower bound on $\nu_{2,h}$ when the coverage of branded statins is reduced (e.g, moving from preferred to excluded) and provides an upper bound on $\nu_{2,h}$ when coverage is increased. The sign of these bounds follow from the properties of demand (negative own–price elasticities and positive cross–price elasticities for substitutes) and the details can be found in Appendix C. Specifically based off Inequality (22), for any vector of mean rebates γ, define the following quantity

$$\mathcal{B}_j(\gamma, f_j, f'_j) = -\Big(\sum_{j \in J_h} \sum_{k \in K_j^b} \Delta L_{jk}(f_j, f'_j) \Big)^{-1} \times \tag{23}$$

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

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:

$$-\min_{k \in K_j^b} \{\gamma_k(f_j)\} \leq \nu_{2,h} \leq 1 - \max_{k \in K_j^b} \{\gamma_k(f_j)\}. \tag{24}$$

We combine the bounds from the data in Equation (23) with the support bounds in Inequality (24) for estimation.

The lower bound function is defined as follows:

$$\mathcal{L}_j(\gamma, f_j, f_j') = \begin{cases} \mathcal{B}_j(\gamma, f_j, f_j') & \text{if } f_j \text{ does not exclude both Crestor and Lipitor} \\ -\min_{k \in K_j^b} \left\{\gamma^k(f_j)\right\} & \text{else} \end{cases} \tag{25}$$

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

$$\mathcal{L}_j(f_j, f_j', \gamma_0) + \Delta\nu_{1j}(f_j, f_j') \leq \nu_{2,h} \leq \mathcal{U}_j(f_j, f_j', \gamma_0) + \Delta\nu_{1j}(f_j, f_j') \tag{26}$$

or a very similar pair of inequalities holds.[34]

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

$$\mathbb{E}[\mathcal{L}_j(\gamma_0, f_j, f_j')|\mathcal{I}_h] \leq \mathbb{E}[\nu_{2,h}|\mathcal{I}_h] = 0. \tag{27}$$

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

$$\mathbb{E}[\mathcal{L}_j(\gamma_0, f_j, f_j')w(z_j)] \leq 0. \tag{28}$$

With $m = 1, ..., M^r$ instruments z_j^m, we have M^r moments corresponding to Inequality (28). For all m, and any rebate vector γ, we define

$$Q_m^{\mathcal{L}}(\gamma) = \max\left\{\mathbb{E}[\mathcal{L}_j(\gamma, f_j, f_j')w(z_j^m)], 0\right\} \tag{29}$$

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

and

$$\hat{Q}_m^{\mathcal{L}}(\gamma) = \max\left\{\frac{1}{H}\sum_{h=1}^{H}\frac{1}{J_h}\sum_{j\in J_h}\mathcal{L}_j(\gamma, f_j, f_j')w(z_j^m), 0\right\} \tag{30}$$

which measure the extent to which sample analog of Inequality (28) is violated for instrument m. Let $Q_m^{\mathcal{U}}$ and $\hat{Q}_m^{\mathcal{U}}$ be upper bound functions defined analogously to the lower bound functions. The identified set is defined as

$$R^I = \{\theta : Q_m^{\mathcal{L}}(\theta) = 0 \text{ and } Q_m^{\mathcal{U}}(\theta) = 0, m = 1, ...M^r\}. \tag{31}$$

To use Equation (29) 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 in the market, all of which are in the firm's information set. Any positive function of these instruments can serve as $w(z_{h_j})$ in Equation (29). 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.[35] After defining the set of moment inequalities from these instruments, we follow Chernozhukov, Chetverikov and

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

Kato (2019) to construct a 90% percent confidence set for the true parameter values. The details of the estimation procedure are given in Appendix C.

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 are 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 (20). Panel A reports statin utility parameters ($\hat{\theta}_t^j$). Panel B reports plan utility parameters ($\hat{\theta}_t^k$). The model is estimated separately for each risk group, and the results are reported in the respective columns. Allowing the parameters to differ by risk group is one dimension by which the model accounts for individual heterogeneity.

Starting with Panel A, we find intuitive coefficients on out–of–pocket statin costs $\hat{\alpha}_t^{OOP}$. LIS beneficiaries, who by definition have low income, are most sensitive to statin out–of–pocket costs with a coefficient of 4.343. Among non–LIS beneficiaries, $\hat{\alpha}_t^{OOP}$ decreases by risk score tercile. Our estimates of mean drug quality show that Lipitor is preferred to Crestor by all risk types

Table 4: Simultaneous Demand Estimates

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

Notes: This table reports estimates from the simultaneous demand model described in Section 4.1. In particular, we minimize the objective in Equation (20) separately for each tercile of risk score and for LIS beneficiaries. All models also include the following components (coefficeints not reported) in θ^j: region fixed effects, an enhanced plan indicator, the number of drugs on the generic tier, and the number of drugs on the preferred tier.

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 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.[36] 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.[37] We find that the elasticity of plan

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

[37]We 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 elas-

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 $[25\%, 52\%]$.[38] 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 $(28\%, 52\%)$.

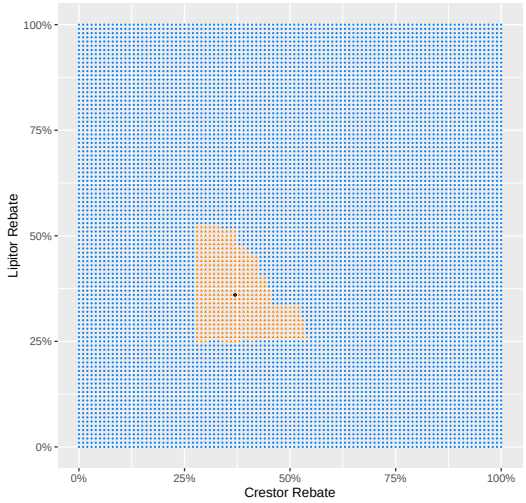
While the rebates paid to Part D insurers are secret, CMS does observe them and reports on the aggregate level annually. In 2010, the average annual Part D rebate was 11.3%.[39] By 2014, the average annual Part D rebate was 14.3%. Moreover, in 2014, CMS released the only summary of Part D rebates using total branded drug costs as the denominator (as opposed to all

ticities must be smaller than the conditional elasticities, because people can change plans in response to an increase in the annual OOP cost of Crestor, thus they may continue to buy Crestor on a different plan.

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

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

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 parameters.

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.

Three facts may account for the large rebates for branded statins relative

[40]CMS 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.

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

Our counterfactuals quantify the effects of changing branded statin rebates on consumer surplus, formularies, and insurer profits. There is substantial policy interest in changing Part D rebate policy and in reducing drug prices more generally. These policies will have direct first–order effects on the costs that insurers face under different formularies. Thus understanding how rebates affect equilibrium formularies is an important question that we quantify for the first time.

Modeling the implications of a change in rebates requires understanding the incentive for insurers to steer beneficiaries towards one branded statin or the other through formulary design. As an example, consider increasing Crestor rebates. An insurer that initially places both Crestor and Lipitor on the preferred tier would try to steer beneficiaries towards Crestor to generate cost savings. However, this would induce some Lipitor users to switch plans, leading to a loss of premium revenue. Understanding which effect dominates is an empirical question that depends on 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

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

$$\max_{f_h} \mathcal{E}\left[\Pi_h(f_h, p_h, f_{-h}, p_{-h}, \gamma, \nu_{2,h})|\mathcal{I}_h\right]. \tag{32}$$

We are interested in policy reforms where all insurers receive the same rebates and then set their formularies.[41,42]

There are two important assumptions implicit in Equation (32). First, we only allow insurers to change their formularies as branded statin rebates change, i.e., we hold fixed other plan characteristics including premiums and the level of copays (or coinsurance) associated with each formulary tier. Thus, our paper is complementary to many papers that allow premiums to change, but keep formularies and other plan characteristics fixed. Changing rebates for any one class of branded drugs is unlikely to have a large effect on premiums or the level of copays associated with each formulary tier. Even statins, which were the largest therapeutic class of drugs by fills in 2010, only comprise around 5% of insurer costs.[43] 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. We formalize this in a framework for calculating the effect of changing branded statin rebates on premiums in Appendix D. Second, we hold list prices fixed in all of our counterfactuals. Relaxing this assumption is difficult to the extent that list prices are set based on profits earned by manufacturers across insurance market segments (e.g., Medicare, Medicaid, and commercial). This assumption is stronger for larger changes in rebates. However, many of our counterfactuals consider different rebate menus that are either within or near our estimated set of rebates (which are all consistent with the status quo list prices in terms of our supply–side model of rebates).

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

[42] Two examples include prohibiting manufacturers paying Part D insurers rebates and government–negotiated rebates.

[43] To calculate this number, we applied an average branded rebate of 13.8% to all branded drugs (based off calculations in Section 6).

Because of the large number of market configurations, calculating the Nash equilibrium for all plans is computationally intractable.[44] Thus, we assume that the formulary choice for all small plans is fixed. A similar assumption is made in Eizenberg (2014).[45] 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.[46]

7.2 Counterfactual Results

In our counterfactuals, we focus on understanding how formularies and consumer surplus would change under various rebate menus. Therefore, we do not estimate the equilibrium rebate under a particular market structure. There are two reasons behind this decision. First, manufacturers need to consider effects across market segments (e.g., Medicare, Medicaid, and commercial) when they set list prices, which is beyond the scope of this paper. Second, equilibrium rebates are likely to be a function of parameters that we have little information about such as the government's bargaining power. However, understanding how formularies and consumer surplus respond to rebates is

[44] The 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.

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

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

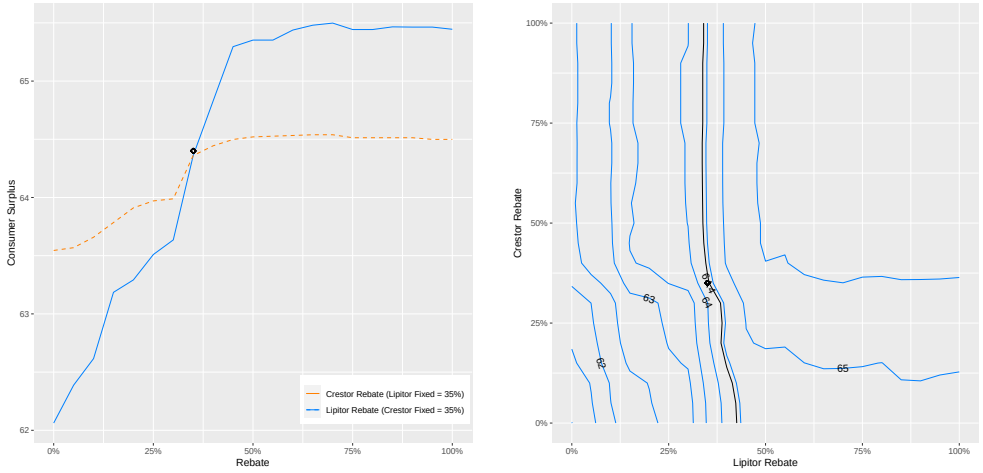
informative about how insurers set non–premium characteristics of their plans and is also an important input into evaluating rebate policy reform.

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

7.2.1 Consumer Surplus Effects of Branded Rebates

Our first set of counterfactual results focus on how changing rebates for different drugs affects consumer surplus. Figure 2 illustrates that the effect of rebates on consumer surplus are subtle. In Panel (a), we show how consumer surplus changes in each branded statin rebate (holding fixed the competing branded statin rebate). The black diamond at 35% (for both Crestor and Lipitor) are close to the mean rebates in our estimated set. As Lipitor rebates increase from 35% to 50% consumer surplus increases by 1.53%. In contrast, increasing Crestor rebates beyond 35% has no effect on consumer surplus. To investigate this further, we plot consumer surplus isocurves in rebate space in Panel (b). When Crestor rebates are above 35%, the consumer surplus isocurves are vertical. Thus increasing Crestor rebates beyond 35% does not increase consumer surplus at any level of Lipitor rebates. Panel (b) also shows that the effect of rebates on consumer surplus exhibits diminishing returns because the space between isocurves increases as rebates get larger.

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



(a) Single Rebate Changes

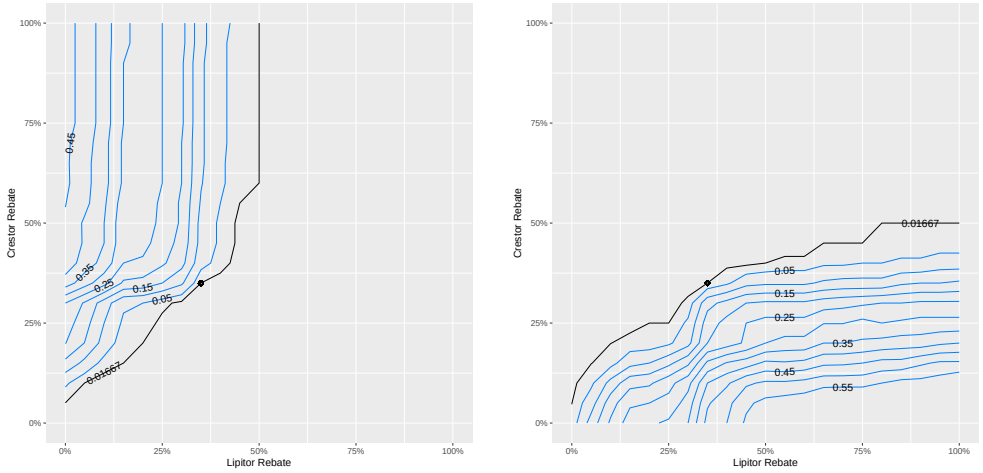
(b) Consumer Surplus Isocurves

Figure 2 suggests that policy reform that changes the rebates for all branded drugs in Part D could have large effects on consumer surplus. Moreover, the effect of rebates on consumer surplus is nonlinear and heterogeneous across drugs. Policy reform that results in uniform rebates, such as prohibiting drug manufacturers from paying Part D insurers rebates, is likely to have heterogeneous and possibly unintended consequences. To understand why there are such heterogeneous effects of rebates on consumer surplus, we quantify how rebates affect formularies.

7.2.2 Formulary Effects of Branded Rebates

Panel (a) of Figure 3 shows that the share of large insurers with Crestor on the preferred tier and excluding Lipitor, intuitively, is increasing in the Crestor rebate and decreasing in the Lipitor rebate. Rebates have a large effect on formulary design. Near the mean of our estimated rebates (35% for each statin), the share of preferred/excluded plans is less than 2%. In contrast, increasing the Crestor rebate to 40% and decreasing the Lipitor rebate to 30%

Figure 3: The Effect of Statin Rebates on Formularies



(a) Preferred/Excluded Share (b) Excluded/Preferred Share

changes the share of preferred/excluded plans to more than 15%. This large effect on insurers' formularies is induced through a small change of rebates (that stays within our estimated set of rebates), which minimizes the possibility that this result would be substantially changed if manufacturer list prices were endogenized. The insurers that choose preferred/excluded formularies benefit from higher Crestor rebates through two channels; they select Crestor users and they steer statin users to Crestor. Panel (b) shows a symmetric situation for the share of plans with Lipitor on the preferred tier and excluding Crestor. Figures for other formulary configurations and the market shares of each branded statin are in Appendix Figures 2 and 3.

Table 6 shows large differences in the share of plans choosing each formulary configuration across several rebate menus. In Column (1), which corresponds to the mean rebates from our set estimates, 90% of insurer formularies place Crestor and Lipitor on the same tier. In Column (2), increasing the Crestor rebate to 50% results in a decrease in the share of plans that place *Lipitor* on the preferred tier (from 75% to 73%). This is important because Lipitor users on

the plans that removed Lipitor from the preferred tier are hurt by the increase in Crestor rebates; as a consequence consumer surplus only increases by 0.24% when Crestor rebates increase to 50% (in line with Figure 2). When Lipitor rebates increase to 50%, in Column (3), the share of plans with Lipitor on the preferred tier increases (from 75% to 93%) and consumer surplus increases by 1.53%. Since the rebate menus in Columns (1)-(3) are all consistent with our set estimates of rebates, these results are likely to be robust to endogenizing list prices. In contrast, in Column (4), we consider prohibiting manufacturers paying Part D insurers any rebates, with the caveat that we do not model the potential endogenous change of list prices or premiums as a response to a large change in rebates. We find that the share of plans placing both Crestor and Lipitor on the preferred tier would fall by 66 percentage points to 6% and insurer profits (from all drugs on the subset of beneficiaries who use statins) would fall by 10.25%. Thus, our model predicts that if the Trump rebate rule is enforced, it will have large effects on formulary design, list prices, or both.

7.2.3 Comparison With Canada

One widely–considered policy proposal is to impose a most–favored–nation clause that limits the prices that Part D insurers pay on the basis of prices paid in other countries. In Figure 4, we benchmark our results against the case where Part D insurers obtained rebates large enough to equate Part D prices with those paid by provincial Canadian governments. We use data on the mean price of branded statins in Canada from Dubois, Gandhi and Vasserman (2019) to calculate the rebates that Part D insurers would need to receive, for preferred placement of branded statins, in order to match prices in Canada (details are in Appendix E). If the rebate for both Crestor and Lipitor were 48.4%, then Part D insurers that place branded statins on the preferred tier would face the same mean cost for branded statins as the Canadian gov-

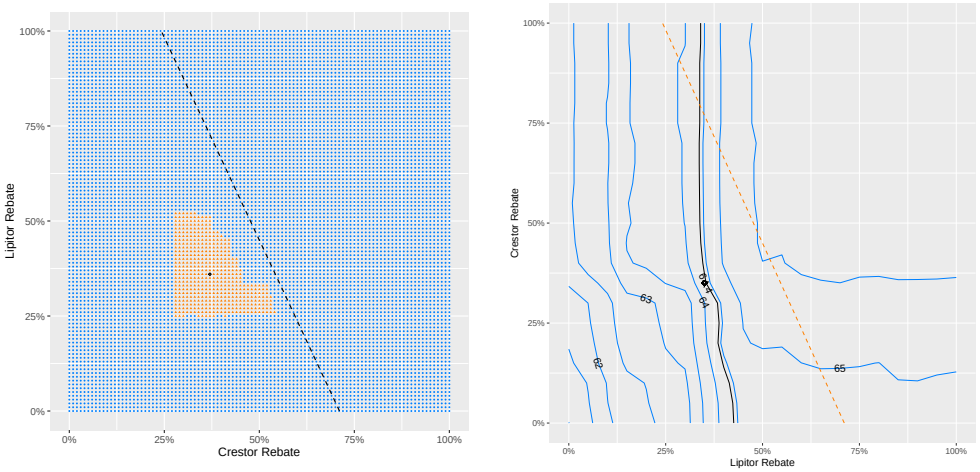
Table 6: Counterfactual Results

	(1)	(2)	(3)	(4)	(5)	(6)
Crestor Rebate	0.35	0.50	0.35	0.50	0.00	0.30
Lipitor Rebate	0.35	0.35	0.50	0.50	0.00	0.25
Share of formularies						
Preferred/Preferred	0.72	0.73	0.78	0.92	0.06	0.55
Non–Preferred/Preferred	0.01	0.00	0.06	0.02	0.03	0.00
Excluded/Preferred	0.02	0.00	0.09	0.00	0.03	0.00
Preferred/Non–Preferred	0.05	0.11	0.00	0.00	0.00	0.03
Non–Preferred/Non–Preferred	0.10	0.06	0.05	0.05	0.29	0.17
Excluded/Non–Preferred	0.00	0.00	0.00	0.00	0.13	0.01
Preferred/Excluded	0.02	0.08	0.00	0.00	0.00	0.03
Non–Preferred/Excluded	0.00	0.00	0.00	0.00	0.01	0.00
Excluded/Excluded	0.08	0.02	0.02	0.02	0.45	0.22
Crestor Market Share	0.08	0.08	0.08	0.08	0.06	0.08
Lipitor Market Share	0.22	0.22	0.23	0.23	0.15	0.22
% Change in Consumer Surplus	–	0.24%	1.53%	1.80%	-5.21%	-1.92%
% Change in Insurer Profits	–	2.81%	4.11%	6.72%	-10.25%	-2.56%

Notes: Each column reports counterfactual outcomes for the given pair of rebates for preferred placement. The share of plans choosing each formulary configuration for Crestor and Lipitor is shown in the first 9 rows, e.g., Preferred/Excluded refers to plans that place Crestor on the preferred tier and exclude Lipitor from the formulary.

ernment. In Panel (a) of Figure 4, the dashed black line shows the pairs of rebates that are consistent with Part D insurers obtaining the same mean branded statin prices as Canada (we use a line because we only have data on mean branded statin prices in Canada as opposed to for Crestor and Lipitor separately). Since the dashed black line does not intersect our estimated set, Part D insurers paid higher prices than Canada even with rebates for preferred placement. This comparison, of the price paid by insurers who place branded statins on the preferred tier, could not be made using data on average net prices such as those used in Kakani, Chernew and Chandra (2020) and are only possible because we estimate formulary–contingent rebates. In Panel (b) of Figure 4, if all insurers could obtain prices as low as those in Canada by

Figure 4: Comparison to Canada



(a) Rebates and Prices (b) Consumer Surplus

placing branded statins on the preferred tier, then consumer surplus would be on the orange dashed line. Combining Columns (4) and (6) in Table 6, which corresponds to the largest increase in consumer surplus consistent with our set estimates, under Canadian prices consumer surplus could increase by up to 3.7%.

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 for preferred placement of 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 Annual OOP Costs and the SBS

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

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

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

on plan j can be written as

$$OOP_{ijkt}(f_j) = oop_{jk}(g^{ns}_{ijkt}(h_{it}, \eta_{it}, f_j). \tag{33}$$

oop_{jk} is a known function (of plan cost–sharing rules) that maps non–statin drug spending g^{ns}_{ijkt} and plan formularies f_j (which, with abuse of notation, in this section refers to the tier placment of all drugs and the associated copays and coinsurance rates) into annual OOP costs for statins OOP_{ijkt}. Non–statin drug spending g^{ns}_{ijkt} depends on beneficiary health h_{it} and preferences η_{it}. We observe g^{ns}_{ijkt} for the actual statin choices that beneficiaries make, however, because of the nonlinear cost–sharing schedule in Part D, we do not observe g^{ns}_{ijkt} for statin choices that beneficiaries could have made. In order to calculate g^{ns}_{ijkt} for every statin, we assume no moral hazard on non–statin drugs.[47] This means that when we calculate the cost of statins on each plan, we hold fixed the non–statin drug choices of each beneficiary. In the context of plan demand, this assumption has been used by many papers following the seminal paper by Abaluck and Gruber (2011).

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

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

prices is nonlinear. With moderate non–statin drug spending, branded statin purchases may fall into the coverage gap region making branded statins very expensive. In contrast, beneficiaries with very high non–statin drug spending may reach the catastrophic coverage region, when the marginal cost of branded statins is relatively low.

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

Appendix B Revenue and Cost Accounting

B.1 Revenues

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

The revenue for plan j from enrolling beneficiary i is

$$R_{ij}(p_j) = p_j + p_j^{LIPSA} + SUB_{ij} + RE_{ij} \tag{34}$$

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.[48]

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

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

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

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

$$SUB_{ij} = CCS_i \cdot BID_j - (p_j + p_j^{LIPSA}). \tag{35}$$

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

4. *Federal Reinsurance* (RE_{ij}) The government also pays plans for 80% of the cost of drugs that enrollees purchase once they reach their an-

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

nual out–of–pocket threshold (net of point–of–sale pharmacy discounts and manufacturer rebates). Let CC_{ijd} denote the total cost of drugs purchased beyond the out–of–pocket threshold (net of point–of–sale discounts) by beneficiary i on plan j on drug type d ($d \in \mathcal{D} = \{K_j, \mathcal{G}_j, \mathcal{B}_j\}$ where plan j covers statins, K_j , non–statin generics, $\mathcal{G}_j$, and branded non–statin drugs, $\mathcal{B}_j$).

$$\begin{aligned} RE_{ij}(f_j, \theta^k, \gamma) = .8 \cdot \sum_{k \in F_j^b} (1-\gamma) \cdot CC_{ikj} \cdot s_{ik|j}(f_j, \theta^k) \\ + .8 \cdot CC_{ij\mathcal{G}_j} \\ + .8 \cdot (1-\gamma^{\mathcal{B}}) \cdot CC_{ij\mathcal{B}_j}. \end{aligned} \tag{36}$$

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%.[49] Finally, we estimate statin rebates as a function of formularies. Thus, we quantify revenues due to federal reinsurance for any counterfactual set of plan choices.

Several of the components of plan revenue depend on bids that plans make to CMS for each Part D plan that they want to offer. A plan's bid specifies the monthly revenue requirement that the plan needs to cover its costs (for basic coverage) and a profit margin. A plan's premium for basic drug coverage is equal to the bid minus the base premium. We observe each plan's premium for basic coverage and we calculate the base premium using public data.[50] Thus we observe plan bids.

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

[50] The base premium is calculated as a proportion of the national average bid amount (weighted

B.2 Costs

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

$$\begin{aligned} C_{ij}(f_j, \theta_t^j, r_j) &= \sum_{k \in K_j} s_{ikt|j}(f_j, \theta_t^k) \cdot ([1 - r_{jk}(f_j)] \cdot TC_{jk} - OOP_{ijkt}(f_j) - LICSA_{ijkt}) + C_{ijt}^{NS} \\ &= \sum_{k \in K_j} (f_j, \theta_t^k) \cdot C_{ijk}(f_j, r_{jk}(f_j)) + C_{ijt}^{NS} \end{aligned} \tag{37}$$

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

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

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

Appendix C Details on Moment Inequalities

C.1 Signing Bounds

In this Section, we show that the bounds on $\nu_{2,h}$ in Inequality (22) can be signed based off the properties of demand. For reference, we write Inequality

by lagged enrollment). In 2010, the national average bid amount was \$88.34 and the base premium was \$31.94.

(22) again here:

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

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

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

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

If f_{j_1}' increases the OOP cost of a single branded statin while holding the OOP cost for the other branded statin fixed, then we obtain a lower bound on $\nu_{2,h}$. Suppose that under f_{j_1} Crestor is not excluded, but Lipitor is excluded. Let f_{j_1}' exclude both branded statins. Both formularies exclude Lipitor, thus the set of branded statins $K_{j_1}^b$ is just Crestor and k refers to Crestor. Since Crestor's OOP cost on j_1 increased, demand for Crestor on j_1 falls, so $\Delta L_{j_1k}(f_{j_1};f_{j_1}') > 0$. The remaining terms in Expression (39) capture the change in the insurer's branded statin costs across all its plans when the formulary on j_1 changes from f_{j_1} to f_{j_1}'. Since branded statins on other plans substitute for Crestor on j_1, these terms are all negative (demand is higher under f_{j_1}'). Since some people substitute to different insurers, Expression (39) is positive. Thus dividing both sides of Inequality (22) by the negative of Expression (39), we get a lower bound for $\nu_{2,h}$.

The argument that shows we obtain upper bounds by considering formulary changes that lower the OOP cost of a single branded statin while holding fixed

the OOP cost of the other branded statin has the exact same logic and hence is omitted.

C.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

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

against the alternative

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

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

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

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

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

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

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

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

Appendix D Endogenizing Premiums

In our setting, there are two challenges to endogenizing premiums. First, in our supply model, we do not use constant marginal costs. Second, and perhaps

more importantly, we do not estimate plan demand for non–statin users. In the remainder of this section, we provide a framework for endogenizing premiums in our setting; the resulting equations suggest that plans are unlikely to change their premiums by much when statin rebates change because the premium are set on the basis of demand for beneficiaries using thousands of drugs.

Conceptually, we can endogenize premiums by calculating insurers' optimal premiums for each formulary configuration and using the resulting profits to calculate formulary best response functions. We consider a single–plan insurer h, ignore measurement error, and assume there is a single type of statin users.[51] Insurer h's profits from *statin users* (suppressing some arguments) are

$$\Pi_h(f_h, p_h, f_{-h}, p_{-h}) = \sum_{i=1}^{N} \left[s_{ih}(f_h, p_h, f_{-h}, p_{-h}) p_h - c_{ih}(f_h, p_h, f_{-h}, p_{-h}) \right] \quad (44)$$

Given statin formularies are (f_h, f_{-h}), the derivative of the profits from *statin users* depends on the following two derivatives:

$$\frac{\partial s_{ih}}{\partial p_h}(f_h, p_h, f_{-h}, p_{-h}) \quad (45)$$

and

$$\frac{\partial c_{ih}}{\partial p_h}(f_h, p_h, f_{-h}, p_{-h}). \quad (46)$$

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

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. An assumption that avoids the need to calculate the second derivative, in Equation (46), is the following: we assume that, mean plan costs per

[51] All of these assumptions are easy to relax.

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

$$\bar{c}_{ih}(f_h, f_{-h}) := \frac{\sum_{i=1}^{N} c_{ih}(f_h, p_h; f_{-h}, p_{-h})}{\sum_{i=1}^{N} q_{ih}(f_h, p_h; f_{-h}, p_{-h})} = \frac{\sum_{i=1}^{N} c_{ih}(f_h, p'_h; f_{-h}, p'_{-h})}{\sum_{i=1}^{N} q_{ih}(f_h, p'_h; f_{-h}, p'_{-h})} \quad \forall h. \tag{47}$$

Profits from *non–statin users* are assumed to not depend on the market statin formulary configuration (f_h, f_{-h}) and to depend on constant marginal costs. Thus the derivative of profits from *non–statin* users has the usual form.

The optimal premium for insurer h given that statin formularies are (f_h, f_{-h}) are given by

$$p_h^* = \frac{\sum_{i \in N}(-s_{ih} + \bar{c}_{ih}(f_h, f_{-h})\frac{\partial s_{ih}}{\partial p_h}) + \sum_{i \in N^n}(-s_{ih}^n + c^n \frac{\partial s_{ih}^n}{\partial p_h})}{\sum_{i \in N} \frac{\partial s_{ih}}{\partial p_h} + \sum_{i \in N^n} \frac{\partial s_{ih}^n}{\partial p_h}} \tag{48}$$

where superscript n denote quantities for non–statin users.[52] Formulary placement of branded statins, f_h, directly affects plan demand and drug costs of statin users, but not of non statin users. Since statins account for 6% of drug fills on Part D in 2010, the optimal premium is unlikely to change much as rebates (and hence formularies) change.

Appendix E Canadian Prices

We calculate mean branded statin rebate that equates the mean price that U.S. insurers pay branded statin manufacturers with the mean price provincial Canadian governments pay using data from Dubois, Gandhi and Vasserman (2019).[53] Their Table 7.23 shows that in Canada the mean price for branded

[52] We abuse notation and use N and N^n to denote both the number of statin and non–statin users as well as the sets of each type of people.

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

statins is $1.77 per pill while in the USA it is $3.43 per pill. Thus U.S. prices would match Canadian prices if there were a mean rebate of 48.4% = 1 - 1.77/3.43.[54]

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

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

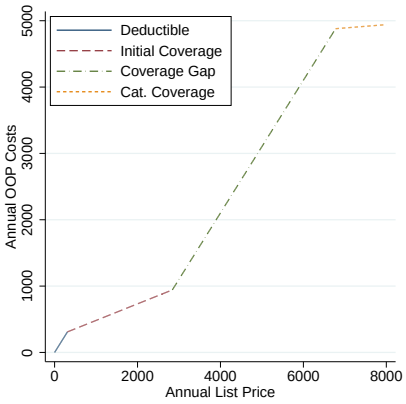
$$1 - \frac{1}{3.97}\left[(1-r_C)\frac{.095}{.095+.211}4.08 + (1-r_L)\frac{.211}{.095+.211}3.92\right] = \frac{1.77}{3.43}. \quad (49)$$

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

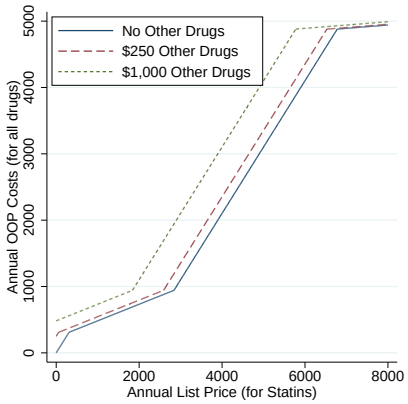
[54]There was exchange rate parity between US dollars and Canadian dollars in 2010.

Appendix F Extra Figures and Tables

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



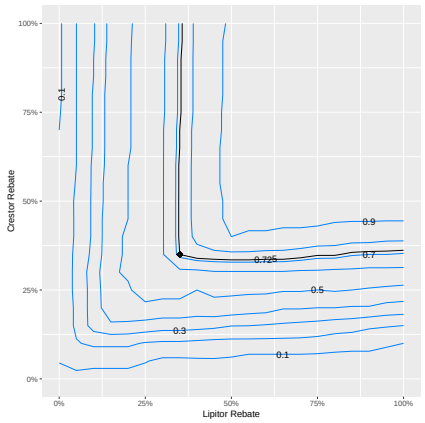
(a) The Standard Benefit Schedule



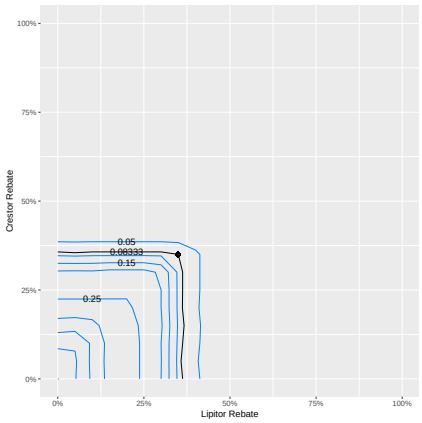
(b) The Effect of Non–Statin Drug Spending on Annual Statin OOP Costs

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

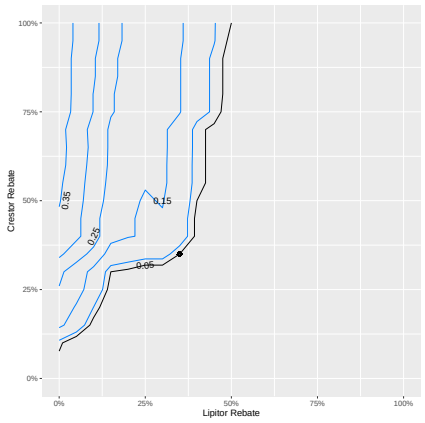
Appendix Figure 2: Equilibrium Preferred Share in Rebate Space



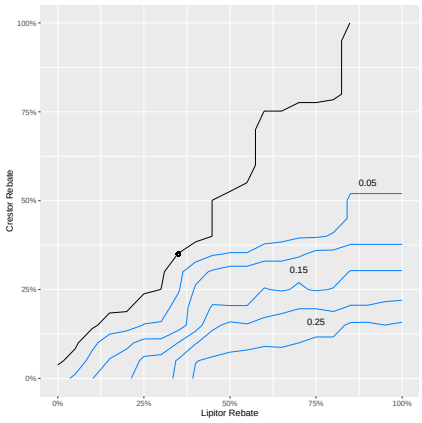
(a) Preferred/Preferred Share



(b) Excluded/Excluded Share



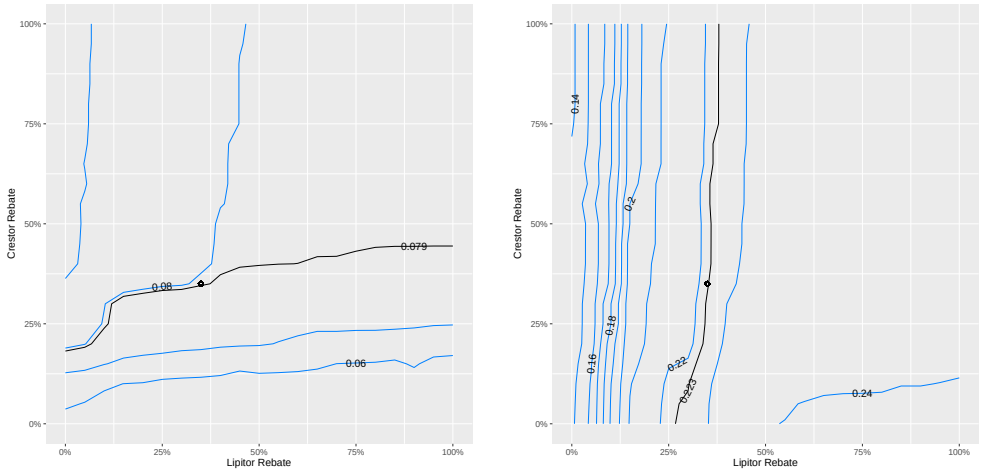
(c) Preferred/Non–Preferred Share



(d) Non–Preferred/Preferred Share

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

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



(a) Crestor Market Share (b) Lipitor Market Share

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

Appendix Table 1: Beneficiary Summary Statistics

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

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

Appendix Table 2: Plan Summary Statistics

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

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

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

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

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