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

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Abstract

The prices charged for on–patent, branded pharmaceuticals represent a large, and controversial, component of medical spending in the U.S. In contrast to many countries and many other government programs, drug prices in the Medicare Part D program are determined by privately negotiated rebates between insurance plans and drug manufacturers. How big are these rebates? What would happen to formularies, consumer surplus, and firm profits if the government could increase the rebates of a blockbuster Medicare Part D drug? We estimate a simultaneous model of insurance demand and statin demand for the population of statin users in 2010. Our demand estimates allow us to quantify how insurer profits change under different statin formulary structures. We use these profit functions to estimate the rebates for Crestor and Lipitor, two blockbuster drugs of the time; we estimate rebates of 20% for the dominant drug Lipitor, and 50% for the later entrant Crestor. In counterfactuals, we analyze the effect that different government negotiated statin prices would have on welfare. If the government negotiated a 20 percentage point increase in Lipitor rebates, then statin utility would increase by 2.2%. In contrast, a 20 percentage point increase in Crestor rebates would have almost no effect on statin utility.

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1 Introduction

Publicly–subsidized, privately–provided social insurance programs have become an increasingly important component of the health–insurance landscape in the United States (e.g., Medicare Part C, Medicare Part D, and the Health Insurance Marketplaces of the Affordable Care Act). The fiscal costs and welfare effects of these programs depend, to a large degree, on input price setting. Given public subsidies, it is reasonable to ask: Should the government be involved in input price setting? The answer to this question naturally depends on another question: What are the welfare consequences of government involvement in input–price setting.

This paper quantifies the welfare effects that would occur if the government negotiated lower input prices (drug prices) in Medicare Part D. Several aspects of Part D make it a particularly interesting environment in which to study the consequences of government–negotiated input prices. Salience around high drug prices has led to several recent proposals that involve a role for the government in Part D drug price setting. Moreover, the program is large: In 2019, Part D provided drug insurance to over 40 million beneficiaries in almost 1,000 plans at an estimated cost to the government of nearly $100 billion. Finally, Part D drug price setting involves unobserved and secret rebates, which are an important component of how the program provides cost–effective drug insurance. Estimating the size of rebates, which we do in this paper, is an important step in understanding how effective the status quo process is at lowering drug prices.

If the government reduced input prices in Part D, then some of the cost savings would be passed along and benefit consumers. However, the interactions between oligopolistic insurers and input prices can produce winners and losers. To see why this can happen, consider insurers deciding which drugs, out of several substitutes, to cover on their plans. Relative input costs are critical for this decision because they determine the cost savings that an insurer can realize from steering enrollees away from high–cost drugs towards low–cost drugs. Thus the government could reduce input prices and induce insurers to reduce coverage of some drugs, making them more expensive for enrollees, because the new relative input costs provide incentives to steer enrollees away from those drugs. This results in winners and losers and consumer surplus effects that can differ across different types of beneficiaries and across markets.

This is the first paper to model the equilibrium drug coverage decisions that determine who

wins and who loses when the drug prices that insurers pay change. We focus on the case of branded statins in 2010. Statins were the largest therapeutic class of drugs by fills in Part D in 2010, which is the most recent year for which Crestor and Lipitor (two blockbuster statins) were both on patent. We substantially extend upon the demand models used to analyze insurer incentives in Part D by modeling drug demand and plan demand simultaneously. This allows our model to explicitly account for adverse selection on the basis of unobserved preferences; consumers with strong unobserved tastes for a specific branded statin search for plans with low cost sharing for that statin. Adverse selection is particularly relevant for statins (and many other drugs) because they treat chronic underlying health conditions and, as a consequence, consumers typically know their statin preferences before they choose their insurance plans. We also estimate demand (for statins and plans) separately for several groups of consumers based on their risk type, which we define on the basis of comprehensive prior health utilization data.

We use our simultaneous demand model to recover insurer profit functions and estimate the size and structure of rebates paid by statin manufacturers to Part D insurers. In our setting, insurers specify the level of coverage for drugs on their plan by setting formularies, which specify a tier for each drug covered (e.g., generic, preferred, non–preferred, or specialty) and the associated cost sharing rules. Our model captures two important aspects of the structure of rebates in Part D. First, rebates are fomulary–contingent; branded drug manufacturers are willing to pay larger rebates to have their drugs placed on the preferred tier of the formulary. Second, rebates can include loyalty discounts; manufacturers are allowed to pay insurers larger rebates to obtain advantageous formulary placement (relative to their competitors). Our paper provides the first framework that is capable of evaluating the relationship between the structure of rebates and formulary competition.

Our approach to identifying rebates relies on a key output from our demand model: the degree to which changes in formulary placement for branded statins translate into changes in profits. We assume that insurers maximize annual profits. Because our demand model accounts for adverse selection on the basis of both unobserved preferences and observed risk types, insurers' average costs can increase as they provide more generous drug coverage. Intuitively, the rebates that we estimate are identified by the extent to which insurer profits (accounting for selection) are maximized by their observed fomulary placement of branded statins as opposed to alternative formularies that they could have chosen.

We find that drug manufacturers pay large rebates to Part D insurers. We estimate the AstraZeneca pays a 50% per unit rebate to plans that place Crestor on the preferred tier. Pfizer pays a much smaller 20% per unit rebate to plans that place Lipitor on the preferred tier. These rebates are both larger than the 13.8% average rebate for branded drugs reported by the Center for Medicare and Medicaid Services. One explanation as to why rebates are larger in this setting is that the therapeutic class has exactly two branded competitors, while the 13.8% average rebate also averages across therapeutic classes with monopolist manufacturers that may not pay any rebates. We find no evidence for the use of loyalty discounts for statins in 2010, a result that we rationalize by showing that drug manufacturers can obtain advantageous formularies without using loyalty discounts.

In light of recent policy debates around drug pricing, the counterfactuals that we quantify are topical. Our counterfactuals answer questions of the following kind: If the government increased rebates, what would happen to equilibrium formularies, consumer surplus, and insurer profits? We do not take a stand on the model of bargaining that the government would use to negotiate with manufacturers. Instead, we demonstrate the range of maximized statin utility that would obtain under different price negotiation outcomes. Due to computational constraints we impose two assumptions. First, we keep small plans formulary placement of branded statins fixed. Second, we assume that premiums and the copays assoicated with each formulary tier are fixed; both of these quantities are set based on the coverage of thousands of drugs, making this assumption plausible. Moreover, under fixed premiums, our counterfactual changes in consumer surplus are lower bounds.

If the government negotiated a 20 percentage point increase in Lipitor rebates, then statin utility would increase by 2.2%. In contrast, a 20 percentage point increase in Crestor rebates would have almost no effect on statin utility. Even though Crestor and Lipitor were blockbuster drugs, and the statin users in our data spend hundreds of dollars on statins each year, reducing manufacturer prices for drugs in this single therapeutic class has modest effects on consumer welfare. There are two factors that contribute to the asymmetric consumer surplus effects of increasing rebates for Crestor and Lipitor. First, increasing rebates creates winners and losers among beneficiaries. To see why this happens, consider increasing Crestor's rebate. This increases the relative cost of Lipitor for insurers. Some insurers move Lipitor off the preferred tier in order to steer consumers toward the relatively cheap Cretor. Beneficiaries who

prefer Crestor win while those who prefer Lipitor lose. Second, the effect of increasing rebates depends on the initial level of rebates because the steering incentives are nonlinear functions of demand. Since the Crestor rebates that we estimate are already large (50%), the formulary response to increasing Crestor rebates further is small relative to the effect of increasing Lipitor rebates. Moreover, these results suggest a complication for government negotiated rebates: when insurers are free to design their formularies, then the marginal 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 small literature on Medicare Part D formularies. Andersen (2017) studies the effect of formulary coverage requirements. Lavetti and Simon (2018) study how the fragmentation of hospital insurance and drug insurance affects formulary design in Medicare Part D. Starc and Town (2018) show that incentives to internalize the cost effects of medical care is as important as selection for Medicare Part D plan design. These papers summarize formularies by the overall coinsurance rate across all covered drugs. In contrast, in this paper, we focus on a specific therapeutic class and model formulary design in terms of tier placement. This allows us to analyze concrete formulary changes that plans would make in response to different negotiated rebates (i.e., a plan could move a branded drug from the preferred tier to the non–preferred tier).

By estimating a model of loyalty rebates, this paper contributes to a literature on competitor contingent pricing and more broadly exclusive dealing. This literature is mostly theoretical. In an early paper, Bernheim and Whinston (1998) show that, in many contexts, exclusive contractual provisions are irrelevant. Recently, Calzolari and Denicoló (2015) show that with a dominant firm, exclusive dealing can be anticompetitive. On the empirical side, Lee (2013) shows that in the context of video games, prohibiting exclusive dealing would increase consumer surplus and incumbent profits. Relative to complete exclusion, this paper analyzes competitor contingent loyalty rebates and finds small effects for consumers.

This paper also contributes to a small literature that estimates drug demand. While there are many models of Part D plan demand,[1] there are far fewer models estimating demand for specific drugs in Part D, even though drug demand is a critical input into models of drug man-

[1]For example, Abaluck and Gruber (2011), Ketcham et al. (2016), Abaluck and Gruber (2016), Heiss et al. (2013), Ho, Hogan and Scott Morton (2017), Starc and Town (2018), Decarolis, Polyakova and Ryan (forthcoming)

ufacturer and insurer behavior. Carrera et al. (2018) estimate demand for statins using data from 12 Fortune 500 firms. Einav, Finkelstein and Polyakova (2016) estimate drug demand in Part D. Dalton, Gowrisankaran and Town (2015) also estimate drug demand in Part D. They focus on behavioral models of consumer behavior and estimate a dynamic model of drug choice. In contrast, we focus on a single class of drugs that treat a chronic condition and define the price of different statins as the increment in annual drug costs. We use this definition of prices to estimate a simultaneous model of drug and plan demand that treats the drug demand component of the model as static. This simplification allows us to focus on endogenous plan selection and firm side behavior while still keeping the analysis computationally tractable.

Last, this paper contributes to a small literature that uses structural modelling to evaluate the effects of drug pricing policy. Dubois, Gandhi and Vasserman (2019) and Maini and Pammolli (2019) both study the consequences of international reference pricing policy using structural models of demand for drugs.

The rest of this paper is structured as follows. In Section 2 and 3, we present institutional background and data. In Section 4, we describe the simultaneous model of demand and the model of insurer formulary setting. In 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

In this section, we describe the institutional detail that is relevant to our demand model, our formulary equilibrium model, and our counterfactual analyses. We split the institutional details into three sections: Medicare Part D, statins, and drug rebate setting.

2.1 Medicare Part D

Medicare Part D is a voluntary, prescription-drug insurance program. All Medicare beneficiaries are eligible to enroll in Part D and enrolling is typically financially favorable because the government pays a subsidy of at least 74.5% of base premiums.[2] As a consequence enrollment

[2]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, who we describe

is high; close to 60% of Medicare beneficiaries enrolled in a Part D plan in 2010. A key component of Medicare Part D is that benefits are administered by private insurers who compete over enrollees; the idea is that competition will keep program costs low.

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

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

Medicare beneficiaries can enroll for 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 their out–of–pocket costs to between $0 and $6.30 per fill and covers between 25% and 100% when they enrol on low premium (below benchmark) plans. 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. Each Medicare beneficiary is assigned to one of 34 geographical regions (based on their state of residence) and can enroll in PDPs from their region. In 2010 every region had at least 30 PDPs. We restrict our sample to plans that have at least 1,000 enrollees (after basic sample restrictions) to ensure we have enough observations in each plan to estimate our model. This restriction results in us excluding 4 Part D regions (Alaska, Hawaii, New Mexico, and Nevada) because these regions have at most one plan in our data with 1,000 or more enrollees. The remaining regions have between 5 and 26 plans in each region and the mean number of plans per region is 14. To facilitate plan choice, the

in detail later, the government further subsidizes both premiums and out–of–pocket costs.

government runs a website that allows beneficiaries to compare plans.[3]

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; 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.[4] Beyond these two rules, plans have substantial freedom to design their formularies and, as we will document below, the variation in observed formularies generates large variation in annual OOP costs for the same beneficiary in different plans.

In addition to formulary requirements, CMS also imposes actuarial requirements on PDPs. Plans must be at least as generous as the Standard Benefit Schedule (SBS), which unlike the vast majority of PDPs is not tiered. Further details on the SBS are in Appendix A.

2.2 Statins

To estimate a drug–demand model, we focus on the therapeutic class of HMG-CoA Reductase Inhibitors (statins). In 2010, statins were the largest therapeutic class of drugs in Part D by fills. Moreover, in 2010, five statins comprised of more than 98% of the market: from newest to oldest, they are Crestor, Lipitor, Simvastatin, Lovastatin, and Pravastatin.[5] In 2010, Crestor (manufacturer by AstraZeneca) and Lipitor (manufactured by Pfizer) were both on–patent branded drugs. Plans place these branded statins on the preferred branded or non–preferred branded tiers of their formularies or remove them from the formulary altogether. Lovastatin, Pravastatin, and Simvastatin are all generic statins and are always placed on the generic tier of insurer formularies. We focus on Crestor and Lipitor because we model the formulary placement of branded drugs and how it responds to changes in rebates.

Statins are lipid-lowering drugs that are taken because they have been proven to prevent cardiovascular disease and related health events. Statins are differentiated on several dimen-

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

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

[5] We exclude Vytorin, which combines Ezetimibe and Simvastatin.

sions besides out–of–pocket costs. First, different statins have different levels of effectiveness in terms of reducing low–density lipoprotein cholestrol (LDL–C). The statins in our data reduce LDL–C by between 20% and 60%. Typically newer statins achieve larger percentage LDL–C reductions. Second, statins can have adverse side effects. The most common, althought still rare, side effect that people experience is muscle pain. The presence of side effects may be linked to a difference in the mechanism by which statins work: Crestor and Pravastatin are hydrophilic, while Lipitor, Simvastatin, and Lovastatin are lipophilic. S

2.3 Rebate Setting

The final component of institutional background that is 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 the three largest firms (OptumRX, Express Scripts, and CVS Caremark) dominating the market.

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 rebates can also specify loyalty terms: AstraZeneca is allowed to offer insurers a higher rebate to plans that do not place Lipitor on the preferred tier and a lower rebate to plans that do place Lipitor on the 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 that is based off estimating insurer profit functions and using data on their observed formulary decisions.[6]

[6]The rebates that we estimate are the rebates the insurers receive. Typically the rebates insurers receive are smaller than the rebates that manufacturers pay because PBMs keep a wedge. Our approach based off insurer decisions is not informative about the size of the wedge and hence does not pin down the exact size of the rebates payments that manufacturers pay. Moreover, our results focus on consumer surplus and insurer profits and, for these quantities, the rebate that insurers receives is the relevant rebate.

3 Data

We use data from the Center for Medicare and Medicaid Services (CMS) in 2010. We use four main datasets.[7] The first data set records plan choices and demographic variables for beneficiaries in our 20 percent random sample. The second data set describes PDPs' financial characteristics such as premiums, deductibles, copays, and coinsurance. The third data set contains the formulary placement of every drug for all PDPs in every Part D geographical regions.[8] The fourth data set consists of claim–level data on Part D drug fills for all of the beneficiaries in our 20% random sample. We use this data set to construct variables related to the statin component of our demand model, including statin choices and out–of–pocket costs. In addition we use three files on non–drug utilization in 2009 and 2010 (the inpatient, outpatient, and physician files) in order to calculate beneficiary risk scores, which are predictions of drug utilization using a 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, race, sex, and ZIP code of residence; and Part D plan choices.

We impose similar sample restrictions to prior papers studying Medicare Part D; we exclude beneficiaries who are younger than 65, who do not have full–year coverage on Part A and B, who enroll in a Part C plan for any month, who do not enroll in Part D for any month, who switch PDPs or LIS status mid year, or who die mid year. The two main difference between our sample restrictions and the sample restrictions in prior papers is that we restrict to statin users and we do not exclude LIS beneficiaries (they account for 32.1% of our sample).[9] The age restriction excludes beneficiaries who are Medicare eligible because they are on disability insurance; and because of their age, they typically do not use statins. The remaining sample

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

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

[9] 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 4 months.

restrictions focus our analysis to statin users whose coverage does not change within the year. After imposing all of these sample restrictions, we are left with 737,057 beneficiaries.

Appendix Table 1 reports summary statistics for the beneficiaries that survive our sample restrictions. The mean age is 76.0 years. And the sample is majority white (86.6%) and female (61.3%). Just over a quarter (28.2%) of the sample are eligible for Medicaid and almost a third (32.1%) of the sample are LIS beneficiaries.

3.2 Plan Data

For each PDP in the 30 Part D regions that we analyze, we observe plan enrollment and the financial characteristics of plans that are relevant to beneficiary plan choice (along with formulary design, which is described in the next subsection). We exclude Employer Group Waiver Plans because they are not open to general enrollment. We also exclude small plans that have fewer than 1,000 enrollees in our data. This reduces the number of plans in our data from 1,542 to 435; however the 435 remaining plans account for 86% of total enrollment.

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

3.3 Formulary Data

Formularies specify which drugs are covered and, for tiered formularies, they assign each covered drug with a unique tier that determines cost sharing. Higher tiers correspond to higher

OOP costs for beneficiaries. In 2010, the typical tiered formulary had separate tiers for generic drugs, preferred branded drugs, non–preferred branded drugs and specialty drugs.[10]

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 (0.3%)
Off	10 (2.6%)	0 (0%)	15 (3.8%)

Notes: Each cell shows the number of plans with the indicated formulary placement for Crestor and Lipitor. The sample consists of the 391 plans with at least 1,000 enrollees. Alaska, Hawaii, New Mexico, and Nevada are excluded because of sample size restrictions. Finally, 44 plans are excluded because they use the standard benefit schedule as opposed to a tiered formulary.

Table 1 enumerates the combinations of tier placement for Crestor and Lipitor across large plans (with more than 1,000 enrollees after sample restrictions) in our data. Just over half (53.2%) of plans have both Crestor and Lipitor on the preferred branded tier. 11.3% of plans have both drugs on the non–preferred branded tier. There is a clear asymmetry between the two branded statins with Crestor generally getting preferential formulary treatment; Crestor is in a favored position on 26.6% of plans (18.4% + 7.9% + 0.3%) while Lipitor is only in a favored position on 5.2% of plans.

Table 2 shows that branded statin formulary placement matters a lot for the branded statin market share of plans. For example, on plans that place both Crestor and Lipitor on the preferred tier, 9.4% of enrollees buy Crestor and 24.8% of enrollees buy Lipitor. In contrast, on plans that place Crestor on the non–preferred tier 14.7% of enrollees buy Crestor and only 4.8% of enrollees buy Lipitor. These drastic changes in branded statin market share across plans with different formularies reflect both moral hazard and adverse selection: holding fixed enrollment, moving Lipitor off the preferred tier reduces the Lipitor market share because Lipitor is more expensive and so fewer people buy it; in addition, moving Lipitor off the preferred tier induces people who have strong preferences for Lipitor to change plans. The model of

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

Table 2: Branded Statins Market Shares by Formulary Design

	Lipitor Tier		
Crestor Tier	Preferred	Non–Preferred	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. 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, 44 plans are excluded because they use the standard benefit schedule as opposed to a tiered formulary.

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,[11] 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.[12] For plans without gap coverage, beneficiaries' OOP cost in the coverage gap is the list price. For plans with coinsurance in the coverage gap, beneficiaries' OOP cost is the coinsurance rate times the list price.

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

[11] There are three codes for classifying drugs in our data: the National Drug Code (NDC), which is administered by the Food and Drug Administration; the Chronic Conditions Warehouse (CCW) formulary drug identifier, which is used by CMS to ensure that plans satisfy their formulary requirements; and the First DataBank (FDB) brand name. The CCW code is useful for working with the formulary files. The FDB code is useful for counting the number of drugs on a formulary because it does not distinguish between package size

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

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

Table 3: Statin Summary Statistics

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

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

Table 3 reports statin–related summary statistics using the claims data. Columns (1), (2), and (3) report statistics for non–LIS beneficiaries and Columns (4), (5), and (6) report statistics for LIS beneficiaries. First, we focus on non–LIS beneficiaries. The mean annual OOP costs from buying Crestor (instead of no statin) is $568. Lipitor is slighlty more expensive, and its mean annual OOP cost is $586. The standard deviations make clear that there is substantial variation in the annual OOP cost of branded statins across beneficiaries. Two factors account for the variation in annual OOP costs across beneficiaries. First, different beneficiaries face different copays for the same drug based on the plan they choose and its formulary placement of branded statins. Second, beneficiaries who purchase a lot of other drugs are more likely to reach the coverage gap region of Part D coverage, which increases annual costs because most plans provide no coverage in the coverage gap. Generic statins annual OOP costs are around $80, which makes them far cheaper than branded statins.[13]

[13]The reason that these costs are all similar is because generic statins are always on the generic tier. The small

LIS beneficiaries annual OOP costs for statins is substantially less than that of non–LIS beneficiaries. The lower annual OOP costs that LIS beneficiaries face appear to translate into larger markets shares for branded statins: 23.3% of LIS beneficiaries buy Lipitor and 11.2% 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 is to have a model and estimates that quantify the effect of different branded–statin formulary decisions on statin choice and plan choice.

For each statin user enrolled in a stand alone Part D Plan in 30 Part D markets in 2010,[14] we estimate a simultaneous demand model; statin users make their decisions over plans and statins at the same time. A key advantage of a simultaneous model is that it explicitly allows for adverse selection based on unobserved preferences; beneficiaries who have strong preferences for expensive branded statins search out plans that have good cost–sharing arrangements for these drugs. This simultaneous approach to estimating demand in a setting with bundled goods

standard deviation of generic prices across plans reflect the difference in copays and coinsurance rates across plans, but do not include the effect of formulary placement.

[14] We exclude plans with fewer than 1,000 enrollees in our data, which results in excluding the 4 smallest Part D markets (Alaska, Hawaii, Nevada, and New Mexico). As in Abaluck and Gruber (2011), we only model the choice of beneficiaries who choose a stand alone Part D Plan (we exclude employer group waiver plans). Thus we normalize the mean utility of an arbitrary plan in each region.

is similar to the strategy used in Crawford and Yurukoglu (2012), Lee (2013), and Crawford et al. (2018).[15]

In Medicare Part D regional market m (subscript suppressed), statin user i chooses a plan $k \in \mathcal{K}_m$ and a statin $j \in \mathcal{J}_k$.[16] Moreover, each statin user is grouped into one of four risk types t.[17] The utility from choosing statin j on plan k is given by

$$v_{ijtk} = -\alpha_t^c c_{ijtk} + \alpha_t^x x_{ijt}^s + \xi_{jt} + \varepsilon_{ijt}, \tag{1}$$

where c_{ijtk} is the annual out-of-pocket costs for statin j, x_{ijt}^s are observed enrolleed characteristics and ξ_{jt} is a statin fixed effect. The error term, ε_{ijt} is assumed to be IID from a Type 1 Extreme Value distribution. It is individual and brand–specific, so unobserved preference for branded statins does not depend on which plan the user is enrolled. Since, group type t appears in all variables, we omit it for notational simplicity.

Annual out-of-pocket costs, c_{ijk}, depend on the cost–sharing rules on plan k (formulary, copays, deductible, and gap coverage) as well as the nonstatin drugs purchased by beneficiary i. In general, c_{ijk} can be calculated given observed formularies, plan cost–sharing rules and the assumption that nonstatin drug choices are unaffected by plan choice (i.e., no moral hazard on nonstatin drug choices). [18] This assumption has been used in similar settings, e.g., Abaluck and Gruber (2011), Abaluck and Gruber (2016), Heiss et al. (2013), Ho, Hogan and Scott Morton (2017).[19] We provide further details on annual OOP cost calculations in Appendix A.

The model includes both observed and unobserved individual heterogeneity. We use statin fixed effects, ξ_j to capture unobserved statin quality. Observed heterogeneity is captured in two ways. First, the model is estimated separately by risk type. Second, x_{ij}^s includes median income (at the 5–digit ZIP code) and age interacted with an indicator for branded statins; thus

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

[16] 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. We use statin fixed effects in our specification of statin utility to capture unobserved quality.

[17] 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.

[18] For nonstatin drugs off formulary, we assume that beneficiaries choose an alternative drug on the same tier.

[19] An alternative assumption, used in Heiss et al. (2013), maintains that beneficiaries choose the cheapest drug by therapeutic class in each plan. In principle, the analysis of this paper could be redone under this alternative assumption, but at considerable extra computational expense.

mean statin utility differs by risk type and by observed individual characteristics.

We are able to include statin fixed effects while still estimating the coefficient on annual OOP costs because of individual–level variation in annual OOP costs. This variation comes from the interaction between the nonlinear price schedule inherent to Part D plan design and nonstatin drug spending. We assume that, conditional on the individual–level heterogeneity in our model, differences in annual OOP costs that arise from the nonlinear schedule (for example the coverage gap) are uncorrelated with preferences for specific statins. 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 plans that place both Crestor and Lipitor on the preferred branded tier account for the fact that removing Crestor from the formulary may drive many consumers to Lipitor to the extent that high–income beneficiaries 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 on plan k, and the utility from this choice is defined as

$$j^*_{ik} = \underset{j \in \mathscr{J}_k}{\operatorname{argmax}}\, v_{ijk}, \qquad v^*_{ik} = \max_{j \in \mathscr{J}_k} v_{ijk}. \tag{2}$$

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

$$s_{ij|k} = \frac{\exp(-\alpha^c c_{ijk} + \alpha^x x^s_{ij} + \xi_j)}{\sum_{j' \in \mathscr{J}_k} \exp(-\alpha^c c_{ij'k} + \alpha^x x^s_{ij'} + \xi_{j'})} \tag{3}$$

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.[20] Moreover, in our data, statin users typically buy a single type of statin, e.g., Crestor or Simvastatin.[21] Second, drug demand dynamics have been modeled in depth by Dalton, Gowrisankaran and Town (2015). However, in the context of statins, we believe that dynamics would not add much and would distract

[20] Essentially all users purchase fills for 30 days or 90 days.

[21] 94.7% of statin users in our data buy a single type of statin.

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.

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

$$u_{ikt} = \beta_t^{v^*} v_{ikt}^* - \beta_t^p p_k + \beta_t^x x_{kt}^p + \zeta_{kt} + \tau_{ikt}, \tag{4}$$

where p_k is the plan premium,[22] x_k^p is a vector of observed plan characteristics, ζ_k is a plan fixed effect, and τ_{ik} error term that is assumed to be IID from a Type 1 Extreme Value distribution. Once again, since, group type t appears in all variables, we omit it for notational simplicity henceforth.

Maximized utility from the statin subproblem is v_{ik}^*. Including the statin utility term is crucial for calculating how insurer profits respond to branded statin formulary placement. Statin formulary placements that were not chosen by plans have different annual out–of–pocket statin costs and thus different statin utility, statin choices, and plan choices. These channels drive the profit considerations that we use to learn about statin rebates.

Besides the term that captures statin utility, we use a similar specification to Decarolis, Polyakova and Ryan (forthcoming).[23] The plan covariates, z_k, are standard and include the annual deductible, the presence of gap coverage, "enhanced" plan status, and formulary generosity measures such as the number of drugs covered on the plan, the number of drugs at each tier the tier cost sharing (copay or average value of coinsurance), insurer (e.g., United Healthcare) fixed effects, Part D market fixed effects and plan age.[24,25] Unobserved plan quality is captured by plan fixed effects ζ_k.

Individual heterogeneity in plan utility is captured through risk types and through the max-

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

[23] Compare our Equation (4) to their Equation (1).

[24] We include plan age as a component of plan utility to account for plan inertia. This approach is used by both Decarolis, Polyakova and Ryan (forthcoming) and Starc and Town (2018). Moreover Decarolis, Polyakova and Ryan (forthcoming) provide theoretical justification for this approach.

[25] Enhanced plans are Part D plans that cover drugs that are not usually on Part D formularies, or offer extra coverage in the donute hole. These plans charge supplementary premiums because of their extra coverage.

imized statin utility term, which captures unobserved heterogeneity. Individuals with an unobserved preference for a particular statin, say Crestor, receive higher maximized statin utility on plans that have good cost–sharing rules for Crestor. Having maximized statin utility enter plan choice is similar to Crawford et al. (2015), who study television channel bundling, but different from Ho and Lee (2017), who use expected utility in health insurance choice (for inpatient and outpatient care). Because statins treat chronic conditions, beneficiaries are more likely to know their idiosyncratic tastes for different brands before they make their choice, which is consistent with using maximized statin utility.

We assume that statin user i in Part D region m chooses a plan $k \in \mathscr{K}_m$ to maximize Equation (4). However, maximizing Equation (4) 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 (4) as

$$u_{ik} = \delta_k + \beta^{\nu^*} \nu^*_{ik} + \tau_{ik}, \tag{5}$$

where the mean utility term δ_k is defined as

$$\delta_k = \beta^p p_k + \beta^z x^p_k + \zeta_k. \tag{6}$$

Finally, the probability of choosing plan k is then given by

$$s_{ik} = \frac{\exp(\delta_k + \beta^{\nu^*} \nu^*_{ik})}{\sum_{k' \in \mathscr{K}} \exp(\delta'_k + \beta^{\nu^*} \nu^*_{ik'})} \tag{7}$$

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 calculate the moment inequalities that we use to infer rebates. In this section, we describe our model of insurer behavior; we specify insurers' profits, insurers' objective functions and optimization problems, and the assumptions that we impose in our model.

4.2.1 Market Shares

A key component of our model is that plan profits account for adverse selection based on both observed and unobserved preferences because beneficiaries consider their maximized statin

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

The market shares that determine firm profits depend on both demand parameters and formulary decisions. Let θ^s and θ^p denote the parameters from the statin utility component of demand in Equation (1) and the plan utility component of demand in Equation (4) respectively. Let f_k denote plan k's branded statin formulary placement and let f_{-k} denote plan k's competitors' branded statin formulary placement. The conditional probability that beneficiary i chooses statin j given that they are on plan k depends on plan k's formulary f_k through the annual out of pocket costs of each statin c_{ijk}. To make the dependence of conditional statin choice probabilities on formularies and demand parameters explicit, we rewrite Equation (3) as

$$s_{ij|k}(f_k, \theta^s) = \frac{\exp(-\alpha^c c_{ijk}(f_k) + \alpha^x x_{ij}^s + \xi_j)}{\sum_{j' \in \mathcal{J}_k} \exp(-\alpha^c c_{ij'k}(f_k) + \alpha^x x_{ij'}^s + \xi_{j'})}. \tag{8}$$

Given that beneficiary i is on plan k, the branded statin formulary placement of plan k's competitors f_{-k} are irrelevant to beneficary i's conditional statin choice probabilities.

The probability that beneficiary i chooses plan k depends all formularies that are available in a region because they determine plan utilities through the maximized statin utility term. To make the dependence of plan choice probabilities on formularies and demand parameters explicit, we rewrite Equation (7) as

$$s_{ik}(f_k, f_{-k}, \theta^s, \theta^p) = \frac{\exp(\beta^p p_k + \beta^z x_k^p + \beta^{v^*} v_{ik}^*(f_k, \theta^s))}{\sum_{k' \in \mathcal{K}} \exp(\beta^p p_{k'} + \beta^z x_{k'}^p + \beta^{v^*} v_{ik'}^{*b}(f_{k'}', \theta^s))}. \tag{9}$$

Maximized statin utility on plan k, $v_{ik}^*(f_k, \theta^s)$, depends on f_k, the formulary on plan k, through

annual out–of–pocket costs; and it depends on θ^s, the parameters determine statin utility.

4.2.2 Revenues

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).[26]

The revenue for plan k from enrolling beneficiary i is

$$R_{ik}(p_k) = p_k + p_k^{LIPSA} + sub_{ik} + re_{ik} \tag{10}$$

where p_k is the annual premium paid on plan k, p_k^{LIPSA} is the Low Income Premium Subsidy Amounts, sub_{ik} is the direct subsidy payments to plan k that is risk adjusted on the basis of individual i's historical medical utilization, re_{ik} are reinsurance payments to plan k for beneficiary i that cover most of the cost for drug fills made after the catastrophic coverage threshold has been reached.[27] Appendix B provides all of the details as to how we calculate each source of revenue.

Then plan k's expected annual revenue is given by

$$R_k(p_k, f_k, f_{-k}, \theta^s, \theta^p) = \sum_{i=1}^{N} s_{ik}(f_k, f_{-k}, \theta^s, \theta^p) \cdot R_{ik}(p_k) \tag{11}$$

Equation (11) shows that plan revenues depend on the parameters of our simultaneous demand model and the branded statin formulary placement decisions of all plans available in each Part D region through plan demand.[28]

4.2.3 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

[26] We ignore risk corridors, which account for less than 1% of revenue for PDPs in the MLR Public Use Files.

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

[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. However, since branded statin rebates do not affect these payments much, we suppressed this dependence for exposition. More precisely, and as done in Appendix B, reinsurance payments can be written as $re_{ik}(f_k, \theta^s, r_C(f_k), r_L(f_k))$, and thus revenues also depend on rebates.

that administrative costs per member per month would not change even if plans altered their branded statin formulary placement. For beneficiary i choosing statin j on plan k, let tc_{jk} denote total costs (net point–of–sale discounts), let c_{ijk} denote annual OOP costs, and let $licsa_{ijk}$ denote LICSA payments. Since f_k and θ^s determine statin demand, they also affect each of these quantities, however we suppress this for expositional clarity. As with revenues, Appendix B contains a detailed description of the different components of cost.

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

$$\begin{aligned} C_{ik}(f_k, \theta^s, r_C, r_L) &= \sum_{j \in \mathscr{J}_k} s_{ij|k}(f_k, \theta^s) \cdot ([1 - r_j(f_k)] \cdot tc_{jk} - c_{ijk} - licsa_{ijk}) + C_i^{NS} \\ &= \sum_{j \in \mathscr{J}_k} s_{ij|k}(f_k, \theta^s) \cdot C_{ij}(r_j(f_k)) + C_i^{NS} \end{aligned} \tag{12}$$

where $r_j(f_k)$ is the rebate for statin j when plan k chooses formulary f_k[29], C_j is the cost to plan k from statin j, C_i^{NS} is the cost that plan k incurs to cover beneficiary i's nonstatin drugs and $s_{i\cdot|k}(f_k, \theta^s)$ is the vector of each conditional statin choice probability. The second line simply defines C_{ij} as total costs, net of rebates, less annual OOP contributions, and LICSA payments for statin j.

We impose two assumptions that allow us to calculate the costs in Equation (12). The assumptions relate to how we calculate nonstatin costs and are necessary because we do not, and can not, estimate drug demand for all Part D drugs. First, we assume no moral hazard on nonstatin drugs, so that we can calculate nonstatin drug costs on any plan. This no moral hazard assumption is common in Part D plan demand models.[30] Second, we assume that the rebate for all branded nonstatin drugs is 13.8%.[31] With these two assumptions and the cost accounting institutional details in Appendix B, we either observe or can calculate every term in Equation (12).

[29] No rebates are paid for generic statins.

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

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

The exepected costs for plan k are given by the sum of the costs of the enrollees that endogenously select into plan k:

$$C_k(f_k, f_{-k}, \theta^s, \theta^p, r_C, r_L) = \sum_{i=1}^{N} s_{ik}(f_k, f_{-k}, \theta^s, \theta^p) \cdot C_{ik}(f_k, \theta^s, r_C, r_L)$$
$$= \sum_{i=1}^{N} s_{ik}(f_k, f_{-k}, \theta^s, \theta^p) \cdot \left(\sum_{j \in \mathscr{J}_k} s_{ij|k}(f_k, \theta^s) \cdot C_j(r_j(f_k)) + C_{NS} \right). \quad (13)$$

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

4.2.4 Profit Maximization

Let $\mathscr{F}$ denote the set of possible configurations of branded statin formulary placement on each plan, e.g., Crestor preferred and Lipitor non–preferred or Crestor non–preferred and Lipitor off formulary. Expected profits for plan k when it chooses statin formulary f_k and its competitors choose formularies f_{-k} is given by revenues less costs.

$$\Pi_k(p_k, f_k, f_{-k}, \theta^s, \theta^p, r_C, r_L) = \sum_{i=1}^{N} s_{ik}(f_k, f_{-k}, \theta^s, \theta^p) \cdot [R_{ik}(p_k) - C_{ik}(f_k, \theta^s, r_C, r_L)]. \quad (14)$$

Insurer h, with plans $\mathscr{H}_h$, can choose a different formulary for each of its plans. Let F_h denote the vector of branded statin formularies for all of insurer h's plans. Insurer h chooses $f_k \in \mathscr{F}$ for each $k \in \mathscr{H}_h$. As a consequence $F_h \in \mathscr{F}^{|\mathscr{H}_h|}$. Let F_{-h} denote the vector of branded statin formularies for all of insurer h's competitors' plans. Then the expected profit for insurer h is just the sum of the profits of the plans that h owns:

$$\Pi_h(F_h, F_{-h}, \theta^s, \theta^p, r_C, r_L) = \sum_{k \in \mathscr{H}_h} \Pi_k(f_k, f_{-k}, \theta^s, \theta^p, r_C, r_L). \quad (15)$$

Because beneficiaries on stand alone Part D plans are separated into 34 Part D markets, we assume that plan characteristics only affect demand within region. Thus within each region, every insurer chooses branded statin formulary placements on all of their plans to maximize

the joint profit of their plans in that region. We assume the level of copays and coinsurance on each tier is fixed for all plans. Insurers simultaneously choose branded statin formulary placement and premiums to maximize their profits. Insurer h solves

$$\max_{\{F_h \in \mathscr{F}^{|\mathscr{H}_h|}, p_k\}} \Pi_h(F_h, F_{-h}, \theta^s, \theta^p, r_C, r_L), \tag{16}$$

where we assume that insurer h takes its competitors' statin formularies as given, i.e., the insurers play a Nash equilibrium of the formulary choice game.

Plan k's expected profit depends on the number of beneficiaries that enroll in plan k as well as which beneficiaries endogenously select into plan k. The main way that plan selection affects profits is through costs.[32] Plans that place branded statins on the preferred tier face more adversely selected enrollees and they also provide stronger incentives for statin users to buy branded statins, which increases plan costs.[33] Insurers trade-off these larger costs against the benefits of increasing enrollment and hence increasing premium revenues. The simultaneous–demand model that we estimate allows for plan selection by LIS status, risk score, observed beneficiary demographics, as well as unobserved statin taste shocks. Thus, in our model of branded statin formulary setting, plans account for the effects of enrollee selection on profits.

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^s and θ^p) jointly using moments from beneficiaries' statin and plan choices.

Combining the statin and plan components of the model, we use Equations (3) and (7) to

[32] Plan selection has small effects on revenues through reinsurance payments, which are paid to cover 80% of drug costs that beneficiaries incur beyond the catastrophic coverage threshold. See Appendix B for further details.

[33] Some of these increased costs are mitigated through risk scores adjustment, which scale direct subsidy payments to plans. These risk scores payments are supposed to cover the costs of a nationally representative beneficiary. We use the CMS risk score software for 2010 and account for these risk score payments to plans when we calculate profits.

calculate the unconditional probability that beneficiary i chooses statin j as

$$s_{ij}(\theta^s, \theta^p) = \sum_{k \in \mathcal{K}} s_{ik}(\theta^s, \theta^p) s_{ij|k}(\theta^s). \tag{17}$$

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

$$E[(y_{ij} - s_{ij}(\theta^s, \theta^p)) Z_i^s] = 0 \quad j \in \{1, ..., J\} \tag{18}$$

where $Z_i = (1, A_i, I_i)'$ is the vector of instruments. A_i denotes the age of beneficiary i, and I_i 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. We obtain 15 moments from Equation (18).

Second, we use moments based on plan characteristics, which are very similar to the moments used in Decarolis, Polyakova and Ryan (forthcoming) and Starc and Town (2018). In particular, we use the following following sample moments:

$$E[\zeta_k(\theta^s, \theta^p) Z_k^p] = 0, \tag{19}$$

where and Z_k is an $L \times 1$ vector consisting of the exogenous plan characteristics and the premium instrument for plan k. We obtain 39 moments from Equation (19), so we have 54 moments in total.

Due to the simultaneous estimation of statin and plan demand, there is no closed-form solution for $s_{ij}(\theta^s, \theta^p)$ and thus we simulate it. Specifically, for a candidate vector of statin utility parameters, we take draws of ε_{ij}. Given these random draws, we solve for a simulated version of ν_{ik}^* from Equation (2). We replace ν_{ik}^* in Equation (4) with its simulated version ν_{ik}^{*b}. For simulation b, the simulated utility is given by

$$u_{ik}^b = \delta_k + \beta^{\nu^*} \nu_{ik}^{*b} + \tau_{ik}, \tag{20}$$

The simulated probability of choosing plan k is then given by

$$s_{ik}^{sim}(\theta^s, \theta^p) = \frac{1}{B} \sum_{b=1}^{B} \frac{\exp(\delta_k + \beta^{\nu^*} \nu_{ik}^{*b})}{\sum_{k' \in \mathcal{K}} \exp(\delta_k' + \beta^{\nu^*} \nu_{ik'}^{*b})}, \tag{21}$$

where B is the total number of simulation draws per beneficiary. Here, simulation provides a way to calculate ν_{ik}^*, which provides a tractable way to calculate s_{ik}.

First, we use moments based on statin shares. Let y_{ij} be an indicator that is one if beneficiary i buys statin j. Let $s_{ij}^b(\theta)$ denote the probability that beneficiary i buys statin j in simulation b (where each simulation takes new draws from ε_{ij}). The sample analog of Equation (18) is given by

$$g_s(\theta^s, \theta^p) = \frac{1}{N}\sum_{i=1}^{N}(y_{ij} - s_{ij}^{sim}(\theta^s, \theta^p))Z_i^s, \tag{22}$$

for $j \in 1, ..., J$ and N is the total number of beneficiaries in our data (summing over all plans and all regions) draws for each beneficiary. The sample analog of the moment in Equation (19) is given by

$$g_p(\theta^s, \theta^p) = \frac{1}{K}\sum_{k=1}^{K}\zeta_k(\theta^s, \theta^p)Z_k^p = 0. \tag{23}$$

To obtain ζ_k we first calculate s_{ik}^{sim} as described above and then use the BLP contraction. We estimate the parameters using statin and plan sample moments, $g_s(\theta^s, \theta^p)$ and $g_p(\theta^s, \theta^p)$. Let $g(\theta_1, \theta_2)$ denote a vector where all sample moments are stacked. We minimize the following objective function to estimate the parameters

$$Q(\theta^s, \theta^p) = g(\theta^s, \theta^p)' W g(\theta^s, \theta^p)$$

Here $g(\theta^s, \theta^p)$ is a $(3J + L) \times 1$ vector and W is a $(3 \times J + L) \times (3 \times J + L)$ positive definite weight matrix. We calculate standard errors by bootstrapping our procedure 100 times.

To account for premium endogeneity we follow the approach in Decarolis, Polyakova and Ryan (forthcoming) and **?**. In particular, for premium endogeneity, we use the Berry (1994) inversion and instrument for premiums with a Hausman instrument, which measures the premium of similar plans offered by the same insurer in other Part D markets. Decarolis, Polyakova and Ryan (forthcoming) justify this Hausman instrument by arguing that it captures variation in prices that come from sources such as an "insurer's price negotiations with pharmaceutical producers", but is not correlated with unobserved market–specific plan quality.

5.2 Supply

This section describes how we use inequalities that are implied from insurers profit maximizing branded statin formulary placement to construct a moment inequality estimator that we use

to recover unobserved rebates. The moment inequalities that we use are based on differences in insurer profits and follows Pakes (2010).

Suppose insurer h chooses F_h (a vector that specifies the branded statin formulary for each of its plans) and that for each of insurer h's plans, $k \in \mathcal{H}_h$, this entails choosing formulary $f_k \in \mathcal{F}$. If insurer h's competitors choose formularies F_{-h}, then an implication of profit maximization, given by Equation (16), is that

$$\Pi_k(F_h, F_{-h}, \theta^s, \theta^p, r_C, r_L) \geq \Pi_k(F'_h, F_{-h}, \theta^s, \theta^p, r_C, r_L), \quad \forall F'_h \in \mathcal{F}^{|\mathcal{H}_h|} \setminus F_h. \tag{24}$$

Each plan has 9 possible branded statin formulary placement configurations ($|\mathcal{F}| = 9$) because Crestor and Lipitor can each be placed in three positions (preferred, non–preferred, or off formulary). As a consequence, a single–plan insurer has 8 inequalities of the form in Equation (24). Insurer h with $|\mathcal{H}_h|$ plans has $9^{|\mathcal{H}_h|} - 1$ inequalities.

Critically, the inequalities in Equation (24) depend on the rebate menus that insurers face and this is key to our approach to estimating rebates. To operationalize a moment inequality approach based off Equation (24), we calculate violations in the inequality at every conjectured value for the rebate parameters. For insurer h choosing formularies F_h, under rebates r_C and r_L, we calculate the violation from not choosing F'_h as:

$$\begin{aligned}\Delta\Pi_h(F_h, F'_h, F_{-h}, \theta^s, \theta^p, r_C, r_L) = \\ \max\{\Pi_k(F_h, F_{-h}, \theta^s, \theta^p, r_C, r_L) - \Pi_k(F'_h, F_{-h}, \theta^s, \theta^p, r_C, r_L), 0\}, \quad \forall F'_h \in \mathcal{F}^{|\mathcal{H}_h|} \setminus F_h.\end{aligned} \tag{25}$$

If insurer h chooses F_h and this yields higher profits than F_{-h}, then there is no violation and the maximum of the two terms in Equation (25) is 0. On the other hand, if F_{-h} yields higher profits than F_h when F_h was chosen, then the difference in the profits is the size of the violation.

We assume that insurers choose their configuration of branded statin formulary placements to maximize their profits. Thus, when a conjectured rebate menu results in large violations, we infer that the rebate menu is unlikely to be the rebate menu that insurers are facing. 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. Next, consider what would happen if we evaluated inequality violations under a conjectured rebate menu that said all rebates are 100%, i.e., the marginal cost to insurers from branded statin placement is zero (before accounting for copays). In that case, our profit functions imply that every firm

should place both Crestor and Lipitor on the preferred tier. Given that Table 1 shows that just over half of the plans in our data actually place both Crestor and Lipitor on the preferred tier, the inequality violations that we calculate under 100% rebates are large. Thus we rule out 100% rebates. On the other extreme, consider 0% rebates. In this case, the marginal cost of branded statins is large, and our profit functions imply that most plans should remove both branded statins from the formulary. However, a very small share of plans actually places both Crestor and Lipitor off formulary, thus we rule out 0% rebates.

For computational tractability, we impose restrictions on the branded statin rebate menus that we estimate. In particular, we assume that branded statins only pay rebates for being on the preferred tier. Moreover, we assume that the rebate that a branded statin manufacturer pays is the same when its competitor is on the non–preferred tier or off the formulary. Table 4 shows the implications of our restrictions on the rebate menu. Given these restrictions on the rebate menu, we have four rebates to estimate that, with abuse of notation, we denote (r_C, r_L, r'_C, r'_L). With four rebates, we replace the formulary–contingent rebate menu functions by the vector of four rebates, which summarizes the same information. The differences $r'_C - r_C$ and $r'_L - r_L$ are loyalty rebates; these differences represent extra rebates that manufacturers pay in order to have their statin occupy a better position on the formulary than their competitor.

Table 4: Restrictions on the Rebate Menu

	Lipitor Tier		
Crestor Tier	Preferred Branded	Non–Preferred Branded	Off Formulary
Preferred Branded	(r_C, r_L)	$(r'_C, 0)$	$(r'_C, 0)$
Non–Preferred Branded	$(0, r'_L)$	$(0, 0)$	$(0, 0)$
Off Formulary	$(0, r'_L)$	$(0, 0)$	$(0, 0)$

Notes: This table shows the restrictions that we impose on the rebate menu for estimation. Rebates are formulary contingent and each plan has four different rebates rates that they can receive. Plans that place both Crestor and Lipitor on the preferred tier receive the base rebates r_C for Crestor and r_L for Lipitor. Plans that advantage Crestor by placing Crestor on the preferred tier and not placing Lipitor on the preferred tier receive a Crestor rebate of r'_C and no Lipitor rebate. The difference $r_C - r'_C$ represents the size of the loyalty rebate. Conversely, the Lipitor rebate when Lipitor is advantaged is r'_L and the Lipitor loyalty rebate is $r_L - r'_L$.

For any conjectured rebate menu $\varphi = (r_C, r_L, r'_C, r'_L)$, we calculate our objective function

based on the sum across insurers of the average insurer violation based off Equation (25):

$$M(\varphi) = \sum_{h=1}^{H} \frac{1}{|\mathscr{F}^{|\mathscr{H}_h|} \setminus F_h|} \sum_{F_h' \in \mathscr{F}^{|\mathscr{H}_h|} \setminus F_h} \Delta\Pi_h(F_h, F_h', \theta^s, \theta^p, \varphi). \tag{26}$$

The identified set of rebate menus φ_0 is the set of rebate menus that have no inequality violations, i.e.,

$$\varphi_0 = \{\varphi \,|\, M(\varphi) = 0\}. \tag{27}$$

In the case that no rebate menu satisfies all of our inequalities, then we estimate the rebate menu by minimizing the sum of negative deviations (following Ho 2009) as

$$\hat{\varphi} = \min_{\varphi} M(\varphi). \tag{28}$$

For computational reasons, we evaluate M on the grid $\{0, .05, .1, ..., 1\}^4$. To calculate standard errors, we use the bootstrap. Specifically, for each of the 100 bootstrap replications that we use to estimate the standard errors for our demand model, we find the rebates that minimize Equation (28) and report standard errors based on the associated distribution of rebate estimates.

The objective function that we use averages violations across formulary choices within an insurer. The advantage of this approach, relative to summing violations over formulary choices, is that it more equally weights insurers. If we did not do this, then an insurer with 3 plans would have 81 times more inequalities than an insurer with 1 plan. More generally, the number of formulary choices an insurer can make is exponential in the number of plans that it offers in a given Part D market. As such, insurers with many plans have many more deviations that enter into the objective in Equation (28). The approach that we use can be thought of as weighting insurers by the number of decisions that they make as opposed to the number of choices that they have available

6 Estimation Results

In this section, we report our estimation results.

6.1 Demand

Table 5 reports estimates from minimizing the simultaneous demand model objective given in Equation (23). A key advantage of estimating a simultaneous model of statin and plan choice is that the model accounts explicitly for adverse selection; beneficiaries with strong unobserved tastes for Crestor are more likely to choose plans with good cost–sharing rules for Crestor. Accounting for this selection is important for calculating plan profits under different formulary configurations, which are a critical component of the supply model that we use to estimate rebates. Panel A reports statin utility parameters ($\hat{\theta}_1$). Panel B reports plan utility parameters ($\hat{\theta}_2$). 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.

Table 5: Simultaneous Demand Estimates

	Risk Type (2009 Risk Score Tercile)			
	Lowest	Middle	Highest	LIS
	(1)	(2)	(3)	(4)
	Panel A. $\hat{\theta}_1$			
OOP Price Sensitivity $\hat{\alpha}^c$	3.586	3.428	3.254	4.343
Crestor Quality $\hat{\xi}_C$	1.231	1.295	1.020	1.531
Lipitor Quality $\hat{\xi}_L$	2.067	2.022	1.680	2.062
Age / 100 $\times \mathbb{1}$(Branded)	-2.175	-2.187	-1.518	-2.263
log(Income) $\times \mathbb{1}$(Branded)	.218	.202	.153	-.910
	Panel B. $\hat{\theta}_2$			
Maximized Statin Utility $\hat{\beta}^{\nu^*}$	3.512	3.484	3.239	3.674
Premium	-.0826	-.0750	-.0690	-.0024
Annual Deductible	-.0094	-.0091	-.0081	.0036
Any gap coverage indicator	1.7224	1.746	2.175	-.2574
Number of drugs covered	.0024	.0023	.0024	.0004
Plan Age	.4206	.3805	.4851	.1911

Notes: This table reports estimates from the simultaneous demand model described in Section 4.1. In particular, we minimize the objective in Equation (**??**) separately for each tercile of risk score and for LIS beneficiaries. All models also include the following components in θ^p: region fixed effects, an enhanced plan indicator, the number of drugs on tier 1, and the number of drugs on tier 2.

Starting with Panel A, we find intuitive coefficients on out–of–pocket statin costs $\hat{\alpha}^c$. LIS beneficiaries, who by definition have low income, are most sensitive to statin out–of–pocket costs with a coefficient of 4.343. Among non–LIS beneficiaries, α^c decreases by risk score tercile. Our estimates of mean drug quality show that Lipitor is preferred to Crestor by all risk types $\hat{\xi}_L > \hat{\xi}_C$ with LIS and the highest risk score tercile beneficiaries having the smallest difference in their preferences between Crestor and Lipitor. This may reflect that these two groups face the most muted price differences between Crestor and Lipitor. Older beneficiaries prefer generic 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 $\hat{\beta}^{\nu^*}$. As in Decarolis, Polyakova and Ryan (forthcoming), 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 $\hat{\alpha}^c$, 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.[34] 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.[35] We find that the elasticity

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

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

of plan demand with respect to premiums among statin users is -2.7. This implies that statin users are less elastic than Part D beneficiaries overall.[36]

6.2 Supply

In this section we report estimates from minimizing the moment inequality based objective function given in Equation (28).

Table 6: Statin Rebate Estimates

	(1)
Crestor Base Rebate r_C	50%
Lipitor Base Rebate r_L	20%
Crestor Loyalty Rebate $r'_C - r_C$	0%
Lipitor Loyalty Rebate $r'_L - r_L$	0%

Notes: This table reports estimates from the supply model described in Section 4.2 using the approach described Section 5.2. In particular, we report estimates that solve the minimization problem in Equation (28).

Table 6 reports our rebate estimates.[37] Our objective averages the profit violations across formulary choices within each insurer as shown in Equation (26). No rebate menu that we consider satisfies all of the implied moment inequalities that we use for estimation. As a consequence, we report the rebate menu that minimizes the magnitude of violations (following Ho 2009). This results in us estimating a rebate of 50% for AstraZeneca's Crestor and a smaller rebate of 20% for Pfizer's Lipitor. We find that the smaller later entrant, AstraZeneca (with market share 9%), offers a substantially larger rebate than the larger incumbent, Pfizer (with market share 21%).

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

continue to buy Crestor on a different plan.

[36]The range of elasticities reported in Lucarelli et al. (2012) range from -2.0 to -6.0. In Starc and Town (2018), the range is -5.0 to -6.3. And in Decarolis et al. (forthcoming) the range is -5.3 to -12.9. No paper that we are aware of reports elasticities for the sample of statin users. Moreover, this is the first paper that simultaneously estimates both drug and plan demand.

[37]For computational reasons, for now, we evaluate the moment inequalities on the grid $\{0, .05, .1, ..., 1\}^4$.

on the aggregate level annually. In 2010, the average annual Part D rebate was 11.3%.[38] By 2014, the average annual Part D rebates was 14.3%. Moreover, in 2014, CMS released the only summary of Part D rebates using total branded drug costs as the denominator (as opposed to all drug costs). Total Part D rebates accounted for 17.5% of branded drug costs in 2014.[39] 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. However, the average annual branded cardiovascular drug rebates in 2014 was 26.3%. Using the same rescaling as before, we calculate that branded cardiovascular drug rebates in 2010 were around 20.7%. Relative to other cardiovascular drugs, the branded statin rebates that we estimate are roughly equal for Lipitor and larger for Crestor.

Two facts may account for Cretsor's large rebate (relative to average 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, Crestor is in a therapeutic class where it is competing directly with a much larger, dominant blockbuster drug Lipitor, which may increase the incentives that AstraZeneca faces to offer larger rebates to obtain better market share.

Table 6 is a key starting point for our counterfactual analyses. It combines estimates from our simultaneous demand model with a model of insurer profit maximization to estimate the manufacturer rebates that influence insurer formulary design. The counterfactuals in the next section consider the consequences of different rebate menus on insurer formulary choice, beneficiary welfare, and firm profits.

7 Counterfactuals

In this section we calculate how equilibrium would change if the negotiated statin rebates were to change. First, we document the effect of a wide range of rebate menus on formulary design and welfare. This exercise quantifies an important aspect of an evaluation of government negotiated prices. For a large range of rebates it answers the question: if the government could negotiate these prices, what would happen to welfare and profits.

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

[39] CMS 2014 Manufacturer Rebate Summary Report.

A key intermediate step for our counterfactuals calculates a new equilibrium for plan statin formulary placement choices given the new rebate menu. 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. Calculating the Nash equilibrium of a game with this number of different payoffs is infeasible, so we first describe the simplifying assumption that we make in order to solve the formulary equilibrium.

7.1 Formulary Equilibrium

Continue to let $\varphi = (r_C, r_L, r'_C, r'_L)$ define the rebate menu. Given the rebate menu, in each Part D market, insurer h chooses the branded statin formulary placement on each of its plans, which we continue to denote by F_h (recall F_h is a vector that specifies the branded statin formulary placement f_k for each plan owned by insurer h, i.e., for all $k \in \mathscr{H}_h$). The branded statin formulary placement for insurer h's competitors is collected in the vector F_{-h}.

Insurers choose premiums and formularies. We make two assumptions in order to calculate the effect of changing rebates on equilibrium branded statin formulary placement. First, we hold fixed the formulary placement of nonstatin drugs; this is necessary because we do not estimate demand for nonstatin drugs. Second, we assume that premiums are fixed. This may be reasonable because premiums reflect thousands of drugs on the formulary. Moreover, the consumer surplus effects of rebates that we focus on are lower bounds if the premium were allowed to adjust. To see this, consider increasing rebates for branded statins. This reduces insurers' marginal costs from covering branded statins. More plans place branded statins on the preferred tier. Copays fall and enrollees benefit. If premiums were allowed to adjust, some of the cost savings would be passed on to enrollees in the form of lower premiums. Thus the consumer surplus effects that we calculate are lower bounds.

A Nash equilibrium of the formulary game involves each insurer choosing the formularies for their plans optimally given the formularies of their competitors. A Nash equilibrium obtains, every insurer h solves

$$\max_{F_h \in \mathscr{F}^{|\mathscr{H}_h|}} \Pi_h(F_h, F_{-h}, \theta^s, \theta^p, r_C, r_L), \tag{29}$$

To estimate rebates, we used implications of each insurers optimal formulary setting. Here, we wish to calculate the full Nash equilibrium. However, because of the large number of

market configurations, calculating the Nash equilibrium without any simplifying assumptions is infeasible.

Thus, for computational reasons, we assume that the formulary choice for all small plans is fixed. A similar assumption is made Eizenberg (2014), who fixes the product entry decisions of all laptop lines except the 4 largest. The intuition is that statin formulary choice is a dimension of plan differentiation. The point of differentiation is to obtain market share. Focusing on large plans captures the main source of beneficiaries that can potentially be attracted by product differentiation. 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.

7.2 Government Negotiated Statin Prices

In this section, we explore the effect that counterfactual branded statin rebates would have on formularies, statin utility, and insurer profits. Quantifying the formulary and welfare responses to negotiated rebates is useful because it allows us to understand how different outcomes of government negotiated rebates map into quantities of interest. We calculate counterfactual branded statin formulary placement, consumer surplus, and insurer profit for all possible branded statin rebates. The strength of this approach is that it does not require us to take a stand on any specific model of bargaining between the government and drug manufacturers. The limitation of this agnosticism is that we do not quantify the exact rebates that the government would obtain if it negotiated.

To map out the effects of different negotiated rebates, we calculate the Nash equilibrium formularies for the 4 largest plans in each region using Equation (16). When plans choose their formularies they take into account endogenous plan selection and its consequences for the cost distribution of their enrollees. After plans set formularies, beneficiaries choose plans and statins optimally. Our measure of consumer surplus is calculated using Equations (1) and

(2) and the demand estimates from Table 5. Insurer profits are calculated using Equation (15).

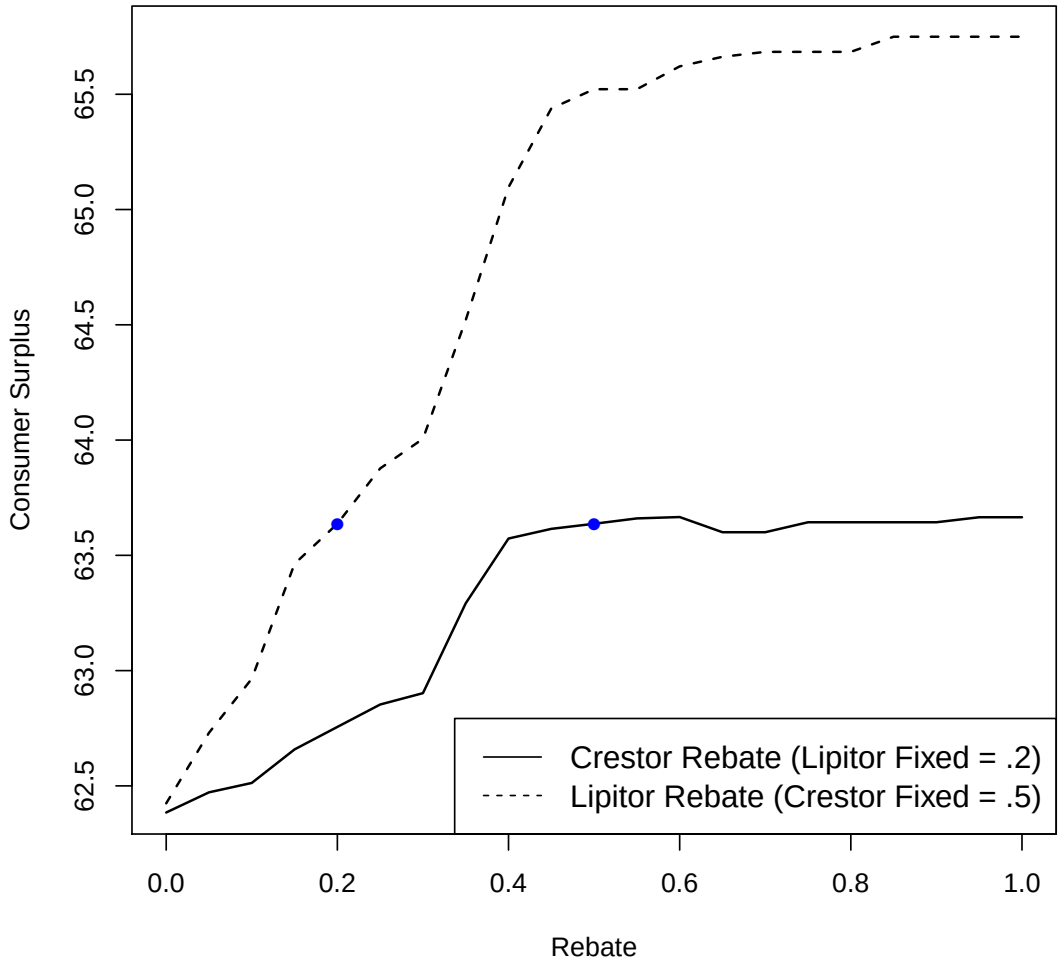
There is no guarantee that the profit functions that we estimate support a unique, pure–strategy Nash equilibrium at every counterfactual rebate menu that we consider. In practice, out of the 441 counterfactual rebate menus we have analyzed[40] we find a unique equilibrium for 429 menus. For the remaining 12, we do not find any pure strategy equilibria. Given the game that we analyze has a finite number of players and a finite strategy space, there exists a mixed strategy equilibrium, however, for now, we do not report results for these menus.

Figure 1 shows one of our main results; increasing the Crestor rebate from the status quo level has no effect on consumer surplus, but increasing the Lipitor rebate has a substantial effect on consumer surplus. Consumer surplus is on the y–axis, and the level of rebates is on the x–axis. The solid line shows the effect of increasing the Crestor rebate holding the Lipitor rebate fixed at 20%. The dashed line shows the effect of increasing the Crestor rebate holding the Lipitor rebate at 50%. The blue circles are reference points. The y–component of the blue dots corresponds to consumer surplus under the status quo. The x–component of the blue dots corresponds to the status quo rebate for the drug on the indicated line. Starting from the status quo point on the Crestor line, we see that there is no effect on consumer surplus to further increasing the Crestor rebate because the line is flat. In contrast, the Lipitor line is relatively steep starting from the status quo point. This indicates that consumer surplus increases as the Lipitor rebate increases. Overall the graph illustrates two results: first, the consumer surplus effect of increasing rebates is heterogeneous across drugs and can even be close to zero for some drugs; second, the effect depends on the reference point, i.e., the status quo rebates.

Figure 2 extends Figure 1 by allowing for any combination of changes in Crestor and Lipitor rebates. The figure shows level curves of consumer surplus in rebate space where rebates vary between 0% and 100%. Crestor rebates are shown on the y–axis and Lipitor rebates are shown on the x–axis. The blue circle is a reference point that shows the rebates that we estimate in the status quo. Figure 1 showed lines corresponding to vertical and horizontal cross sections of Figure 2 that pass through the blue circle. Increasing the Crestor rebate from the status quo point move parallel to the level curves and so does not increase consumer surplus, while increasing the Lipitor rebate moves perpindicular to the level curves and therefore increases

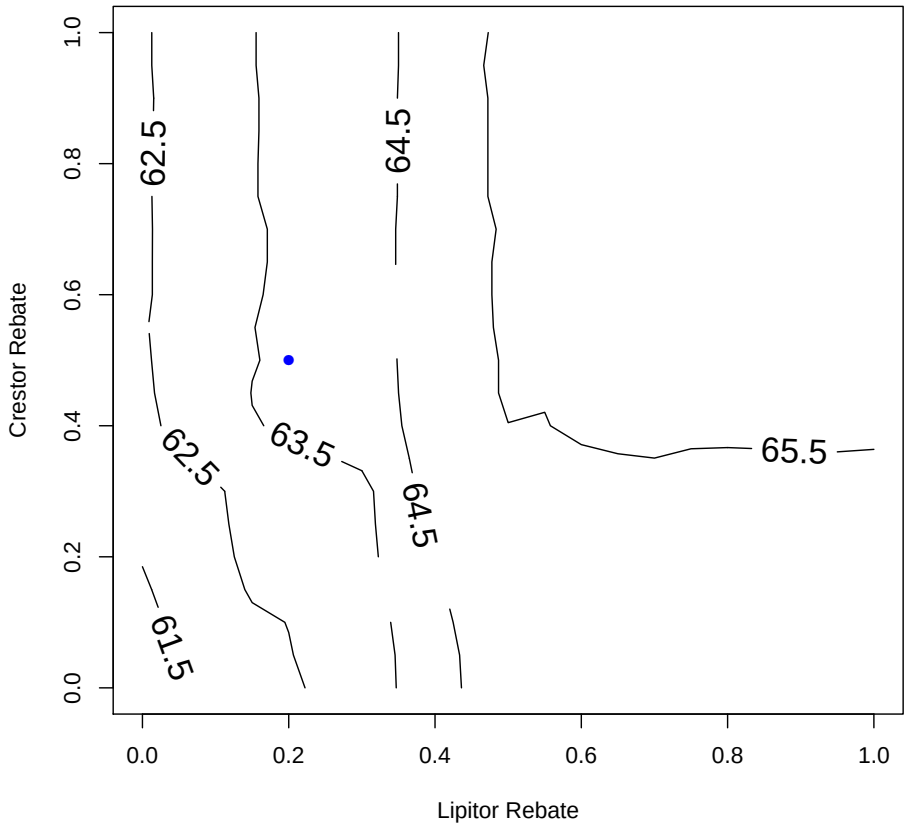
[40] We estimate our counterfactual with Crestor and Lipitor rebates on the grid $\{0, .05, .1, ..., 1\}$

Figure 1: The Effect of Each Statin Rebate on Consumer Surplus



Notes: This figure plots the effect of increasing either the Crestor rebate or the Lipitor rebate holding fixed the other branded rebate at its estimated status quo value. Consumer surplus is on the y–axis and the level of rebates is on the x–axis. The solid line shows the effect of increasing the Crestor rebate holding the Lipitor rebate fixed at 20%. The dashed line shows the effect of increasing the Crestor rebate holding the Lipitor rebate at 50%. The blue dots are reference points that correspond to the status quo equilibrium. Consumer surplus is calculated using Equations (1) and (2) and the demand estimates from Table 5. I use Equation (29) to calculate the Nash equilibrium formularies for the 4 largest insurers in each region, where insurers account for endogenous plan selection. Finally, beneficiaries choose plans and statins optimally given equilibrium formularies.

Figure 2: The Effect of Statin Rebates on Consumer Surplus



Notes: This figure plots level curves of consumer surplus, which is calculated using Equations (1) and (2) and the demand estimates from Table 5. For each pair of Crestor and Lipitor rebates (Crestor rebates are on the y–axis and Lipitor rebates are on the x–axis.), we use Equation (29) to calculate the Nash equilibrium formularies for the 4 largest insurers in each region, where insurers account for endogenous plan selection. Finally, beneficiaries choose plans and statins optimally given equilibrium formularies.

consumer surplus most quickly (i.e., it is in the direction of the gradient of the consumer surplus function). The figure also shows that the effect of rebates on consumer surplus is nonlinear. At the status quo point, consumer surplus only increases if Lipitor rebates increase. However if the Crestor rebate were 20%, so that it were the same size as the Lipitor rebate, then increasing *either* rebate would increase consumer surplus. Once rebates exceed 40%, the level curves exhibit a Leontieff pattern. Finally, the level curves make it clear that based on the preferences that we estimate in our demand function, Lipitor rebates are far more important than Crestor rebates for consumer surplus. For example, when Lipitor rebates are 45% and Crestor rebates

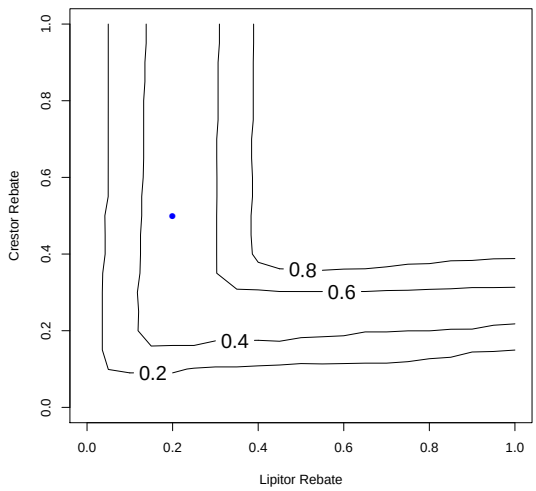
are 0% consumer surplus is the same as when Lipitor rebates are 35% and Crestor rebates are 100%.

To understand what drives the effects of rebates on consumer surplus, we examine the effect of rebates on the distribution of branded statin formulary placement and statin demand. We show that starting from our estimates of status quo rebates, increasing Crestor rebates does not change the distribution of formularies much, which makes sense because Crestor is already substantially discounted under the status quo. On the other hand, increasing Lipitor rebates has substantial effects on the distribution of formularies. We also show that the effect of rebates on formularies does result in winners and losers; this happens because some plans respond to increases in the Crestor rebate by moving Lipitor off of the preferred tier, which makes Lipitor more expensive and results in some beneficiaries who would have bought Lipitor changing to a different statin.

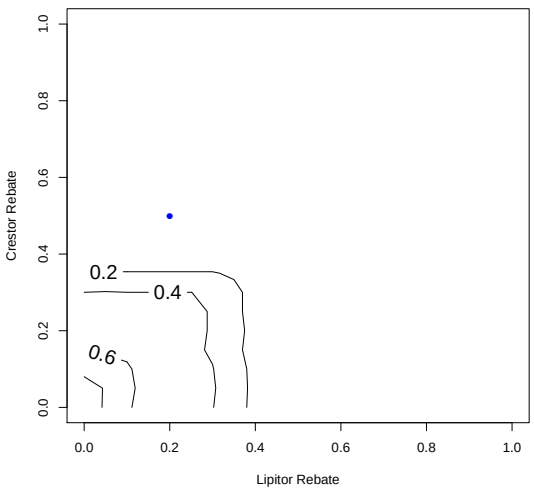
Appendix Figure 2 shows the effect of branded statin rebates on the equilibrium share of plans that place Crestor and Lipitor on the preferred tier. Panel (a) shows that the equilibrium share of plans that place Crestor on the preferred tier is increasing in the Crestor rebate. Similarly, Panel (b) shows that the equilibrium share of plans that place Lipitor on the preferred tier is increasing in the Lipitor rebate. Moreover, as the Lipitor rebate increases plans move Crestor off the preferred tier; this can be seen by the way that the level curves in Panel (a) slant upwards, which shows that the share of plans with Crestor preferred is decreasing in the Lipitor share. The effect of the Crestor rebate on the Lipitor preferred share is also negative, but is smaller.

Figure 3 show the effect of rebates on the full distribution of equilibrium branded statin formulary placement. To summarize the effects of rebates on equilibrium formulary placement, we group non–preferred and off–formulary tiers together and refer to this group as not on the preferred tier. After grouping these tiers, we have four possible formulary structures that are shown in each of the panels of Figure 3. The striking feature of Panel (a) is its Leontieff pattern. Starting from the status quo rebates, increasing the Crestor rebate does not increase the share of plans that place both branded statins on the preferred tier. This happens because the status quo Crestor rebate is so large that almost all large plans want to place Crestor on the preferred tier. On the other hand increasing the Lipitor share does increase the share of plans that place both branded statins on the preferred tier. This is important because when plans change their

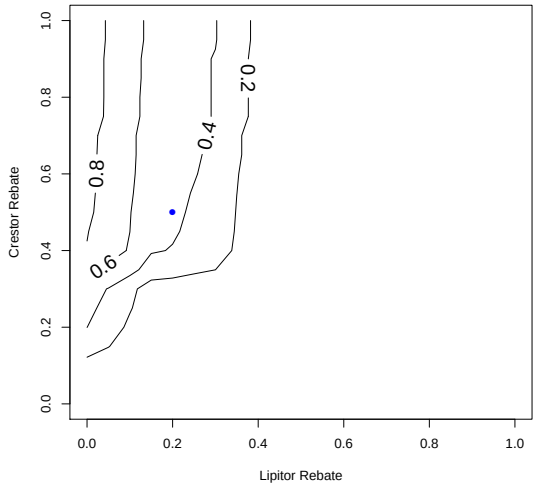
Figure 3: The Effect of Statin Rebates on Formulary Placement



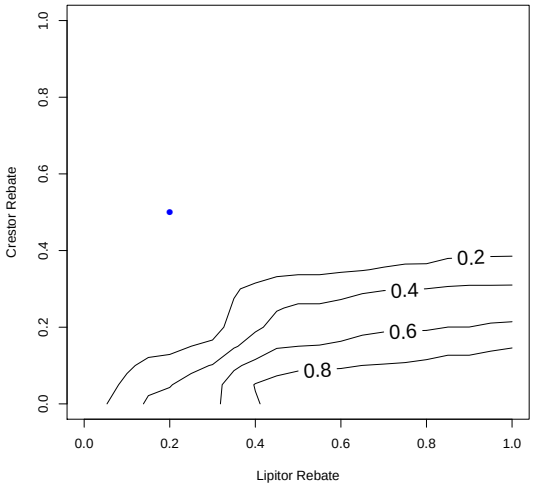
(a) Both Preferred Share



(b) Neither Preferred Share



(c) Crestor Advantaged Share



(d) Lipitor Advantaged Share

Notes: This figure plots the effect of branded statin rebates on the distribution of branded statin formulary placement. Each panel plots level curves of the market share of plans with the corresponding formulary type. Panel (a) plots the share of plans that place both Crestor and Lipitor on the preferred tier. Panel (b) plots the share of plans that place neither Crestor nor Lipitor on the preferred tier. Panel (c) plots the share of plans that have Crestor advantaged, so that Crestor is on the preferred tier, but Lipitor is not on the preferred tier. Finally Panel (d) plots the share of plans that have Lipitor advantaged. For each pair of Crestor and Lipitor rebates (Crestor rebates are on the y–axis and Lipitor rebates are on the x–axis.), we use Equation (29) to calculate the Nash equilibrium formularies for the 4 largest insurers in each region, where insurers account for endogenous plan selection. Finally, beneficiaries choose plans and statins optimally given equilibrium formularies.

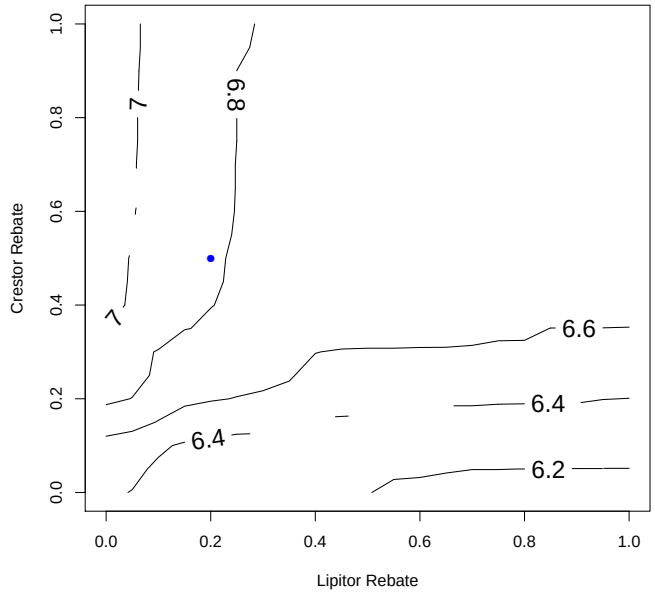
formularies to place both branded statins on the preferred tier all beneficiaries are made better off. Panel (c) shows that the share of plans that are Crestor advantaged (place Crestor on the preferred tier, but do not place Lipitor on the preferred tier) is increasing in the Crestor rebate and decreasing in the Lipitor rebate. Panel (d) shows the reverse situation for the share of plans that are Lipitor advantaged. Together Panels (c) and (d) provide a plausible explanation for the absence of loyalty rebates for branded statins in 2010. Our results show that branded statin manufacturers can already provide incentives to obtain advantageous formularies using the base rebate alone and without using loyalty rebates.

Together, Figure 3 shows that the distribution of equilibrium formularies is very responsive to branded statin rebates. In Figure 4, we show how equilibrium formulary design translates into demand for branded statins. Panel (a) shows Crestor's equilibrium demand is increasing in the Crestor share and decreasing in the Lipitor share. The effect of each rebate is nonlinear. Relative to status quo rebates, increasing the Crestor rebate further (from a base of 50%) has litte effect on Crestor's demand, while increasing Lipitor's rebate decreases Crestor's demand. Panel (d) shows that Lipitor's demand is increasing in the Lipitor rebate and decreasing in the Crestor rebate.

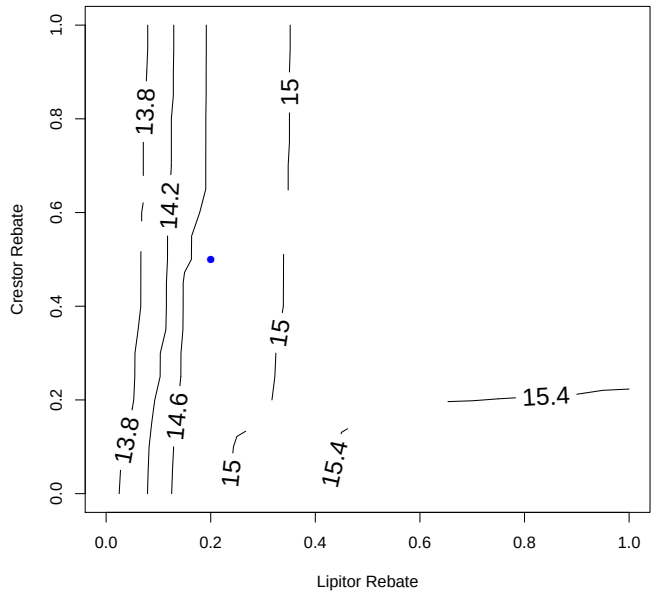
These result suggests a new complication for government negotiated rebates: when insurers are free to design their formularies, then the marginal effect of reducing the rebate on a single drug depends on both the levels and differences between rebates for competing drugs. Starting from our status quo estimates of branded statin discounts (50% for Crestor and 20% for Lipitor), increasing Lipitor's rebate by 20 percentage points increases statin utility by 2.2%. In contrast, if Crestor's rebate is increased (starting from 50% for Crestor and 20% for Lipitor), there is no effect on average statin utility. Three effects mute the consumer surplus effect of increasing Crestor's rebate. First, starting from the initial level of rebates, increasing the Crestor rebate has modest effects on formularies because the Crestor rebate was already large to begin with. Second, as the Crestor rebate increases, some formularies advantage Crestor, which benefits Crestor users and harms Lipitor users. Third, beneficiaries in our model choose plans partially on the basis of the formulary placement of branded statins and this mitigates the harm to Lipitor users whose plans begin to favor Crestor.

While the consumer surplus effects, that are mediated through equilibrium formulary placement, are nuanced, the effects on insurer profits are straightforward. Figure 5 shows the effects

Figure 4: The Effect of Statin Rebates on Statin Demand



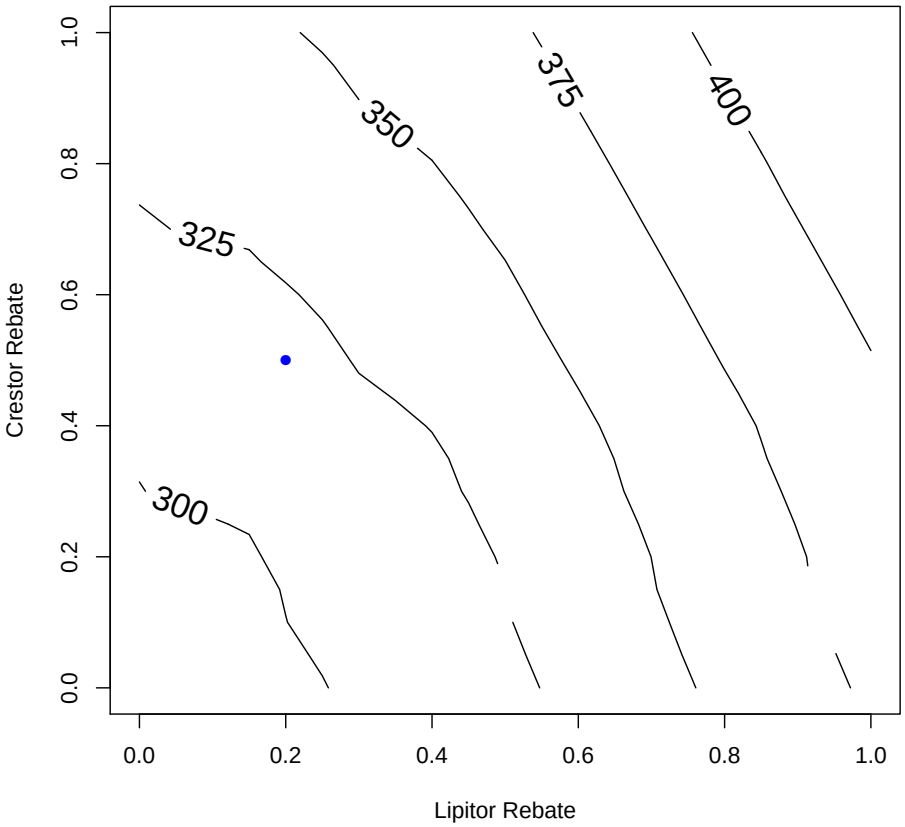
(a) Crestor Demand (10,000s beneficiaries)



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

Notes: This figure plots the effect of branded statin rebates on the demand of branded statins. Panel (a) plots the demand of Crestor and Panel (b) plots the demand of Lipitor. For each pair of Crestor and Lipitor rebates (Crestor rebates are on the y–axis and Lipitor rebates are on the x–axis.), we use Equation (29) to calculate the Nash equilibrium formularies for the 4 largest insurers in each region, where insurers account for endogenous plan selection. Finally, beneficiaries choose plans and statins optimally given equilibrium formularies.

Figure 5: The Effect of Statin Rebates on Total Insurer Profits



Notes: This figure plots level curves of total insurer profits, which is calculated using Equation (15). For each pair of Crestor and Lipitor rebates, we use Equation (29) to calculate the Nash equilibrium formularies for the 4 largest insurers in each region, where insures account for endogenous plan selection. Finally, beneficiaries choose plans and statins optimally given equilibrium formularies, and this determines insurer profits. We ignore administrative costs when calculating insurer profits and assume that they are fixed across all equilibria.

of branded statin rebates on insurer profits. Increasing either rebate reduces insurer marginal costs. Small insurers profits increase due to lower marginal costs. Large insurers (more specifically insurers who own any of the 4 largest plans in any region) can further adjust their formularies in response to lower marginal costs. These formulary adjustments can only further increase profits beyond the first–order effect of lower marginal costs. The level curves indicate that the profit function is steeper in the direction of Lipitor rebates (since the gradient, which is perpindicular to the level curves and is not shown, is typically flatter than the 45 degree

line). This makes sense because Lipitor has a much larger market share than Crestor and so reductions in its cost have larger effects on insurer profits.

8 Concluding Remarks

In this paper, we estimate a simultaneous model of Medicare Part D plan demand and statin demand for the population of statin users. We use these demand estimates to 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 the equilibrium effects of negotiated drug rebates on formulary design.

We estimate that Medicare Part D insurers receive large rebates for branded statins. For Lipitor, the dominant branded statin, we estimate a rebate of 50%. For the later entrant, Crestor, we estimate a rebate of 50%. We show that increasing the rebates for either branded statin, starting from the status quo rebates, has heterogeneous effects on consumer surplus; increasing Crestor rebates has little effect on consumer surplus, but increasing Lipitor rebates by 20 percentage points would increase consumer surplus by 2.2%. The consumer surplus effects of increasing branded statin rebates are nonlinear and depend on the initial level of staus quo rebates. The main reason that increasing Crestor rebates does not increase consumer surplus is because status quo rebates are already large and further inreases have modest equilibrium formulary effects. We also provide the first evidence on the magnitude of branded statin formulary placement responses to changes in rebates. The distribution of equilibrium formularies depends heavily on rebates; at low levels of rebates almost no plans place both Crestor and Lipitor on the preferred tier, but when both rebates exceed 50% more than 80% of plans place both drugs on the preferred tier. Moreover, the equilibrium formulary model that we use in counterfactuals quantifies the extent to which plans steer beneficiaries to relatively cheap (high rebate) branded statins. The share of plans that advantage the high rebate branded statin increases quickly as the difference in rebates grows.

As pointed out earlier, our analyses have several limitations. First, we hold premiums and the copays and coinsurance rates for every formulary tier fixed in all counterfactual analyses. Given that premiums, copays, and coinsurance rates reflect the formulary placement of thou-

sands of drugs, it is plausible that holding these quantities fixed is immaterial to our results. Second, we only allow large plans to change their formularies in counterfactual equilibria. This assumption is a computational necessity and is typical in these types of analyses. However, accounting for the formulary response of smaller plans could still have important implications for the distribution plan types available in each market. Finally, when calculating formulary equilibrium, we assume that insurers are static profit maximizers and I model the effects of inertia in plan choice with plan age following (Decarolis, Polyakova and Ryan forthcoming and Starc and Town 2018). Extending the analyses in this paper to analyze other therapeutic classes of drugs and to account for dynamics are left as directions for future research.

References

Abaluck, Jason and Jonathan Gruber (2011) "Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program," *American Economic Review*, Vol. 101, No. 4, pp. 1180–1210, June.

——— (2016) "Evolving Choice Inconsistencies in Choice of Prescription Drug Insurance," *American Economic Review*, Vol. 106, No. 8, pp. 2145–84, August.

Andersen, Martin (2017) "Constraints on Formulary Design Under the Affordable Care Act," *Health Economics*, Vol. 26, No. 12, pp. e160–e178.

Bernheim, B. Douglas and Michael D. Whinston (1998) "Exclusive Dealing," *Journal of Political Economy*, Vol. 106, No. 1, pp. 64–103, February.

Berry, Steven T. (1994) "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, Vol. 25, No. 2, pp. 242–262, Summer.

Calzolari, Giacomo and Vincenzo Denicoló (2015) "Exclusive Contracts and Market Dominance," *American Economic Review*, Vol. 105, No. 11, pp. 3321–51, November.

Carrera, Mariana, Dana P. Goldman, Geoffrey Joyce, and Neeraj Sood (2018) "Do Physicians Respond to the Costs and Cost-Sensitivity of Their Patients?" *American Economic Journal: Economic Policy*, Vol. 10, No. 1, pp. 113–52, February.

Crawford, Gregory S., Robin S. Lee, Michael D. Whinston, and Ali Yurukoglu (2015) "The Welfare Effects of Vertical Integration in Multichannel Television Markets," NBER Working Papers 21832, National Bureau of Economic Research, Inc.

——— (2018) "The Welfare Effects of Vertical Integration in Multichannel Television Markets," *Econometrica*, Vol. 86, No. 3, pp. 891–954, May.

Crawford, Gregory S. and Ali Yurukoglu (2012) "The Welfare Effects of Bundling in Multichannel Television Markets," *American Economic Review*, Vol. 102, No. 2, pp. 643–85, April.

Dalton, Christina M., Gautam Gowrisankaran, and Robert Town (2015) "Myopia and Complex Dynamic Incentives: Evidence from Medicare Part D," NBER Working Papers 21104, National Bureau of Economic Research, Inc.

Decarolis, Francesco, Maria Polyakova, and Stephen Patrick Ryan (forthcoming) "Subsidy Design in Privately-Provided Social Insurance: Lessons from Medicare Part D," *Journal of Political Economy*.

Dubois, Pierre, Ashvin Gandhi, and Shoshanna Vasserman (2019) "Reference Pricing as a Deterrent to Entry:Evidence from the European PharmaceuticalMarket."

Einav, Liran, Amy Finkelstein, and Maria Polyakova (2016) "Private Provision of Social Insurance: Drug-specific Price Elasticities and Cost Sharing in Medicare Part D," NBER Working Papers 22277, National Bureau of Economic Research, Inc.

Eizenberg, Alon (2014) "Upstream Innovation and Product Variety in the U.S. Home PC Market," *Review of Economic Studies*, Vol. 81, No. 3, pp. 1003–1045.

Gowrisankaran, Gautam, Aviv Nevo, and Robert Town (2015) "Mergers When Prices Are Negotiated: Evidence from the Hospital Industry," *American Economic Review*, Vol. 105, No. 1, pp. 172–203.

Heiss, Florian, Adam Leive, Daniel McFadden, and Joachim Winter (2013) "Plan selection in Medicare Part D: Evidence from administrative data," *Journal of Health Economics*, Vol. 32, No. 6, pp. 1325–1344.

Ho, Katherine (2006) "The welfare effects of restricted hospital choice in the US medical care market," *Journal of Applied Econometrics*, Vol. 21, No. 7, pp. 1039–1079.

——— (2009) "Insurer-Provider Networks in the Medical Care Market," *American Economic Review*, Vol. 99, No. 1, pp. 393–430, March.

Ho, Kate, Joseph Hogan, and Fiona Scott Morton (2017) "The impact of consumer inattention on insurer pricing in the Medicare Part D program," *RAND Journal of Economics*, Vol. 48, No. 4, pp. 877–905, December.

Ho, Kate and Robin S. Lee (2017) "Insurer Competition in Health Care Markets," *Econometrica*, Vol. 85, No. 2, pp. 379–417.

Ketcham, Jonathan D., Nicolai V. Kuminoff, and Christopher A. Powers (2016) "Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program: Comment," *American Economic Review*, Vol. 106, No. 12, pp. 3932–3961, December.

Lavetti, Kurt and Kosali Simon (2018) "Strategic Formulary Design in Medicare Part D Plans," *American Economic Journal: Economic Policy*, Vol. 10, No. 3, pp. 154–92, August.

Lee, Robin S. (2013) "Vertical Integration and Exclusivity in Platform and Two-Sided Markets," *American Economic Review*, Vol. 103, No. 7, pp. 2960–3000, December.

Lucarelli, Claudio, Jeffrey Prince, and Kosali Simon (2012) "The Welfare Impact Of Reducing Choice In Medicare Part D: A Comparison Of Two Regulation Strategies," *International Economic Review*, Vol. 53, No. 4, pp. 1155–1177, November.

Maini, Luca and Fabio Pammolli (2019) "Reference Pricing as a Deterrent to Entry:Evidence from the European PharmaceuticalMarket."

Pakes, Ariel (2010) "Alternative Models for Moment Inequalities," *Econometrica*, Vol. 78, No. 6, pp. 1783–1822, November.

Starc, Amanda and Robert J. Town (2018) "Externalities and Benefit Design in Health Insurance," NBER Working Papers 21783, National Bureau of Economic Research, Inc.

A Annual Out–of–Pocket Costs and Variation

We assume that beneficiaries consider the effect of statin brand choice on their total annual drug spending, i.e., the price for Crestor is the difference between annual drug spending when Crestor is chosen and when no statin is chosen.

Before we describe the calculation of annual OOP costs, we need to describe the Standard Benefit Schedule and the different coverage regions of Part D plans. Appendix Figure 6 shows the SBS in 2010. The y–axis shows the annual out–of–pocket (OOP) cost to a beneficiary as a function of the annual list price of drugs (x–axis). The marginal cost of filling a prescription on the SBS (given by the slope of the function in Figure 6) is a piecewise constant function. In the deductible region, beneficiaries pay 100% of the list price for any prescriptions that they fill. In the initial coverage region, beneficiaries pay 25% of the list price of drugs. In the coverage gap, beneficiaries once again pay 100% of the list price of drugs. Finally, for beneficiaries whose annual OOP costs exceed $4,880, the marginal cost of filling further prescriptions is 5% of the list price. Despite the fact that more than 90% of plans are tiered and hence are more complicated than the SBS, all Part D plans have nonlinear pricing based on the same coverage regions; some plans remove the deductible or provide some gap coverage.

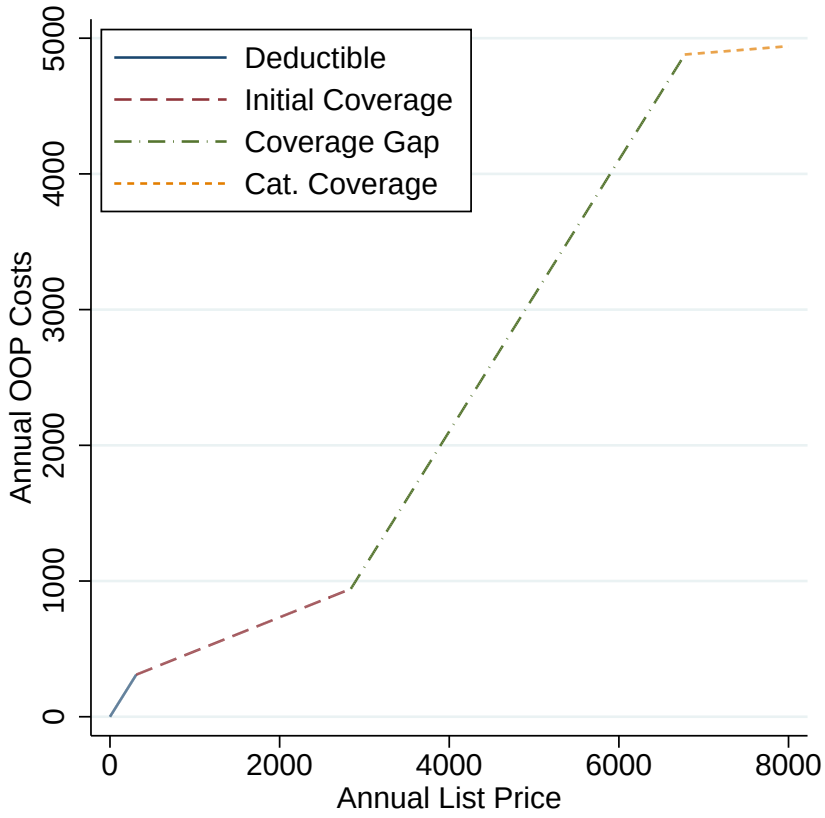
Because of the nonlinear price schedule in Medicare Part D, the effect of different statin choices on total annual drug spending varies across beneficiaries based on how much they spend on non–statin drugs. Given the institutions, the annual OOP cost c_{ijk} for beneficiary i choosing statin j on plan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

$$c_{ijk} = oop_k(g_{ik}^{ns}(h_i, \eta_i), f_k). \tag{30}$$

g_{ik}^{ns} is an unknown function that maps health h_i and preferences η_i into spending on nonstatin drugs; oop_k is a known function that maps spending on nonstatin drugs g_{ik}^{ns} and the formulary f_k (which, in this section refers to the tier placment of all drugs and the associated copays and coinsurance rates) into annual OOP costs for statins c_{ijk}.[41] The fact that g_{ik}^{ns} is unknown means that we need to make an assumption in order to calculate c_{ijk}.The assumption that we use has been used many times in the literature on plan choice: We assume no moral hazard

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

Figure 6: The Standard Benefit Schedule



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

on nonstatin drugs. This means that we calculate the cost of statins on each plan, we hold fixed the nonstatin drug decisions of each beneficiary. In the context of plan demand, this assumption has been used by many papers following the seminal paper by Abaluck and Gruber (2011).

Appendix Figure 1 illustrates the source of beneficiary variation in prices in the context of the standard benefit schedule described in Section 2. The figure shows the relationship between the annual cost of drugs (the y–axis) and the annual list price of a statin (the x–axis) for beneficiaries who spend different amounts on other (non-statin) drugs. Changes in non–statin drug spending shift the nonlinear schedule to the left by an amount determined from the known function oop_k. The solid line shows the schedule corresponding to no spending on other drugs; the dashed lines show the schedules when annual spending on other drugs is \$250 or \$1,000. A simplification in the context of the standard benefit schedule is that the

function oop_k is particularly simple. In tiered plans with copays, oop_k is high–dimensional, but still known; and I can still compute the effect of changes in non–statin drug spending on oop_k.

Annual OOP costs c_{ijk} raise endogeneity concerns in our model if the preferences that determine nonstatin drug spending η_i are correlated with preferences for statins ε_{ij} conditional on the control variables in our model. We assume that the individual–level heterogeneity that we specify in our model captures the component of η_i that is correlated with ε_{ij}.

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.

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

1. *Beneficiary premiums* (p_k). 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_k^{LIPSA}). The government subsidizes premiums for LIS beneficiaries (the subsidy can cover up to 100% of the premium and depends on the beneficiaries' cost–sharing group, which is a function of income and is observed in our data). We observe the size of LIPSA payments for each cost–sharing group on every plan. Thus, we observe the premium that each LIS beneficiary would face for any counterfactual set of plan choices.

3. *Direct subsidy* (sub_{ik}). 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):

$$sub_{ik} = ccs_i \cdot bid_k - (p_k + p_k^{LIPSA}). \tag{31}$$

We use the CMS risk score software to calculate each beneficiary's risk score based off their claims data. We recover plan bids from their premiums and public data on the national average bid amount and the base premium. We assume that bids would not change if the statin formulary changed. Thus, we observe the size of the direct subsidy that would be paid for any counterfactual set of plan choices.

4. *Federal Reinsurance* (re_{ik}) The government also pays plans for 80% of the cost of drugs that enrollees purchase once they reach their annual out–of–pocket threshold (net of point–of–sale pharmacy discounts and manufacturer rebates). Let cc_{idk} denote the total cost of drugs purchased beyond the out–of–pocket threshold (net of point–of–sale discounts) by beneficiary i on plan k on drug type d ($d \in \mathscr{D} = \{\mathscr{J}_k, \mathscr{G}, \mathscr{B}\}$ where $\mathscr{J}_k$ are the statins on plan k, $\mathscr{G}$ are non–statin generics, and $\mathscr{B}$ are branded non–statin drugs).

$$\begin{aligned} re_{ik}(f_k, \theta^s, r_C, r_L) = .8 \cdot \sum_{j \in \mathscr{J}_k} (1 - r_j(f_k)) \cdot cc_{ijk} \cdot s_{ij|k}(f_k, \theta^s) \\ + .8 \cdot cc_{i\mathscr{G}k} \\ + .8 \cdot (1 - r_{\mathscr{B}}) \cdot cc_{i\mathscr{B}k}. \end{aligned} \tag{32}$$

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, $r_{\mathscr{B}}$, is 13.8%.[42] Finally, we estimate statin rebates as a function of formularies. Thus, we quantify revenues due to federal reinsurance for any counterfactual set of plan choices.

Several of the components of plan revenue depend on bids that plans make to CMS for each Part D plan that they want to offer. The bid for plan k, bid_k, specifies a monthly revenue

[42] 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% base off the Medicare Trustees Reports.

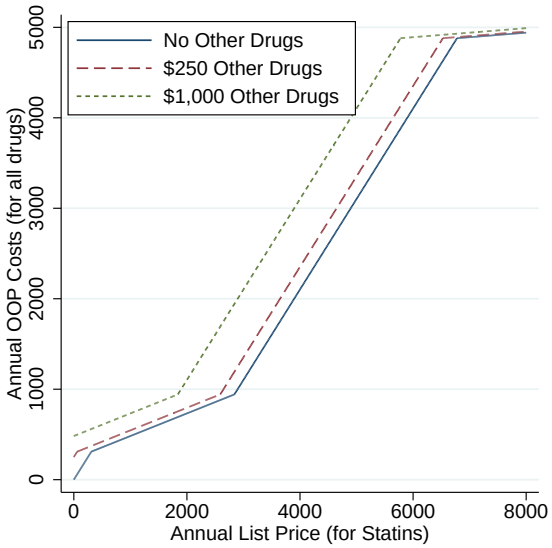
requirement that the plan needs to cover its costs (for basic coverage) and a profit margin. The premium for basic drug coverage is equal to the bid minus the base premium. The base premium is calculated as a proportion of the national average bid amount (weighted by lagged enrollment). In 2010, the national average bid amount was $88.34 and the base premium was $31.94.

B.2 Costs

Most of the quantities that we require to calculate $C_{ik}(f_k, \theta^s)$ were described in the section on Federal Reinsurance revenues. The only extra quantities that we need are beneficiary out–of–pocket payments and LICSA payments, which are observed functions of plan cost–sharing rules, beneficiary cost–sharing groups (for LIS enrollees), and branded statin formularies.[43]

[43]Because we assume no moral hazard on non–statin drugs, only branded statin out–of–pocket payments and LICSA payments depend on f_k. Thus $oop_{ik\mathscr{G}}(f_k)$ and $oop_{ik\mathscr{B}}(f_k)$ are constant (or trivial functions of f_k).

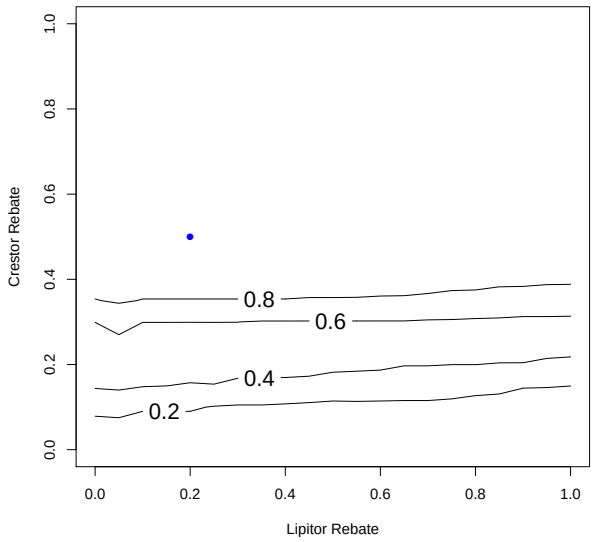
Appendix Figures and Tables



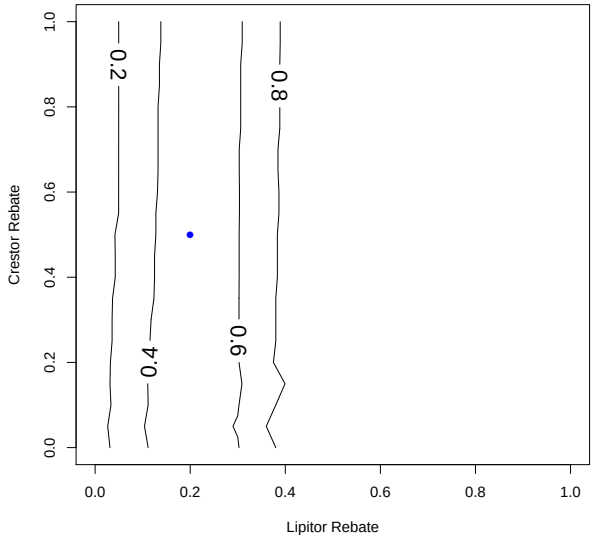
Appendix Figure 1: The Effect of Non–Statin Drug Spending on Annual Statin OOP Costs

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

Appendix Figure 2: Equilibrium Preferred Share in Rebate Space



(a) Crestor Preferred Share



(b) Lipitor Preferred Share

Notes: This figure plots the effect of branded statin rebates on the share of formularies that place each branded statin on the preferred tier. Panel (a) plots the share of plans that place Crestor on the preferred tier and Panel (b) plots the share of plans that place Lipitor on the preferred tier. For each pair of Crestor and Lipitor rebates (Crestor rebates are on the y–axis and Lipitor rebates are on the x–axis.), I use Equation (16) to calculate the Nash equilibrium formularies for the 4 largest insurers in each region, where insurers account for endogenous plan selection. Finally, beneficiaries choose plans and statins optimally given equilibrium formularies.

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	0.95	0.06	0.77	1.00
Number of Tier 2 Drugs	642	121	48	821
Number of Tier 3 Drugs	330	122	145	769
Tier 2 Copay ($)	34.4	9.3	4.0	45.0
Tier 3 Copay ($)	73.4	17.5	24.0	95.0
Plans			435	

Notes: This table reports formulary design summary statistics for the 435 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 distinguish between different drugs because it does not differentiate between package size. 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 (we exclude plans that use coinsurance from these calculations).

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

Number of plans	Mean	Min	Max
1	0.23	0.14	0.41
2	0.40	0.26	0.64
3	0.53	0.36	0.83
4	0.62	0.44	0.91
5	0.70	0.51	0.96
6	0.76	0.56	1.00
7	0.81	0.61	1.00
8	0.85	0.65	1.00
9	0.88	0.70	1.00
10	0.91	0.73	1.00

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