Pricing Intermediaries in Prescription Drug Markets: 
To Leverage or Replace?

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Abstract

I address the debate over whether Pharmacy Benefit Managers (PBMs) are effective at controlling prescription drug prices. First, I collect data on the average negotiated prices of anti-cholesterol drugs to better measure PBM-influenced outcomes. Second, I embed PBM formulary design and price negotiation in a dynamic oligopoly model of drug pricing, and estimate the model using the negotiated price data. Compared to outcomes under a pricing structure without negotiation, PBMs reduce overall spending by 15%. This is the net result of a 25% decrease in drug company revenues and PBMs capturing part of the savings. PBMs achieve this by leveraging credible threats of restrictive formularies, without actually having to greatly limit patient access in equilibrium. My results speak to competing Medicare drug policy proposals that aim to either leverage or replace PBMs.

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Can market-based institutions control prescription drug prices? Drug manufacturers appear to have significant pricing power, given the combination of patent protection, price-insensitive demand, and consumer inertia. Concerns about pricing power have grown in recent years, following large sticker price increases associated with Martin Shkreli, the EpiPen, cancer drugs, and insulin. This has led to a number of pricing-related policy proposals from the current administration and from Congress.

One potential countervailing force in private insurance markets is the presence of pharmacy benefit managers (PBMs). PBMs are intermediaries that negotiate prices on behalf of commercial insurers, employers, unions, and Medicare Part D plans, leveraging the formulary design power given to them by payers to control demand. PBMs claim that their actions help control spending on prescription drugs, while critics of PBMs, including Health and Human Services (HHS) Secretary Alex Azar and Garthwaite and Scott Morton (2017), argue that they increase overall costs to consumers, as the PBM industry is highly concentrated. This debate has been difficult to assess, given a lack of data on negotiated prices and the difficulty in modeling the US pricing system, but having some answers can help us assess the larger policy debate over whether to leverage market-based entities to control drug prices or have the government replace them.

In this paper, I contribute to our understanding of PBMs and drug prices using a combination of novel data and modeling. First, I establish that the average prices negotiated by PBMs have very different dynamics relative to list prices typically used in existing research. More specifically, I construct data on negotiated prices in the anti-cholesterol market from 1996 to 2013, leveraging drug company financial filings. Second, I embed negotiation between drug companies and a representative PBM in a competitive dynamic pricing model, basing the negotiation structure on descriptions from industry decisionmakers. In the model, each drug company makes a price bid to the PBM in every period. Given the prices, the PBM places each drug in a copay tier or excludes

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1. Einav, Finkelstein and Polyakova (2016) shows that consumers are unresponsive to cost sharing across a wide range of drug markets. Several existing papers find persistence in drug demand, including Crawford and Shum (2005), Dickstein (2014), Sinkinson and Starc (2018) and Lee (2016). A companion paper, Feng (2018), offers quasi-experimental evidence of history-dependent demand in the anti-cholesterol market, as well as diabetes, asthma, and HIV/AIDS.


3. PBMs do not serve the uninsured, Medicaid, Medicare Part B, and the VA. However, both Medicaid and Medicare Part B reference prices paid in private markets, which are negotiated by PBMs.

4. Duggan and Scott Morton (2010) speculate that PBMs are potentially a reason that drug prices did not go up significantly after the introduction of Medicare Part D.

5. See Section 1 for details on PBMs and some theory that puts a structure on this debate. For comments from Secretary Azar, see Financial Times article “Trump is losing the war on drug prices”: https://www.ft.com/content/2b57448e-94a4-11e8-b747-fb1e803ee64e.

6. See Section 1.1 for a discussion of specific Medicare policy proposals.

7. I also provide evidence in the Appendix that negotiated price dynamics in a broader set of markets follow similar trends.

8. Dynamics are necessary due to the nature of demand. I also discuss later how demand dynamics help explain key aspects of the price data.
it from coverage. The model allows me to uncover the forces governing PBM formulary choice, specifically how much they trade off patient access and spending when choosing formularies. Finally, I compute counterfactuals without PBMs to quantify the impact of PBMs on drug prices, overall spending, and welfare.\(^9\)

I find that PBMs are effective at controlling overall drug spending in the market segments they serve, without creating significant access restrictions. PBMs reduce overall spending by at about 15\%, by cutting drug company profits by 25\% and capturing the rest of the savings.\(^10\) While PBMs do restrict patient access, particularly through formulary exclusions, my results show that they increase consumer surplus. This results from the fact that the exclusion threat from PBMs is enough to control costs without significant restrictions in equilibrium. The overall welfare impact of PBMs is less clear, as their revenues come at the expense of drug companies, the drivers of innovation in the industry.\(^11\)

My research contributes to the literature on drug pricing and bargaining in health care markets, by overcoming key challenges in modeling drug prices and incorporating dynamics in a tractable way. First, my research is related to papers that study drug pricing patterns. Papers such as Caves et al. (1991), Lu and Comanor (1998), and Aitken et al. (2016) establish patterns in list price dynamics, including launch prices and trends around generic entry. My contribution is to collect data on negotiated prices, which better reflect market outcomes for insured individuals. Second, I also contribute to the literature on competitive drug pricing models. Previous papers have typically modeled drug companies as directly setting prices for consumers.\(^12\) This assumption leads to two inferences that contradict institutional details: high and fluctuating marginal costs and price sensitive consumers.\(^13\) My addition of PBMs to drug pricing models solves both problems simultaneously. Finally, my paper also contributes to the growing literature on bargaining in drug markets and health care more generally, which have mostly focused on static incentives. Dubois and Saethre (2016) and Maini and Pammolli (2017) use bargaining models to study drug pricing in European markets. More generally, Ho and Lee (2017, 2019) model insurer-hospital bargaining over prices. In the second paper, they incorporate network exclusions, which are akin to formulary exclusions in my setting. While my analysis is limited by the fact that data is only available at the market level, my contribution is to model price negotiation in a way that is tractable enough to fit into a dynamic oligopoly framework, while still addressing key policy questions.

More broadly, my results contribute to the literature on vertical markets, inertia and

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\(^9\)In my calculations of overall spending, I also factor in fees paid to PBMs, which I estimate using PBM financial filings to be about 8\% of pass-through payments to drug companies. See Appendix C for more details.

\(^10\)As a comparison, Dranove, Ody and Stacre (2017) find a 22\% reduction in Medicaid drug spending when Managed Care Organizations (MCOs) are hired by states to manage drug benefits.

\(^11\)There may also be spillovers to the uninsured market and other impacts on consumer health not captured by demand. I discuss this in greater detail in Section 5.2.

\(^12\)See papers by Dunn (2012), Arcidiacono et al. (2013), and Bokhari and Fournier (2013).

\(^13\)Small molecule drugs are known to have negligible marginal cost. Recent research by Einav, Finkelstein and Polyakova (2016), which finds very inelastic demand with respect to cost sharing in many drug markets, including the anti-cholesterol market.
pricing, and behavioral industrial organization. One classic concern in vertical markets is double-marginalization, which can occur if there is market power at multiple levels in a supply chain. In my context, PBMs serve as the bridge between drug manufacturers and patients, and the PBM industry is highly concentrated. Despite this concentration, PBMs may not have particularly strong market power, as payers can obtain drugs without having to hire a PBM, which they may choose if PBM services are not effective. Consistent with this view, my results suggest that PBMs end up reducing prices and overall spending. My paper is also related to the growing literature on the pricing implications of consumer inertia.\textsuperscript{14} My contribution here is to add a more complex pricing structure that reflects the complex institutions in prescription drug markets. More broadly, my paper contributes to research on whether markets can correct for behavioral consumers. In my setting, inertia may have rational foundations, e.g. learning with risk aversion as modeled in Crawford and Shum (2005), but it can lead to high prices that payers and consumers do not want. My results suggest that there exists an incentive for private players to emerge to solve the problem, in contrast with findings in other markets.\textsuperscript{15}

The rest of the paper is organized as follows. In Section 1, I provide background and theory on the drug pricing debate and PBMs. In Section 2, I describe the anti-cholesterol market and how I collect data on negotiated prices. In Section 3, I lay out my empirical model of drug pricing. In Section 4, I discuss model estimation. In Section 5, I run counterfactuals to study the impact of PBMs and discuss policy implications. Section 6 concludes.

1 The Drug Pricing Debate and PBMs

In this section, I provide additional background on drug pricing and PBMs that are relevant for my analysis. I conclude the section with some simple theory that frames the PBM debate.

1.1 Drug Pricing – Background, Literature, and Proposed Medicare Policies

The literature on prescription drugs has documented several dynamic pricing patterns. Early papers that presents facts on drug pricing include Caves et al. (1991) and Lu and Comanor (1998). The former finds different dynamic pricing strategies depending on the quality of the drug and type of market (chronic vs. acute), while the latter finds significant price increases in the two years leading up to patent expiration. Subsequent analyses, such as Dunn (2012) on the anti-cholesterol market, have noted increasing trends in prices over time, despite competitor and generic entry. Recent work by Aitken

\textsuperscript{14}Klemperer (1987a,b) explore the theory behind oligopoly pricing with consumer inertia. Recent empirical work includes Dubé, Hitsch and Rossi (2009), Honka (2014), Fleitas (2016), and Shcherbakov (2016).

\textsuperscript{15}For example, Gabaix and Laibson (2006) look to explain the absence of market incentives to correct myopia in markets with add-ons.
et al. (2016) provides a broad overview of pricing trends in recent years, including the fact that price increases on incumbent branded drugs generate a sizable fraction of the overall growth in drug expenditures, about 6% of the 15% total spending growth in 2014.

One shortcoming in the literature is the use of list prices, an especially large problem for analysis of US market. List prices, which are known as Average Wholesale Price (AWP) or Wholesale Acquisition Cost (WAC), are akin to sticker prices for cars. Most payers end up receiving an unobservable but significant discounts and rebates, in effect paying a net price to drug companies. This creates a problem when analyzing pricing dynamics, because discounts do not necessarily remain constant or move in lockstep with list prices. For example, Gilead, makers of the new generation of Hepatitis C drugs, set similar list prices in 2013 and 2014, but reported average discounts off the list price of 46% in 2014, after only offering 22% in 2013, likely due to competitor entry and PBM exclusion threats. A broader analysis by Bloomberg and SSR Health suggest that prices paid to drug companies is increasing, albeit at a slower rate than list prices. Therefore, using list prices can lead to incorrect inferences, an issue addressed here that is not accounted for in most analyses of prescription drug markets.

In terms of policy, recent controversies have led to a series of recent proposals to change drug pricing policy in Medicare Part B and Part D, some related to PBMs. In May 2018, the US government released a plan titled “American Patients First” that proposed several measures for reducing drug expenditures. Included in this was a proposal to move some doctor-administered drugs from being covered by Medicare Part B to Medicare Part D. This spirit of this proposal is to bring in PBMs to directly negotiate prices on the set of drugs affected, replacing current Part B rules, which do not allow exclusion from coverage and only indirectly incorporate negotiation through anchoring prices to private market outcomes. My estimates of PBM impact directly address this potential policy.

A second major proposal contained in the plan is to relax Medicare Part D protected class rules, which would also leverage PBMs. Current Part D rules mandate that plans cover at least two drugs from each market, and almost all drugs in six “protected classes,” including HIV, cancer, and antipsychotics. The proposal would relax these rules for

16See Berndt and Newhouse (2012) for a detailed overview of the institutional details behind these prices and the pricing system more generally.
18Data available at: https://www.bloomberg.com/graphics/2016-drug-prices/
19Exceptions in the literature include Arcidiacono et al. (2013) and Aitken et al. (2016), who collect some data on post-rebate prices but primarily use list price data in their analysis.
20See P30 of “American Patients First” proposal. HHS Secretary Azar described this as “negotiating for drugs in Medicare that have never been negotiated for.” The potential seriousness of the proposal is highlighted by the fact that Medicare Advantage plans have been given permission to use access restrictions to negotiate prices. See announcement: “Medicare Advantage Prior Authorization and Step Therapy for Part B Drugs” available at https://www.cms.gov/newsroom/fact-sheets/medicare-advantage-prior-authorization-and-step-therapy-part-b-drugs.
21See detailed list of rules on the CMS website: https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/downloads/Chapter6.pdf. The anti-cholesterol market is not
drugs that have price increases that outpace inflation, which applies to almost all of the drugs in these classes.\textsuperscript{22} The effectiveness of the policy will depend on how PBMs use exclusion as a tool to control prices, which my analysis will speak to.

A final proposal that has gained some traction is centralized price negotiation, which would essentially replace PBMs with the government. This proposal stands in contrast to the previous two, but the President and some congressional members have voiced support for it.\textsuperscript{23} The potential benefits of this policy depends on the relative effectiveness of PBMs and the government. My analysis will speak to the former, while HHS Secretary Alex Azar has suggested that the government may be ineffective in price negotiation due to the political infeasibility of restricting access.\textsuperscript{24}

1.2 PBM Industry – Background and Fee Estimates

Next, I turn to PBMs, outlining their importance in prescription drug markets and providing an estimate of the fees they charge their customers. In Appendix C, I discuss additional PBM incentives that are relevant for my empirical model.

PBMs manage prescription drug claims for both public and private payers. PBMs emerged in the late 1960s to help insurers manage drug benefits, which became more complicated as a growing number of drugs were approved by the FDA. Today, PBMs design drug plans for large health insurance companies (including Medicare Part D plans), large employers that self-insure, and other entities such as unions.\textsuperscript{25} The range of services PBMs provide include insurance design, discount negotiation, helping patients and doctors understand benefits, and running mail order pharmacies.\textsuperscript{26}

The main function performed by PBMs is to help design drug insurance, a position they use to negotiate prices with drug manufacturers. PBMs have the power to assign drugs to different copay tiers and can also limit patient access by requiring prior authorization or excluding drugs from coverage entirely. While PBMs pick tiers, their customers usually set the cost sharing amount associated with each tier.\textsuperscript{27} Using the threat of access restrictions, PBMs negotiate with drug manufacturers to obtain discounts and rebates.\textsuperscript{28} They then pass some of the savings onto their customers.

The PBM industry is highly concentrated and large PBMs are quite profitable and are often owned by other entities, all pointing to the possibility that they are hurting protected.

\textsuperscript{22} Based on ongoing analysis using price data from SSR Health. I discuss this data source in Section 2.3.


\textsuperscript{25} The market segments they are not directly involved in are uninsured patients, Medicare Part B, and Medicaid. However, both Part B and Medicaid reference net prices in commercial markets.

\textsuperscript{26} These mail order services mainly profit from margins on generic drugs. See Barron’s 2005 article “Pfizer’s New Headache”, available at: http://www.barrons.com/articles/SB112872627432763274.

\textsuperscript{27} For example, an employer might set the copay tiers to $30 and $50, and then the PBM would assign drug A to the cheaper tier and drug B to the more expensive tier.

\textsuperscript{28} Rebates are payments for reaching certain volume targets.
consumers. According to the Pharmacy Benefit Management Institute, the top three PBMs in terms of total prescription claims in 2015 were Express Scripts, CVS/Caremark, and OptumRx, totaling 73% of all prescription claims in the US.\textsuperscript{29} PBMs are highly profitable, as evidenced by the market cap (about $50 billion in 2016) and annual profits ($3.4 billion in 2016) of Express Scripts, the biggest standalone PBM at the time.\textsuperscript{30} There have been several large horizontal mergers in recent years, including mergers between Express Scripts and Medco in 2012 and OptumRx and Catamaran in 2015.\textsuperscript{31} Finally, throughout the past twenty years, both drug companies and pharmacy chains have periodically owned large PBMs. This includes the 1993 acquisition of Medco by Merck that lasted until 2003, which is relevant for my analysis of the anti-cholesterol market, as Merck owned one of the best-selling drugs, Zocor.\textsuperscript{32} Appendix C has a more detailed discussion of PBM mergers.

Finally, I estimate using financial filings that the fees paid to PBMs are 8-13\% of net payments to drug companies. One piece I need to evaluate PBM impact on overall spending is how much their customers pay in fees. To obtain an estimate, I make the assumption that most of the variable costs of PBMs are pass-through payments to drug companies.\textsuperscript{33} Then, I take the ratio of the revenue number to the variable cost number to estimate the fee percentage that PBMs earn relative to the volume of claims they process. I arrive at a fee ratio of 8-13\%, which is fairly stable across PBMs and years. This number does not represent pure profits to the PBM, as they also have to pay for overhead, but it does capture the additional drug-related payer spending. I estimate profits to be 4-5\% of net payments to drug companies.

1.3 Framing the PBM Debate – Some Simple Theory

As noted earlier, there is a debate over the impact of PBMs on drug markets, one that is also relevant for the drug pricing policies discussed in Section 1.1. Here, I provide some theory to frame the debate.

As a starting point, I focus on the decision of an insurer to contract with a PBM, which I assume not to be mandatory.\textsuperscript{34} In the model, there are four major players on the pricing side of prescription drug markets: drug companies, pharmacy benefit managers, drug companies, and patients.

\textsuperscript{30}Express Scripts was acquired by Cigna, an insurance company, for $67 billion in 2018. This is on par with the $74 billion purchase price of Celgene, a mid-sized biotech company, announced in the same year. The largest standalone drug company is Pfizer, which had a market cap of $196 billion in 2016.
\textsuperscript{31}Note that these mostly occur towards the end or after my period of analysis.
\textsuperscript{32}See Quartz article “Big pharmacies are dismantling the industry that keeps US drug costs even sort-of under control” for a detailed overview of major PBM industry events. https://qz.com/636823/big-pharmacies-are-dismantling-the-industry-that-keeps-us-drug-costs-even-sort-of-under-control/
\textsuperscript{33}See Appendix C.1 for details on my approach.
\textsuperscript{34}Most payers end up contracting with a PBM. According to the Pharmaceutical Care Management Association, an industry group, PBMs covered 266 million people in 2016, although the aggregate may double-count individuals.
payers, and patients. Payers hire PBMs to simultaneously design insurance and negotiate with drug companies, patients choose plans among payers, and drug companies offer discounts and rebates to PBMs.

The payer’s choice to hire a PBM will provide some signal as to the PBM’s impact on spending. First, under a scenario without PBMs, let the amount that the payer ends up paying to drug companies be $\Pi$ and the amount patients pay in copayments and insurance premium to the payer be $S$. The payer can choose to hire a PBM at a cost of $F$, which leads to overall payments of $\Pi'$ to the drug company, and patients will cover $S'$ of the spending.

To focus the analysis on spending, I make the following assumption:

**Assumption 1** *PBM activity does not affect product quality.*

This is just a simplifying assumption, as one could just normalize everything to quality-adjusted prices.

I then explore the implications of imposing rationality on payers:

**Assumption 2** *Payers are rational, i.e. $S' - \Pi' - F \geq S - \Pi$ if they contract with PBMs*

Under this assumption, we can provide an upperbound on PBM-generated savings for patients:

$$S - S' \leq \Pi - \Pi' - F$$

The intuition is that patient savings cannot be greater than the amount payers save by contracting with PBMs, as payers would lose money.

We can also make additional assumptions on the relationship between payers and patients to further pin down the total spending when payers do contract with PBMs:

**Assumption 3** *Payers are aligned with patient incentives ($S - S' \geq 0$)*

This assumption would hold, for example, if there is some competition in insurance markets and patients made rational insurance choices (i.e. they wouldn’t choose a more expensive plan).

Combining Assumptions 2 and 3 then helps pin down the relationship between total profits by drug companies and PBMs:

$$\Pi' + F \leq \Pi$$

This means that if we see payers choosing to contract with PBMs and all the assumptions hold, total profits to drug companies and PBMs must be less than total drug company profits without PBMs.

### 1.4 Relating the Theory to Conjectures on PBM Impact

Three main possibilities exist as to PBM impact on drug company profits and overall spending. I later test these using model and data.
1.4.1 PBMs Increase Spending and Drug Company Profits

The first possibility, as outlined in Garthwaite and Scott Morton (2017), is that PBMs drive up both overall spending and drug company profits. In terms of the model, this would equate to $\Pi - \Pi' \leq 0$, which implies that $S - S' \leq -F \leq 0$. This means that PBMs provide a service that significantly increases patient spending.

One way in which this story can hold is if payer incentives are not aligned with patient incentives. The hypothesis violates Assumption 3. Therefore, the story would rely on payers not caring about patient spending. This could be the case if patients are irrational in their plan choice, as has been documented in a series of papers starting with Abaluk and Gruber (2011). Another possible channel is if employers want to appear generous to employees, but again, this relies on employees wanting a higher spending plan that does not bring increased quality.

Another possibility is that payers are not acting rationally or are forced to contract with PBMs. The example described in Garthwaite and Scott Morton (2017) has PBMs asking drug companies to set higher list prices, negotiating a large discount that still results in a higher net price, and pocketing a fraction of the discounts. This story would rely on payers valuing the size of discounts rather than total spending, which is only possible if they sign unfavorable contracts. An extreme version of irrational payers would be that they are forced to contract with PBMs, creating double-marginalization in the market.

1.4.2 PBMs Reduce Drug Company Profits but Increase Spending

The second possibility is that PBMs reduce drug company profits but make more money than they save their customers, leading to higher overall spending. In terms of the model, this equates to $\Pi - \Pi' \geq 0$ but $S - S' < 0$. Again, this means that payers not be aligned with patient incentives (Assumption 3). However, patient loss is no longer bound above by $-F$, which means that losses to patients may be much smaller under this hypothesis.

1.4.3 PBMs Reduce Both Drug Company Profits and Spending

A final possibility is that PBMs lower both drug company profits and overall spending. This story is consistent with the set of assumptions listed above.

Even if this is the case, we would still want to know how efficient PBMs are. For example, a PBM could generate a 1% net savings while capturing very high profits. Under this scenario, it would be unlikely that PBM activity is improving welfare, given their potential dampening effect on innovation.

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35 Their analysis likely picks up on the markets perceiving a decrease in the chance government involvement, which can hurt both PBMs and drug company profits. This is not the same as evaluating the impact of PBMs versus a counterfactual that does not involve the government.

36 While having an obvious incentive to do so, PBM consultants argue that many private companies sign contracts that depend on discounts rather than price levels.
The factors that affect the size of savings include the competitiveness of the insurance industry and the trade-off between scale and competition in the PBM industry. If insurance were perfectly competitive or acted on behalf of patients, then all of the net savings generated by the PBM would be passed onto patients, making the savings greater. Another important factor is the PBM production function. PBMs need size to be effective at negotiating, but size also leads to greater market power and higher fees. In other words, there is a mechanical trade-off between $F$ and $\Pi - \Pi'$. If PBMs can be effective at negotiating even when small, then savings will be large.

2 The Anti-Cholesterol Market – Background and Data

In this section, I provide relevant background on the anti-cholesterol drug market, which is the focus of my empirical analysis. I then discuss the data I use to analyze the market, including the how I construct negotiated prices and how they differ from list prices.

2.1 Anti-Cholesterol Market – An Overview

I choose to focus on the anti-cholesterol market due to its importance, representativeness, and tractability for analysis.

The anti-cholesterol market is one of the biggest drug markets, and is similar in nature to several other large markets for chronic conditions. In terms of importance, anti-cholesterol drugs represented 10% of all prescription drug spending in 2004 and 2005, and therefore 1% of all health expenditures.\textsuperscript{37} This figure went down due to generic entry in 2006, but the market still represents about 7% of all drug claims and a recent CDC report estimates that 27.9% of US adults over the age of 40 are currently taking anti-cholesterol medication.\textsuperscript{38}

In terms of representativeness, the anti-cholesterol market shares the features of other several large chronic drug markets such as diabetes, high blood pressure, and asthma. First, demand exhibits inertia and high rates of switching to generics, which appears to be true in many chronic drug markets.\textsuperscript{39} Second, anti-cholesterol drugs are not doctor-administered, making them covered under drug benefits, and thus PBMs are involved in Medicare as well as the commercial insurance market. Finally, the drugs in the market are small molecules rather than biologics, and thus have negligible marginal costs and will eventually face generic competitors.

The tractability of my analysis is aided by the fact that there were only three dominant drugs in the anti-cholesterol market during my period of analysis (1996-2013): Zocor, Lipitor, and Crestor. All three were in the drug class known as statins, and had similar efficacy and side-effect profiles, making them viable substitutes.\textsuperscript{40} Each drug was owned by a different company (Merck, Pfizer, and AstraZeneca), further simplifying my

\textsuperscript{37}My estimates based on gross spending data from the Medical Expenditure Panel Survey (MEPS).
\textsuperscript{38}National Center for Health Statistics Data Brief No. 177, December 2014.
\textsuperscript{39}Based on analysis in Feng (2018).
\textsuperscript{40}Lipitor was considered to be safer at high dosages, but a large majority of patients take medium dosages.
The major entry events in the period are as follows: Zocor is present at the start of the period and goes generic in 2006; Lipitor enters in 1997 and goes generic in late 2011; Crestor enters in 2003 and eventually goes generic in 2015.

A simplification I make in this paper is to focus on the most popular dosages for each drug. In this market, each of the three main drugs and other statins not considered here are available in different dosages, depending on the intensity of treatment. Complicating matters is the fact that Zocor and Lipitor have different list prices associated with each dosage. I focus here on the most popular dosage levels for each drug, which all end up being medium-intensity dosages that patients tend to start on and substitute between. This helps focus my analysis on the biggest sub-market, and ignore issues surrounding dosage, as well as other drugs that are mostly used for high or low intensity treatment, such as Mevacor, Pravachol, Zetia, and Vytorin. The downside is that these drug by dosage pairs may not be exactly comparable, an issue I revisit when interpreting my results.

2.2 Demand Data – Truven MarketScan and MEPS

To start, I discuss the data I collect on demand in the anti-cholesterol market. This will be used in demand estimation, as well as for calculating negotiated prices.

To measure demand and market size, I use prescription claims and medical conditions data from Truven MarketScan and Medical Expenditure Panel Survey (MEPS). The Truven MarketScan data contains individual-level panel data on prescription drug claims. Its key advantage over MEPS is that it contains plan identifiers, which allows me to infer the formularies facing each patient and in turn copay sensitivity. I also estimate switching costs using MarketScan, leveraging the approach in Feng (2018). On the other hand, MarketScan data is not intended to be representative, unlike MEPS. Therefore, I use market size and market share data from MEPS to calibrate the demand model.

The data from MEPS reveal a growing market size and market shares that are responsive to generic entry events. Figure 1 summarizes market demand based on MEPS data. I compute market size in number of individuals, counting those on medium-intensity dosage levels plus those diagnosed with high cholesterol but not taking medication. The market size grows steadily over time, but the growth rate slows down starting around 2003. The share of users on each drug generally remains pretty steady, outside of the initial entry of Lipitor and Crestor, and the impact of Zocor generics on Lipitor market share. Branded market shares drop very quickly after generics enter:

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41 Crestor has uniform list prices, although it is possible that negotiated prices vary by dosage. I also account for dosage issues in my negotiated price estimates, detailed in Appendix B.

42 In Table 4 of the Appendix, I lay out in detail the mapping from drug and dosage to intensity of treatment, based on the medical literature.

43 See Appendix A for an overview.

44 This assumption is based on my analysis of the dosage levels that new patients start on, which is predominantly in the medium-intensity class from 1998 onwards.

Zocor drops from 20% to 4% a year either side of generic entry and Lipitor drops from 12% to a little over 1% from 2011 to 2013.

2.3 Negotiated Prices – Methodology and Differences vs. List Prices

A crucial part of my analysis is having data on market-level negotiated prices in the United States, which I obtain through SSR Health and additional work with company financial filings, earnings call transcripts, and IMS Health Top-Line data. My analysis shows that negotiated prices exhibit very different dynamics to list prices.

My basic approach to deriving prices proceeds in three steps. First, I obtain drug company net revenue by drug from SSR Health from 2007 onwards. Second, I replicate their analysis and extend the series backwards by collecting net revenue data from financial filings, available through SEC EDGAR, and earnings call transcripts, available through NASDAQ and Factiva. Finally, I take the revenue data and divide by sales data from MEPS in order to arrive at average negotiated price (or net price).

Given that I focus on the medium-intensity market, I make some minor adjustments to deal with different prices across dosages within a given drug. The data I use for my core estimates are based on assuming constant discounts across dosages and that market-level net prices are reflective of private market prices.

I also derive two additional price series, which I use in later robustness checks. The first assumes constant percentage discounts across dosages within a drug, and results in very small differences. The second attempts to purge the calculations of revenue and quantities from the uninsured, Medicaid, and Veteran’s Administration (VA) segments of the market, which do not involve PBMs, which again exhibits fairly small deviations as the unaccounted for segments roughly balance each other out.

Turning to the results, negotiated prices exhibit very different dynamics to those of list prices. The inflation-adjusted gross and negotiated price data for the three major statins is summarized in Figure 2. The list price graph, as is usual in most drug markets, shows a steady growth over time for all three drugs. However, the negotiated price graph suggests that the prices paid to drug companies exhibit quite different dynamics, which validates the need to collect them to analyze PBMs.

The most striking features of negotiated prices are the gap between Lipitor and Zocor and the price fluctuations around the entry of generic Zocor, which appears to be a broader phenomenon. First, Zocor appears to have a significantly higher list and negotiated price relative to Lipitor and Crestor, despite being less popular than Lipitor. Merck does begin to offer increasingly large discounts starting in 2002, but Zocor remains significantly more expensive. My subsequent analysis suggests that this is due to a combination of the incentives created by consumer inertia, PBM vertical integration, and potential issues in the comparability of dosage. Second, unlike the monotonically-increasing list prices, negotiated prices fluctuate around 2006, coinciding with the entry of generic Zocor. Traditional models had justified list price increases after competitor

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46 See Appendix B for a detailed description.
47 Prices are adjusted to price levels in 2000.
drugs go generic as evidence of price discrimination, where firms target the most price insensitive users. In the data I collect, net prices for Lipitor and Crestor increase in anticipation, drop right after, and recover over time.

The list and net price patterns for Lipitor and Crestor appear to be consistent with average patterns in a broader sample of drugs. One obvious concern with the pricing patterns is that they could be influenced by policy changes such as Medicare Part D, which began in 2006, roughly coinciding with the entry of generic Zocor. To verify that these patterns hold elsewhere, I obtain average net prices for drugs in other large markets from SSR. Figure 7 in the Appendix documents average unit prices (list and net) for drugs relative to when the first drug in the class goes generic. While the pre-trend is flatter, there is once again a drop in price post-generic entry followed by a recovery. More generally, net prices are significantly below list prices.

Before turning to the formal analysis, I use the raw net and gross revenue to provide a sense of the impact of PBMs. The gross revenue earned by branded drugs over the whole period is $158 billion, while the net-of-rebate revenue is $123 billion. If the list price is an approximation of outcomes without PBMs, this equates to a 22% reduction in drug company revenue.48 As a note of caution, the list price reflects demand from uninsured patients, while insured patients face only a share of the price, so they may not provide a good counterfactual. This motivates my development of a competitive model.

2.4 Formulary Coverage of Anti-Cholesterol Drugs

Given my focus on the role of PBM formulary design, I briefly note the evidence on formulary coverage of anti-cholesterol drugs in my period of analysis. Systematic data on formularies is difficult to come by, although there is better data available for commercial insurance plans post-2010. I will later use the available formulary patterns as a test of model fit.

There are three main patterns based on industry commentary and available data. First, there is essentially no formulary exclusion in the late 1990s and early 2000s, consistent with MarketScan formulary data and industry commentary, although Crestor does face some exclusion when it first enters.49 Note that this does not mean that there was no exclusion threat. Second, Zocor has a higher probability of ending up in the high copay tier in the 1996-2006 period. A 2001 report by the California HealthCare Foundation showed that all the major PBMs put Lipitor in the preferred tier, whereas Zocor was only in the preferred tier of the formularies of Medco and AdvancePCS.50 Finally, I analyze Medicare Part D formulary data, which becomes available starting in 2007, and find significant exclusion rates for Lipitor and Crestor.51

48 The formal analysis I later conduct arrives at a similar percentage impact of PBMs on drug company revenue.
51 See Figure 8 in the Appendix.
3 Empirical Pricing Model – Demand, Drug Companies, and PBMs

I turn to the task of uncovering the role played by PBMs in generating the price data described in Section 2.3. I start by constructing an empirical pricing model that captures the interplay between drug companies, PBMs, and consumers.

The goal of the model is twofold. First, I want to pin down parameters governing PBM formulary selection, using data on demand and pricing and institutional knowledge of the pricing structure. The estimates and counterfactuals will then provide insights into the effectiveness of PBMs and various policy proposals. Second, I want to verify that a dynamic oligopoly model can fit observed price dynamics. If a competitive framework does work well, then it increases the confidence that a competitive model can accurately capture countercfactual markets.

3.1 Model Overview – Bidding and Dynamics

My pricing model takes the form of a finite-period dynamic game, which ends for each drug company once its drug goes generic. The game involves drug companies and a representative PBM. Dynamics are required due to the nature of demand, and I later argue that dynamic incentives are important in explaining observed price dynamics. I assume perfect foresight and perfect information on demand and behavior of the other firms, which helps ease computation burden, but may miss out on the impacts of unexpected changes in the environment during the period.

The period game structure is a simplified version of the structure used by Express Scripts, one of the three large PBMs in the market. Based on conversations with former Express Scripts executives, their approach is to set up annual auctions for formulary positions in each drug market. In the auction, Express Scripts lays out a set of formulary arrangements, with each arrangement placing each drug in the low copay tier, high copay tier, or excluded tier. Companies submit a price bid for each arrangement, and Express Scripts then picks the arrangement that maximizes its profits.

My model is a simplified version of the structure. I summarize the period game structure in Figure 3. In each year, drug companies each send a single bid to the PBM. The PBM then picks a formulary arrangement, which is just a copay tier or exclusion for each drug. Patients then make drug choices based on the formulary they face. This simplification from arrangement-specific bids to a single bid potentially misses out on more complex equilibrium play by drug companies, but captures the essence of the trade-offs they face. If they bid too high, the PBM will pick an arrangement that excludes them. If they bid too low, they would unnecessarily sacrifice price without obtaining too much more quantity. In equilibrium, neither drug companies nor the PBM want to deviate from their choices.

In conversations with other executives, other PBMs sometimes choose to sign longer-term contracts with drug manufacturers in mature markets, and may bargain over a portfolio of drugs. I discuss this further in Section 3.5.
Under this structure, the PBM is essentially creating a different demand curve, using credible formulary threats governed by the parameters of the model.

3.2 Demand Model – Incorporating History-Dependence, Copays

My demand system incorporates the two forces that drug companies and PBMs can control: previous market share (inertia) and copays. The structure is motivated by findings in Feng (2018) that show large effects of previous choices on current choices.53

My demand model takes the general form

\[ D_t(D_{t-1}, f) \]

where \( D_t \) represents the current market shares, \( D_{t-1} \) represents previous market shares, and \( f \) is the current formulary. Any demand function that takes this form will work for my model.

In practice, I will use a switching cost model of demand.54 More formally, consumers have utility functions

\[ u_{ijkt} = \delta_{jkt} - \alpha p_{j(t)} + \gamma I_{j=m_i, t-1} + \nu I_{m_i, t-1} \neq 0 + \epsilon_{ijkt} \] (1)

where \( i \) indexes the patient, \( j \) the molecule (0 is the outside option), \( k \) the form of the option (brand/generic), and \( t \) the year. \( \delta \) reflects current period drug quality, which absorbs variation in advertising and changes in medical evidence, \( \alpha \) is a copay sensitivity parameter, \( \gamma \) is a switching cost between drugs, \( \nu \) is a switching cost from any drug to the outside option, and \( \epsilon \) represents an idiosyncratic “logit” error. I will have data on the copay \( p \) and indicators for whether consumer \( i \) picked choice \( j \) in the previous period \((I_{j=m_i, t-1})\) and whether consumer \( i \) chose any drug \((I_{m_i, t-1} \neq 0)\).

The main limitation from incorporating dynamic demand in my pricing model is that I cannot include patient heterogeneity. Adding observed heterogeneity would dramatically increase the state space, because the identity of previous users then matters for the current period. Adding persistent unobserved heterogeneity would greatly increase computational burden, as I need to evaluate the demand function many times during estimation.55 I would also need to assume that firms do not try to infer the taste shocks of individual patients.

3.3 Drug Company Pricing – Bidding for Formulary Position

Drug companies maximize dynamic profits by submitting price bids to the PBM in each period to compete for formulary positions. In selecting a bid, drug companies take into account competitor, PBM, and patient behavior. Realized negotiated prices then represent an equilibrium outcome of the game.

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53See Appendix A for a detailed description of methodology and results from that paper.
54This is the approach taken in much of the structural literature on inertia, including Dubé, Hitsch and Rossi (2009) and Handel (2013).
55I later perform some welfare calculations that incorporate unobserved heterogeneity.
The core components of the dynamic game are the state variable, previous market share, and the control, which is the price bid submitted by drug companies to PBMs. Having previous market share as the state variable allows me to capture the history-dependent nature of demand. Drug companies trade off prices and market share today, as lower prices will lead to lower profits today but better market position tomorrow.

More formally, drug company \( j \) chooses price bid \( P_{jt} \) in period \( t \) to maximize dynamic profits represented by the following value function:

\[
V_{jt}(x_t; N_t) = \max_{P_{jt}} P_{jt} N_t \sum_{k=0}^{n} x_{kt} Pr(m_t = j | m_{t-1} = k, f(P)) \\
+ \beta^{dc} V_{jt+1}(x_{t+1}(P), N_{t+1})
\]

\( P_t \) is a vector of price bids and \( x_t \) is a vector representing the state variable, as drug companies make simultaneous bids each period and affect each other’s states. I assume that each drug company owns one drug. \( N_t \) represents the market size in period \( t \), which I assume to be exogenous to the game.

The key functions here are the mapping from price offers to formularies and the mapping from a formulary to choice probabilities. \( f(P) \) represents the mapping from the vector of price offers to a formulary, which is based on PBM considerations. I discuss this in detail in the following section. \( Pr(m_t = j | m_{t-1} = k, f(P)) \) represents the realized market share for company \( j \) in this period for the set of patients with previous choice \( k \) facing a formulary \( f \). I assume the outside option is represented by \( k = 0 \), and there are \( n \) drugs each owned by a different drug company. \( \beta^{dc} \) is the drug company discount rate.

The state variable for each drug updates according to the equation:

\[
x_{j,t+1} = [1 - \mu_{t+1}(1 - \kappa)] Pr(m_t = j), \forall j > 0
\]

so the state variable just reflects previous period market shares diluted by new patients in the subsequent period \( \mu_{t+1} \). Since I cannot pin down the role of doctors in carrying over previous market outcomes to new patients, I flexibly allow for a carryover term \( \kappa \), where \( \kappa = 0 \) means there is no carryover, and \( \kappa = 1 \) means new patients behave as if they are probabilistically assigned a previous choice based on previous period market shares.\(^{56}\)

The value function contains no expectations, as I assume perfect foresight. This is a reasonable starting point, as Lipitor is in late-stage development at the start of the period, and Crestor is in clinical trials as of 1998. Furthermore, there are no large changes in medical evidence for these three drugs.

The main benefit of this assumption is that eases the computation burden, as having shocks to the system would mean computing later periods several times, once for each

\(^{56}\text{Feng (2018) finds evidence against doctor-driven dynamics.}\)
realization of shocks. My model will miss out on effects generated by unpredictable changes in medical evidence, market size growth, and macroeconomic conditions such as the great recession.

3.3.1 Generics – A Passive But Important Player

One key factor in the anti-cholesterol market during this period is generic entry. I model generics as replacing their branded versions in the dynamic game, and then influencing prices in a passive but important way.

The key assumption to make the model work in a non-stationary environment is that drug companies play a finite period game that ends when generics enter. Generics typically enter when a branded drug’s patents expire, although some drugs are also granted FDA marketing exclusivity that could run longer. Here, I assume companies become inactive players once the patent on their drug expires at $T_j$, and that the terminal payoff $V_{j,T_j}$ is a constant that I normalize to zero. This assumption is based on the evidence in Figure 1 that demand for the brand essentially drops to zero within a few quarters of patent expiration.\(^{57}\)

Another assumption I make is that existing market shares transfer from branded drugs to generics, which creates anticipatory effects. As documented in Feng (2018), over 80% of patients on a branded drug switch over to the generic once it becomes available. I make the assumption that the generic inherits the branded drug’s state in its first period, and replaces the branded drug in the game. This reflects the history-dependence in generic choice found in Feng (2018), and the mechanics will influence play in earlier periods, as competitors of the expiring drug will want to avoid giving the generic a large base. On the other hand, PBMs may try to move patients to the expiring branded drug to save costs in the future, as anecdotal evidence suggests Express Scripts did in anticipation of the entry of generic Zocor.\(^{58}\)

Once generics enter, I assume they play a passive role in the pricing game, but they will end up having a significant impact on the remaining branded drugs. Typically, PBMs automatically place generics in a separate generic copay tier, which has a lower associated copay than the preferred tier copay. Therefore, I assume generics do not play an active role in the pricing game, and are assigned a price equal to the average pharmacy price in the data, which is significantly lower than prices for branded drugs. However, generics still affect PBM formulary decisions, as they present a cheap and efficient option that would be available even if all branded drugs were excluded. This stronger threat then affects the bidding behavior of the remaining patent-protected drugs.

\(^{57}\)The Hatch-Waxman act does create an 180-day duopoly between the first generic entrant and its branded equivalent, which I do not explicitly model.

\(^{58}\)In the demand data, I also find a small uptick in new user Zocor demand in 2006 before generic entry.
3.4 PBM Behavior – Choosing a Formulary Arrangement

The final actor in the model is the representative PBM. I parametrize PBM formulary selection behavior as weights on factors that affect their demand. These factors were highlighted in conversations with executives, which I discuss further in Appendix C.2.

Given data limitations, my model simplifies the pricing structure to include a representative but competitive PBM. As alluded to earlier, the PBM industry is opaque, as contracts between drug companies and PBMs, as well as PBMs and its customers, are not publicly available. Currently, I am only able to collect data on market-level outcomes for each drug. Therefore, I include a representative PBM in my model, which one can think of as a black box representing the PBM industry. The PBM takes one price offer from each drug company, and chooses a probabilistic distribution of formularies.

The PBM primarily looks to provide an attractive service, which roughly equates to providing cost savings while still providing a generous enough drug benefit. In order to obtain large discounts, PBMs need to be willing to restrict access to expensive drugs. However, their willingness to move drugs to higher copay tiers hinges on demand being responsive, while their willingness to exclude drugs depends on potential customer dissatisfaction. Their customers are typically large employers and insurance companies, who are acting on behalf of employees or members who may strongly dislike plans that exclude a drug they have been taking.

In addition, PBMs may have additional profit considerations when selecting formularies. First, PBMs make some margin on selling generic medication through its mail order programs. Second, PBMs may push consumers towards drugs owned by their parent company. One caveat here is that in a more competitive environment, PBMs would not be able to favor drugs owned by their parent company. However, given the lawsuits surrounding the Merck-Medco relationship, it is likely that these incentives are not competed away.

I now formalize PBM behavior as a weighted sum of these factors. Given price vector \( \mathbf{P} \) bid by drug companies, PBMs maximize profits by choosing a probabilistic distribution over formulary arrangements \( f_t \in \mathcal{F}_t \), where \( \mathcal{F}_t = \{ \mathbf{p}_t, \mathbf{p}_t^\infty \} \). \( n_t \) is the number of branded drug competitors active in period \( t \), with generic drugs automatically assigned to a lower copay tier \( p_g \).

PBMs choose the optimal formulary distribution in every period based on the following profit function:

\[
K_t(x_t; N_t) = \max_{f_t} N_t \left[ W(f_t | x_t) - \theta \sum_j P_{jt} s_{jt}(f_t | x_t) - \chi \sum_j I(p_j = \infty) x_{jt} + M(s_t(f_t | x_t)) + \sigma \omega f_t \right] + \beta^{PBM} K_{t+1}(x_{t+1}(f); N_{t+1})
\]

The first three terms represent demand for PBM services. As discussed informally above, PBMs want to pick a formulary that will attract the most customers. The first
factor is the consumer surplus generated by the formulary, \( W(f|x_t) \), which is derived from the demand system. Higher copays and exclusions will lead to lower surplus for all patients. The second term represents expected spending on anti-cholesterol drugs, with \( s_{jt}(f|x_t) \) representing the realized market share for drug \( j \) in period \( t \) as a function of the formulary chosen and the current state variable. Together, these two terms form a cost-effectiveness measure of the services offered by PBMs, with \( \theta \) serving as the weight.

The third term contains an indicator for exclusion, \( I(p_j = \infty) \), and the parameter \( \chi \) looks to capture any additional aversion to formularies with exclusions on the part of PBM customers.

The fourth term, \( M(s_t(f)) \), represents a catch-all for other motivations that drive PBM profits. As mentioned in Section 1.2, several large PBMs were owned by drug companies, including the Merck-Medco relationship relevant for my current study. This may create an incentive for Medco to favor formularies that generate higher Zocor market share. The other highly-discussed aspect of PBMs is their profit margin on running mail-order services for generic drugs. Therefore, they may also favor formularies that lead to more generic market share. I add in flexible terms for these factors in the following way:

\[
M(s_t(f)) = b_1 s_{1t}(f) I(t < 2004) + b_g \sum_{j \in G_t} s_{jt}(f)
\]

where \( b_1 \) represents a boost for Zocor (indexed to be \( j = 1 \)) in the years during which it owned Medco, and \( b_g \) represents any margins PBMs make on selling generic drugs. \( b_g \) may also capture any mis-measurement in the price of generic drugs. \( G_t \) is the set of drugs that have gone generic by period \( t \).

The fifth term, the error term \( \omega_{ft} \), captures idiosyncratic noise in the profit function of PBMs. The error term is not known to drug companies when making bids, and helps ensure the existence of an equilibrium. Without the smoothness introduced by the error, the discrete copay tier structure can generate best response functions that never intersect, as one drug company may want to undercut another by a small amount to gain a large bump in demand. Effectively, the resulting realization will be a probabilistic distribution across potential formularies, although only small values of \( \sigma_\omega \) can generate the pricing patterns observed in the data.\(^{61}\)

The final term captures the dynamic incentives for PBMs, who prefer certain states to others. In the model, PBMs are limited in their ability to move volume by history-dependent demand, as highlighted by the presence of \( x_t \) in the first four terms of their objective function. Therefore, some states may be more favorable for them. For example, if many patients are already a given generic drug coming into the period, then PBMs will have an easy time generating high generic demand and pressing for higher discounts from remaining branded competitors. I flexibly allow for PBMs to have some dynamic motives through the parameter \( \beta^{PBM} \).

\(^{61}\)With large \( \sigma_\omega \), drug companies can rely on the error term to guarantee some volume, which leads them to bid very high prices that are not reflected in the data.
3.5 Discussion of Generalizability and Simplifying Assumptions

The goal of the model is to help us better understand the impact of PBMs on drug prices and drug spending. Here, I discuss the generalizability of my model and the simplifying assumptions that I am making. By making my assumptions clear, I hope to also shed light on potential limitations and elucidate areas for future research.

3.5.1 Generalizability – Coinsurance and the Nature of Demand

My model can adapted to evaluate drug markets with slightly different institutional features, including different forms of cost sharing and demand features. First, my model can be adapted to studying drug markets where cost sharing takes the form of coinsurance, which is often the case for expensive biologic drugs. Although plans rarely have multiple coinsurance tiers, the PBM still possesses the ability to exclude a drug, as Express Scripts famously did in the case of Hepatitis C drug Sovaldi. Therefore, instead of picking copay tiers, the PBM’s decision is just a binary exclusion decision.

Second, my model can also be used for studying other important drug markets that have different demand structures. The simplest demand structure is one with no dynamic linkage, which my model nests. Other demand structures will also work as long as it exhibits a Markovian structure. For example, Hepatitis C markets have the opposite dynamic linkage to the ones in chronic drug markets. The more users previously treated, the less future demand there will be. The structure of my model will be able to handle this. One weakness of my model is the inability to handle heterogeneity in parameters such as price sensitivity while still including dynamics. Once heterogeneity is introduced, the state space would then need to keep track of additional parameters capturing the type of patient currently on a given drug.

3.5.2 Modeling Price Negotiation – Assumptions and Limitations

Here, I detail the advantages and limitations of the simplifications I make to the negotiation structure in my model.

One key simplification I make due to data limitations is that drug companies bid the same price across all PBMs, which helps capture key forces but goes against traditional bargaining models. The prevailing negotiation framework in the health care literature is a Nash-in-Nash framework, which is used in Ho and Lee (2017) and extended in Ho and Lee (2019) to incorporate exclusions in hospital-insurer bargaining. The most detailed data available is average negotiated prices. Therefore, to match the data, my model aims to capture average patterns, which I do so by restricting firms to making the same bid to all PBMs Despite this simplification, my model is still able to capture the presence of formulary exclusions in equilibrium. Drug companies know that some PBMs, as captured by the idiosyncratic term $\omega_{ft}$, may favor more inclusive formularies.

62In addition to not having PBM-drug specific prices, I also do not have good data on demand for PBM services. Anecdotally, insurers and private employers do switch PBM services from time to time. This includes a recent case involving Anthem discontinuing their use of Express Scripts. Harvard University also switched from OptumRx to Express Scripts in 2017.
Therefore, drug companies may be willing to trade off some exclusion for better prices from the PBMs that do include them.

The absence of the Nash-in-Nash framework precludes the ability to study PBM mergers and to deal with potential negotiation over a portfolio of drugs. First, the simplified model is unable to accurately assess the impact of PBM mergers. Typically, merger analyses compute firm-specific bargaining parameters, and assume that a merged entity takes on the stronger parameter of the two merging firms. In my case, I can only guess that PBM mergers would shift PBM behavior towards focusing more on cost. Second, the model does not deal with the possibility that companies with a large portfolio of drugs may have a more favorable negotiation position. This is raised as a potential concern in recent anti-trust cases, and there is anecdotal evidence that PBMs negotiate with drug companies across multiple markets. However, in the anti-cholesterol market, there do not appear to be any large changes in prices as a result of the introduction of new drugs in other markets by Merck, Pfizer, or AstraZeneca.

Finally, the model does not allow for long-term contracts, which were sometimes used by PBMs during the analysis period. Industry decisionmakers suggest that some PBMs do sign multi-year contracts with drug companies in mature drug markets. Having long-term contracting would allow for richer bargaining dynamics, as parties can agree to a price path rather than just a price for the current period. Depending on their ability to commit, PBMs could control prices without as strong an exclusion threat, as they could use the threat of a persistently high copay tier. For tractability reasons and based on institutional details, I abstract away from this possibility. Multi-year contracting greatly complicates the nature of the game, as drug companies and PBMs would have a much richer action space. In addition, in recent years, the largest PBMs have likely employed annual contracting, as they announce formularies annually, with many changes from year-to-year within each drug market.

3.5.3 Other Simplifications – List Prices and Volume Discounts

My model simplifies away from two commonly discussed aspects of drug markets: list prices and volume discounts. Here, I argue for why these simplifications do not greatly affect my analysis, but also note work to be done in these areas. I discuss additional institutional details I abstract away in Appendix D.1.

First, my model does not use or address list prices. One common critique of PBMs is that their profits depend on list price, which then pushes drug companies to set higher list prices to create greater joint surplus. This can be the case if PBM customers sign

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63PBMs would also likely be able to charge a higher fee.
64See 2002 Wall Street Journal Article “Pharmacy-Benefit Managers At Times Toil for Drug Firms.”
65One major concern would be that the drop in Zocor prices from 2003 to 2006 is influenced by Merck drugs in other markets, but the major drug launches by Merck in the 1996-2013 period were Remicade in late 1999, Januvia in late 2006, and Isentress in late 2007. Pfizer introduced Lyrica in late 2004.
66Industry analysts closely follow annual formulary announcements from Express Scripts, CVS, and OptumRx.
67The list price can be important for uninsured patients, who tend to pay the list price minus any support from patient advocacy groups. These individuals make up about 25% of the anti-cholesterol
contracts that pay fees to the PBM based on the difference between negotiated price and list price for each drug.\textsuperscript{68} Here, I choose to just model the negotiated price, which helps me avoid the complexity of having two pricing decisions for each drug in every period while still capturing the key forces. The downside of not modeling list price is that it misses out on the distributional impact of PBMs, which may reduce average prices, but raise prices on uninsured patients.\textsuperscript{69}

In addition, I also abstract away from a distinction made in the industry between per-unit discounts and rebates (volume-based discounts), which is less of a problem in my setting. Per-unit discount is the difference between list price and the per unit payment made to the drug company. Rebates, on the other hand, are payments that reflect quantity discounts. My negotiated price data reflects both discounts and rebates. Rebates can create both different incentives and allow for richer bidding equilibria, but these are unlikely to be important in my setting. First, the main action of the PBM is to set a formulary, so the standard effort-inducing effect of volume discounts is unlikely to be important.\textsuperscript{70} Second, allowing firms to offer both a discount and a rebate can lead to richer equilibria. This structure would move towards allowing arrangement-specific bids, as is the actual Express Scripts structure, but the additional complexity may not be necessary for understanding average price outcomes.

4 Estimates and Model Fit

In this section, I present estimates from my model and discuss features of the model that help fit the data. I first estimate the demand system offline, recovering switching cost coefficients and revealed-preference drug qualities. Then, I plug the demand system into the dynamic game, recovering parameters of the game by matching model predictions to negotiated price data.

4.1 Demand Parameters – Switching Costs and Copay Sensitivity

Since demand is not the focus of this paper, I make use of parameter estimates from a version of the demand model in Feng (2018).\textsuperscript{71} The three key parameters from Equation (1) are \((\alpha, \gamma, \nu)\). The estimates in Feng (2018), based on MarketScan data, are \((0.668, 1.46, 1.385)\). The switching cost parameters are identified using cohort-based variation in choices, and the copay sensitivity is estimated using plan-level variation in copays.\textsuperscript{72} The parameters imply switching rates of around 15% from year-to-year, market, based on self-reported insurance information in MEPS.

\textsuperscript{68} Consultants working for PBM customers argue that some employers do make the mistake of making payments to PBMs based on savings off list price.

\textsuperscript{69} As I note later in my discussion of welfare, list price growth can naturally arise from demand inertia, and may not reflect negative spillovers from PBM activity.

\textsuperscript{70} PBMs do spend some effort persuading doctors to prescribe drugs in the preferred tier of their patient’s insurance.

\textsuperscript{71} See Appendix A for a short summary.

\textsuperscript{72} The assumption for these employer-based plans is that copay differences are exogenous to the specific needs of an individual. An additional concern is that price sensitivity estimated using Marketscan is not
consistent with both MarketScan and MEPS data, and generates copay elasticities in 
line with estimates found by Einav, Finkelstein and Polyakova (2016) for anti-cholesterol 
drugs. I run robustness checks to see how sensitive my counterfactual estimates are to 
these parameters.

As a second step, I use the nationally representative MEPS data to calibrate drug 
quality. Taking the parameters as given, I match the predictions of the demand model 
to observed market shares, in order to estimate period-specific drug quality. Figure 9 
in the Appendix provides the estimates of $\delta_{jkt}$ from Equation (1). In terms of relative 
quality, Lipitor has a significantly higher quality at the start of the period relative to 
Zocor, which lasts until generic Zocor enters. Crestor has lower implied quality than the 
other two. In terms of trends over time, Zocor stays relatively flat, while Lipitor and 
Crestor drop in quality after the generic entry of Zocor in 2006. This is due to the fact 
that generic Zocor steals market share rather than expanding the fraction of patients 
choosing a drug. Other fluctuations in implied quality may be driven by advertising 
campaigns, macroeconomic conditions, and changes in medical evidence.73

4.2 Model Computation and Estimation

Before turning to the estimation results, I describe my approach to computation and 
estimation. The inner loop of the computation plays out the pricing game under a given 
parameter guess, and the outer loop finds parameters that best fit the price data, under 
a maximum likelihood framework.

For the inner loop, I use an iterative approach to compute equilibrium price bids 
given some parameter vector. I start by computing value functions by iterating back 
from the final period. I use 2015 as my final period, the year before Crestor goes generic, 
which allows me to recover the final period value function by solving a static problem. 
I then iterate backwards, by having drug companies play simultaneous pricing games 
on each point in state space in a given year. In each state, they reach an equilibrium 
where no one can gain in dynamic profits by deviating from their price bid.74 The 
dynamic profits in equilibrium serve as the value for that state. Once I have the value 
functions, I play the game out from the known starting condition in 1996, recovering a 
set of equilibrium price paths.75

Given the inner loop, I then estimate the model by minimizing squared prediction 
error in an outer loop. For the outer loop, I search over parameters to minimize the 
squared error between predicted and observed prices

$$\min_{\theta, \chi, \beta^{PBM}, b_1, b_2, \kappa} \sum_t \sum_{j \in G_t} (\hat{P}_{jt}(\theta, \chi, \beta^{PBM}, b_1, b_2, \kappa) - P_{jt})^2$$

reflective of price sensitivity in other segments covered by PBMs such as Medicare.73

As shown in Figure 1, the fraction of patients choosing the outside option (one minus the “All Drugs” 
number) increases during the Great Recession.74 Continuation values are evaluated using a scattered interpolant, which speeds up the computation.75

Zocor has about 20% market share in 1996 before Lipitor enters in 1997.
where $\hat{P}_{jt}$ is the model’s predicted equilibrium price. This is valid under the assumption of uncorrelated measurement errors in the prices.

The additional pieces needed for model computation are the growth in market size, the fraction of new patients in every period, copay tier amounts, and generic prices. To estimate these quantities ($N_t$ and $\mu_t$), I use MEPS data. The market size is based on the number of people taking anti-cholesterol medication or diagnosed with high cholesterol. The $\mu_t$ is based on assuming a 5% patient attrition from year-to-year, possibly from improving medical condition, and assuming that the difference $N_t - 0.95N_{t-1}$ represents the count of new patients, so $\mu_t = \frac{N_t - 0.95N_{t-1}}{N_t}$. Next, I use the available MarketScan formulary data to construct $p_t$, $\bar{p}_t$ in every period. I do this by taking the copay tier dollar values for each plan, and then taking the median value for the preferred and non-preferred tiers, weighting by the number of users on each plan. The use of MarketScan is necessary, as MEPS does not provide plan identifiers, and therefore I am unable to construct copay tiers. Finally, I also use median generic prices and copays from MarketScan to set $P_g = 1$ and $p_g = 0.33$.

4.3 Parameter Estimates – Identification and Discussion

Each parameter is roughly derived from a moment in the price data. Although the model is non-linear, the PBM equation is simple enough to generate a rough mapping from data to parameters. $\theta$, the weight on expected cost, is identified by the average price levels in the data. The less the PBM’s customer cares about costs relative to consumer surplus (or access), the more likely drug companies will set higher prices, as they know PBMs will still put them in a favorable position. $\chi$ captures the exclusion penalty, which reflects whether higher previous market share leads to higher prices in the current period, as the threshold for exclusion is pushed up. $\beta^{PBM}$ is identified based on actions around generic entry, as discussed earlier in the case of their generic Zocor strategy. $b_1$ is identified off any abnormal gap between Lipitor and Zocor prices in the pre-2003 period. Similarly, $b_g$ is identified off lower brand drug price levels after generic entry, as they would face PBMs looking to switch people to generics. Finally, $\kappa$ is derived from differences in pricing versus future new patient fraction $\mu_{t+1}$. If there is no relationship, it would suggest significant carryover of previous market shares through any doctor channels.

The best fit parameter values, shown in Table 1, suggest PBMs prioritize cost-effectiveness but also consider other factors. The importance of cost reduction relative to consumer surplus is estimated to be $\theta = 0.973$. It is statistically indistinguishable from 1, suggesting something close to a cost-effectiveness criteria. Another key parameter $\chi$ is large and significant, suggesting that PBMs are less likely to exclude popular drugs. The other parameter with statistical significance is $b_1$, which suggests that Medco may have had incentives to increase the market share of Zocor based on ownership. However, as I noted earlier, part of this difference may be attributable to Zocor 20MG and Lipitor 10MG not being perfectly comparable.

\footnote{Attrition is required to avoid negative numbers of new patients in a given year.}
The statistically insignificant parameter estimates suggest weaker effects from PBM dynamic incentives and not much carryover of history-dependence through doctors. The estimates show a small and insignificant value for $\beta^{PBM}$. The lack of a dynamic effect may come from the fact that PBMs may only care about dynamics around generic entry, and do not factor in future savings on branded drugs. It is also possible that many of their contracts are short-term, which leads to weak incentives to manipulate market shares for their current customers. The carryover parameter, $\kappa$, is also small and insignificant, suggesting that drug companies dampen dynamic strategies if they anticipate an influx of new patients.

4.4 Model Fit – The Importance of Dynamics, Copay Structure, and Exclusion

In terms of fit, the model captures the key patterns in the data, including the relative prices between the drugs and the trends in prices around generic entry.\footnote{I discuss minor discrepancies in Appendix D.2.} Figure 4 presents a comparison of the price dynamics predicted by the model under the best-fit parameters versus the price data presented earlier. The predictions accurately capture the absolute and relative price levels of the three main drugs, in particular the higher price of Zocor relative to Lipitor in earlier years. In addition, it captures the trends in drug prices before and after generic entry. Prices tend to increase for all drugs before generic entry, except for Lipitor in 2006, reflecting a desire to “harvest” existing market share before competition intensifies.

The combination of inertia and discrete copay structure in the model helps to explain the higher price of Zocor in the earlier period. As noted before, a key aspect of the negotiated price data is that Zocor maintains a significantly higher price relative to Lipitor in the early part of the sample period. This is unusual, as Lipitor is the more popular drug and quickly leads in market share. Although having $b_1$ in the model helps to match the quantitative difference, I show in Figure 11 that Zocor is still priced above Lipitor in equilibrium even with $b_1 = 0$. This is because Lipitor has a stronger dynamic incentive to gain market share, but can only do so by undercutting Zocor significantly to push it out of the preferred tier, as PBMs have difficulty satisfying existing Zocor patients.\footnote{An alternative explanation is that Zocor attracts price-insensitive consumers and therefore exists as a high-end product relative to mass-market Lipitor. This is an implausible explanation, as characteristics such as income, age, and gender are very similar across the group of patients taking each drug, based on MEPS data.}

Another key aspect of the model is the PBMs ability to exclude drugs, which limits the range over which drug companies can price, in turn curbing more extreme dynamic strategies. As shown in the negotiated price data, there are no significant price increases, contrary to the existing literature on the market impacts of consumer switching costs. This is mostly due to the threat of exclusion in the model, which limits the range over which drug companies can price, even if they have significant market share. This then has an effect on previous periods, as drug companies have less leeway to execute an
“invest-then-harvest” type strategy.

As a final check on model fit, I show that the model yields reasonable predictions for formulary outcomes and exclusion probabilities. As noted earlier in Section 2.4, systematic data on formularies and exclusions are hard to come by, but my model’s predictions does qualitatively line up with the available evidence. First, in the pre-Crestor period, my model predicts that Zocor is more likely to be in the higher copay tier while formulary exclusions are minimal. Second, after Crestor enters, it is excluded with some probability. Third, after generic Zocor enters, both Lipitor and Crestor see formulary exclusions, with Lipitor having a lower rate, which is consistent with the evidence from Medicare Part D in Figure 8.

5 Quantifying PBM Impact and Policy Implications

I now use the model to quantify the impact of PBMs on equilibrium prices and spending. In addition, I discuss the primary components governing the welfare impact of PBMs. To conclude, I use additional counterfactuals to assess the essence of recent policy proposals surrounding Medicare Part B and Part D and government-led price negotiation. I relegate the discussion of the impact of inertia to Appendix D.3, given the lack of relevant policy discussion.

Tables 2 and 3 provide a summary of all of the counterfactuals discussed below. The outcomes reported are drug company profits, average drug prices, spending, demand, and consumer welfare over the period from 1996-2013, under various pricing structures and parameters.79

5.1 Do PBMs Reduce Drug Expenditures?

First, I quantify the impact of PBMs on drug prices and spending. I find support for the view that PBMs reduce overall spending.

For my primary counterfactual, I remove the PBM from the model and have patients face a coinsurance. This counterfactual has the flavor of the current Medicare Part B price setting framework, where payers are passive and do not have the ability to negotiate prices.80 The primary reason for moving from a copay structure to a coinsurance one is that without the threat of exclusion, drug companies will price at a near-infinite level and be happy to stay in the high copay tier. For the exercise, I fix a coinsurance rate \( r = 0.33 \), which is roughly equal to the copay-to-net price ratio, and slightly higher than typical coinsurance rates. A smaller ratio would lead to even higher equilibrium prices and in turn a larger estimate of PBM savings.

79The revenue numbers are computed by multiplying together predicted per-unit prices, market shares, market size, and the fraction of days a person takes medication if they choose to do so. I set this fraction quantity to 90% to match model predictions of branded net revenue to actual branded net revenue in the data. In the end, what matters in my exercises is percentage differences, which are invariant to these assumptions.
80Part B does reference prices negotiated in the private market, but some drug markets serve mostly elderly consumers.
The results of the counterfactual suggest that PBMs decrease overall drug expenditures by 15%. Table 2 shows that net revenue earned by drug companies over the 18 year period would be $221.4 billion under the structure without PBMs (“33% Coinsurance”), as opposed to $169.8 billion in the data, which is about a 25% reduction in drug company profits. To arrive at an estimate for net spending impact, I also need to account for payments from payers to PBMs, which I estimated earlier to be 8-13% of payments to drug companies. At the upperbound, this still equates to a reduction in overall payer spending of 13-17%, with PBMs earning profits equal to half of the fees and the remaining part covering overhead costs. As I discuss later in robustness checks, the PBM profit number is scaled to market size, and therefore the percentage savings should be invariant to assumptions about market size.

Breaking down the savings, I find that PBMs curb drug company profits the most in the period right before the first generic entrant. As shown in Figure 6 in the Appendix, the reduction in drug company profits is highest, as a percentage, in the years right before the entry of generic Zocor. Initially, drug companies want to price low in the market to build a consumer base, and the calculations suggest that the presence of PBMs actually increases drug company profits slightly. Towards the end, generics generate strong enough competition even in the absence of PBMs. In the middle period, PBMs have the biggest impact. This is the period in which drug companies want to cash in on their consumer base before generic competition enters. Note that in markets without inertia, PBMs may be more effective early, as was the case with Hepatitis C drugs.

The components that pin down this result are consumer demand and data from outside the model on PBM profits. The first piece is consumer demand, which drives the counterfactual price and revenue estimates. Given that demand is strongly history-dependent, one would expect even higher spending and prices than the quantities in the actual data. The fact that they are not suggest that PBMs are having some effect on prices. In addition, my evaluation of total spending impact incorporates PBM profits, which come from financial filings outside of the model.

The structure of my model does not dictate the savings result. The estimate from PBM financials is not bound by the model, and thus is not constrained to be smaller than the estimated reduction in drug company profits. Furthermore, the PBM decision structure in my model means that it does not have to reduce drug company profits. For example, if the PBM were extremely averse to excluding drugs (high $\chi$) or did not care about expected spending (small $\theta$), then the equilibrium profits of drug companies can be higher under the presence of PBMs versus a coinsurance structure. This is due to the tiered copay system, where drug companies would want to offer a high per-unit price if their worst outcome is to be in the non-preferred copay tier.

Overall, my results are consistent with somewhat rational demand for PBM services. As noted earlier, critics of PBMs point to the opaque contracts and rebates system as

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81 The savings could potentially be higher if we factor in PBM-drug company vertical integration from 1996-2003. This form of integration no longer exists today. I discuss in greater detail in Appendix C.3.
82 Note that generic takeup may be affected by PBMs, which I am not factoring into the counterfactual.
83 Lu and Comanor (1998) spell out this idea that chronic markets are more likely to have penetration pricing, while acute markets are more likely to have skimming pricing.
a potential reason why PBMs may make more than they save. This seems unlikely, as many PBM customers are large insurance companies, which should only care about offering attractive insurance plans at low cost. Any PBM that is not reducing total costs would lose customers, as insurance companies could revert to just setting coinsurance, a plausible alternative.

5.2 Are PBMs Good for Welfare? Health Impacts, the Uninsured, and Innovation

My model also makes predictions about consumer surplus under different market structures. However, it misses out on other factors that are relevant for assessing the impact of PBMs on social welfare. These are the patient health, innovation, and spillovers to uninsured.

To start, I use the model to compute consumer surplus and other demand statistics with and without PBMs. I report the results in Table 3. In this setting, consumer surplus is the sum of the surplus created from having access to a given formulary, \( W(f) \), minus the remaining spending not covered by cost sharing. The assumption here is that any increases to cost sharing is offset by decreases to premiums, which would be the case with perfectly competitive insurance markets. My model suggests that PBMs greatly improve consumer surplus, by lowering costs without hurting consumer surplus. Put another way, PBMs rely on the threat of access restrictions to control prices, and do not actually end up greatly restricting access in equilibrium, whereas the coinsurance structure relies on the actual extensive margin to control prices. This difference is reflected in the difference in the number of people taking any medication.

A major caveat here with welfare calculations is the lack of structural heterogeneity in my demand model. As noted earlier, the dynamic analysis makes modeling demand heterogeneity infeasible, which means that I miss out on the heterogeneous impacts of formulary across patients with different needs. The estimated quality coefficients and welfare from my model reflect the needs of the average patient. In reality, some patients may have extremely high value for a specific drug, which would mean that formulary exclusions have a sharper welfare impact.

Beyond this simple short-term economic analysis of welfare, there are several additional important factors relevant for policy. First, there may be a disconnect between revealed-preference value and actual health outcomes for patients. Two particular issues stand out: adherence and switching costs. In terms of adherence, some patients may choose not to take medication even when it would be beneficial. Therefore, any reduction in the number of people taking medication may be detrimental to health outcomes. In terms of switching costs, there has been research in the medical literature, starting with Huskamp et al. (2003), suggesting that copay increases or exclusions can lead to poor patient adherence to drugs. Therefore, exclusions could lead to inefficiencies and negative health outcomes, even if the choices are medically comparable, as they are in my setting. In Table 3, I have computed average switching rates between drug options year-to-year and the fraction of individuals diagnosed with high cholesterol who end up taking medication. The results reveal surprisingly little variation in switching rates
across the specifications and a sizable increase in the number of people taking any medication. Both results are driven by the fact that PBMs do not actually greatly restrict access in equilibrium, while still controlling prices effectively. Although these statistics provide some sense of the differences to patients, more research is needed to understand the effects of PBMs on patient health.

From a dynamic perspective, reduced drug company profits may significantly dampen innovation incentives. My estimates suggest that drug companies would make 25% more profit if they did not have to compete for formulary position. In the anti-cholesterol market alone, this averages out to about $1.9 billion less profit per year. PBM activity in certain drug markets may deter drug companies from investing in new drugs in those areas, which will have dynamic welfare impacts. Further research is needed to assess the size and nature of the impact of PBMs on innovation.

Finally, PBMs may hurt uninsured individuals or individuals with high deductible plans if their actions spill over to the uninsured segment. As noted earlier, I simplify my analysis by not including list price as an additional control in my model. However, list prices matter for uninsured individuals, which make up a quarter of patients on anti-cholesterol drugs. My results certainly do not rule out the possibility that PBM actions have spillover effects on list prices, especially if rebates are the mechanism through which they are paid. However, my analysis here also suggests that list price growth may be a natural result of patient inertia in drug markets.

5.3 PBM Effectiveness – The Threat of Access Restrictions

Beyond a simple comparison of the baseline model with the coinsurance counterfactual, I also compute additional counterfactuals to highlight the value of the threat of access restrictions, particularly formulary exclusions, on prices and welfare. For these counterfactuals, I assume that PBM fees are 25% of the savings they extract from drug companies (“Drug Company Net Revenue” difference in Table 2), in line with the estimates discussed above.84

The exclusion threat is the key factor in controlling prices and spending without sacrificing welfare. To explore the role played by the exclusion threat, I compute counterfactuals where the PBM i) commits to only including one branded drug in the formulary or ii) do not face a penalty from excluding popular drugs. Committing to one exclusive drug, as PBMs and Louisiana’s Medicaid program have recently done with Hepatitis C drugs, leads to a 32% reduction in total spending relative to the current outcome, without having large negative impacts on formulary welfare, \( W(f) \) and the rate of patients taking medication.85 A slightly less extreme version of this is removing the popular drug exclusion penalty, which leads to a 15% reduction in spending without significant formulary welfare and demand differences. Under the current system, drug companies know that payers dislike exclusions on drugs that many of their patients are taking, which provides them slightly more scope to increase prices.

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84 The results are similar if I assume the rate to be 40%, which is the ratio of the high-end PBM fee estimate to extracted savings.
85 The overall consumer surplus effect is positive, as savings dominate the formulary welfare loss.
Leveraging formulary tiers can also generate savings, albeit on a smaller scale. To explore the role played by formulary tiers, I run counterfactuals where PBMs commit to i) having only one copay tier or ii) only including one preferred branded drug. The results are shown in Tables 2 and 3, under “Single Tier” and “Commit one preferred,” respectively. Removing the threat of the non-preferred tier does not have a large impact on prices and spending, and the small increase in \( W(f) \) is not enough to prevent overall consumer surplus from going down. Committing to only including one preferred drug is more effective, as it reduces spending by $15 billion without having much of an impact on formulary welfare.

Overall, the counterfactuals highlight the benefits to consumers of having an actor provide the threat of access restrictions. If exclusions and restrictions were actually high in equilibrium, then patient welfare will be significantly impacted. However, having the threat or the ability to commit to more restrictive formularies ends up controlling costs without significantly sacrificing patient access, raising overall consumer surplus. Of course, as noted earlier, this short-term view neglects the impacts on innovation.

5.4 Policy Implications – Exclusion Threat, Medicare Drug Pricing Reforms, and Government-Led Price Negotiation

As discussed in Section 1.1, there have been several recent proposals for reducing drug prices, either seeking to leverage PBMs or to replace them entirely. I discuss the implications of my analysis for these policies.

My results suggest that moving drugs from Part B to Part D can lead to significant savings. Medicare Part B covers doctor-administered drugs, and prices are currently determined as a function of private market prices (average sales price or ASP), with patients facing a coinsurance. However, many drugs garner a large fraction of revenue from Medicare, weakening the impact of the price control and essentially turning the market into the “33% Coinsurance” counterfactual discussed earlier. By moving drugs from Part B to Part D, the government would essentially be treating these drugs with PBM negotiation, which lines up exactly with my estimate of PBM impact. The 15% savings I find is roughly in line with estimates produced by the Center for Medicare and Medicaid Services (CMS). As noted above, my estimates are relevant for drugs that mostly serve older patients. Drugs with significant sales to non-Medicare markets would already benefit some from some negotiation.

The formulary choice structure in my model also allows me to qualitatively assess proposed changes to Medicare Part D protected class rules. As shown in my analysis, the threat of exclusion is the most useful tool for curbing costs without significant impact on patient access. The proposal would give PBMs the threat to exclude drugs, which my

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analysis shows would make them more potent in reducing spending without actually imposing significant access restrictions. A caveat here is that payer and patient preference in protected areas may naturally prevent exclusion, which would reduce the effectiveness of the policy. In other words, the PBM parameters I estimated for the anti-cholesterol market may be very different in markets with different customer considerations.

In contrast to these policies that aim to leverage PBM negotiation, there are also proposals to replace PBMs with government-led negotiation in Medicare Part D. There are two main factors at play in evaluating this proposal. First, the government can replace PBMs and do the negotiation itself, saving on the profits currently captured by PBMs. My estimate is that the savings would be $6 billion in the anti-cholesterol market over the period. Second, the government would need to have a strong exclusion threat for popular drugs, in order to achieve prices close to the current negotiated prices. Political pressure, especially in the US, may limit the governments ability to exclude drugs from coverage. However, one potential silver lining of this policy, as long as the government offers enough of a negotiation threat, is that it could increase innovation without increasing overall spending. In other words, the government and drug companies would be splitting PBM profits, and drug companies would then have greater innovation incentives.

The key assumption I am making here is that centralized negotiation would have similar pricing structure to the one in my model. As discussed earlier, the period-by-period bidding by drug companies is based on the structure employed by some PBMs. In other countries, governments use other measures such as reference pricing, price increase caps, and cost-effectiveness based criteria to increase their bargaining power. However, due to political constraints, these options are less likely to be implemented in the US. Price increase caps, which are present in Medicaid pricing rules, may be more feasible, and could replace exclusion as an effective tool. However, this may also lead to higher initial prices.

5.5 Robustness of Counterfactual Calculations

Finally, I test the robustness of my estimates. This includes re-assessing estimates under different non-PBM counterfactuals, net price methodology, demand parameters, and PBM objective function specification.

One potential issue with my coinsurance counterfactual is that equilibrium prices go above observed list prices in the market. As discussed earlier and shown in Figure 5, the absence of the exclusion threat gives firms more room to execute penetration or “invest-then-harvest” type dynamic pricing strategies. However, one concern is that other constraints external to the model, such as political pressure (Ellison and Wolfram, 2006) or Medicaid price increase rules, may limit price growth and rule out outcomes.

87The assumption is that the government’s overhead cost is similar to the combined overhead costs across PBMs. If the overhead were cheaper, then there would be greater savings.

88In fact, as noted above, Medicare Part D rules currently go in the opposite direction, and require the inclusion of a certain number of drugs.

89Reference pricing was included in the aforementioned “American Patients First” plan.
predicted by the model. One way to assess potential outcomes with these constraints is
to evaluate outcomes in a setting where firms are bound to set prices equal to observed
list prices while patients still face a coinsurance rate of 33%. As shown in Table 2, drug
company profits under this scenario is $187.3 billion, which is on par with spending
under the current PBM system. Consumer surplus levels are also similar. Compared
against this counterfactual, PBMs appear to be much less efficient, essentially keeping
most of the discounts they extract from drug companies. List prices may not provide a
good upperbound for prices, as they currently represent optimal prices set for uninsured
patients, who may be more price sensitive as they face the full price. Therefore, it is
not unreasonable for equilibrium prices to be higher if they became directly relevant for
insured patients.

Second, I use alternative price derivations to estimate my model, which ends up making
little difference. A more accurate estimate PBM negotiated prices requires netting out
the uninsured, Medicaid, and Veterans Administration (VA) parts of the market. I also run specifications using prices derived from assuming a constant percentage discount across dosages. These adjustments have relatively minor impact on parameter estimates, as shown in Table 1, and computed outcomes. If anything, the adjustments lower negotiated prices and PBMs look more effective.

Next, I explore estimates under different demand parameters. I first explore how
sensitive my estimates of PBM savings are with respect to demand parameters. Since
the potential error is in measuring demand, I assume that spending under the current
system still $184 billion, which reflects the underlying data. I then re-run the coinsur-
ance counterfactual under different parameters, recording the expected spending in each
scenario. Figure 15 provides a visualization of the results. Under high price sensitivity
or low inertia, counterfactual spending becomes lower than observed levels. However,
the results also show that spending can be higher even if inertia is minimal, as long as
consumers are price insensitive.

I also explore how much my consumer surplus estimates change when I add unob-
served heterogeneity to the demand system. Under my basic demand model, exclusions
are not as detrimental to welfare since I am roughly capturing the preferences of the av-
erage person. However, there may be individuals who strongly value a particular drug,
in which case exclusions create more losses. To test when PBMs may have a negative
impact on welfare, I evaluate welfare under a demand system with varying degrees of
unobserved heterogeneity, holding fixed the market outcomes for tractability reasons:

\[ u_{ijkt} = \delta_{jkt} - \alpha p_{j(f)t} + \gamma I_{j=m_{i,t-1}} + \nu I_{m_{i,t-1} \neq 0} + \xi_{ij} + \epsilon_{ijkt} \]  

where \( \xi_{ij} \) is a person-drug specific value that is distributed \( \mathcal{N}(0, \sigma_r) \). I vary \( \sigma_r \) in simulations.

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90 List prices may also reflect spillovers from other segments such as Medicaid and PBM activity.
91 See details in Appendix B.
92 The uninsured part of the market is the largest of the three, and pays an amount close to list price.
93 Medicaid and the VA are known to pay much less than the average private market price.
94 For example, at \( \alpha = 0.4 \) with no inertia, total spending is still $197 billion.
The results suggest that very high degrees of unobserved heterogeneity are required to make PBMs look ineffective from a welfare standpoint. I report the welfare comparisons for some selected scenarios in Table 5. As noted above, the coinsurance structure compares poorly to the baseline model under the “basic” demand model, even if we ignore overall costs and just focus on the formulary surplus. This is because it relies on higher cost sharing, whereas the PBM structure tends to offer at least one preferred tier drug. Once unobserved heterogeneity increases, the coinsurance structure starts to look better, as patients with high values for specific drugs prefer having some access. However, the coinsurance formulary surplus is still smaller for $\sigma_r = 2$, which is on par with switching costs. Under very high unobserved heterogeneity, the coinsurance structure will be better.\footnote{94 I already have PBMs account for a form of consumer attachment to a specific drug by including the exclusion penalty term.}

\section*{6 Conclusion}

In this paper, I have used novel data and modeling to gain insights into the role played by pharmacy benefit managers in the drug pricing system. I find that PBMs reduce overall drug spending by 15%, while cutting drug company profits by 25%. The results suggest that market-based counterweights can be effective at controlling drug prices, but their significant profitability may leave room for policy intervention.

I make two methodological contributions that can serve as a starting point for future research into drug pricing. First, my model captures the interplay between drug companies, PBMs, and consumers demand in forming drug prices. This structure can help us assess the impact of other policy-relevant institutions in the industry, such as advertising and copay assistance.

Second, I construct and use negotiated (or net) price estimates for understanding the forces in prescription drug markets. Negotiated prices differ significantly from list prices in the anti-cholesterol market, and this is true, on average, across all drug markets. I encourage future research to make use of negotiated prices in order to better capture actual outcomes in the industry, especially given that this data has become more readily available over time.

From a modeling standpoint, my paper solves some of the problematic aspects in existing models, but leaves open room for additional improvements in future work. As noted earlier, existing models of drug pricing use a standard differentiated goods Bertrand model, which leads to implausible estimates of marginal cost and consumer price sensitivity. In addition, they do not account for history-dependence in demand, a key feature of many of the largest drug markets. Although I have made some progress, there is still work to be done to incorporate patient heterogeneity and to unpack the PBM industry, which I treat as a black box in my paper. My analysis here is partly constrained by the lack of PBM-specific drug price data and PBM demand data. Obtaining some of this data will help us better model the system, which would give us deeper insights into merger policy in the PBM industry.
Overall, there is more work to be done in terms of evaluating the welfare impact of PBMs. As described in the paper, there has been limited work done on quantifying the health impacts of PBM activity, which includes disruption costs and equity issues. In addition, PBM activity may also affect drug development incentives, which could have significant dynamic welfare consequences. Having a better grasp of these components would help us design better regulation of an important industry.
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Feng, Josh. 2018. “History-Dependent Demand in Chronic Drug Markets: Evidence and Implications.”


<table>
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Standard errors in parentheses

Notes: Parameter estimates for the pricing model laid out in Section 3. Model is estimated on different prices: “Basic” refers to the basic construction of negotiated prices, “Pct Discount” reflect prices based on common percentage discount across dosages, “Private” reflects prices that are purged of sales and quantity in other market segments not directly affected by PBMs. Standard errors are computed using the standard maximum likelihood approach.
Table 2 Summary of Counterfactual Market Outcomes

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<th>Average Unit Price ($)</th>
<th>Payments ($ bill)</th>
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<td>(High PBM fee)</td>
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Pricing Structure Changes:

<table>
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<th>Scenario</th>
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<td>33% Coinsurance</td>
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<tr>
<td>List Price</td>
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<tr>
<td>Single Tier</td>
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<td>1.96</td>
</tr>
<tr>
<td>Commit one preferred</td>
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<td>1.95</td>
</tr>
<tr>
<td>Commit one exclusive</td>
<td>1.99</td>
<td>1.07</td>
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Varying Model Parameters:

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Average Unit Price ($)</th>
<th>Payments ($ bill)</th>
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</thead>
<tbody>
<tr>
<td>No Merck-Medco</td>
<td>2.27</td>
<td>1.99</td>
</tr>
<tr>
<td>No inertia</td>
<td>2.19</td>
<td>1.49</td>
</tr>
<tr>
<td>No exclusion penalty</td>
<td>2.10</td>
<td>1.39</td>
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</tbody>
</table>

Notes: Statistics summarizing the results from the counterfactual exercises. Baseline: Best fit model. No Merck-Medco: no relationship between the two, sets $b_1 = 0$ No inertia: no drug-specific inertia, with effects shifted to preferences for any drug ($\gamma' = 0, \nu' = \nu + \gamma$). No exclusion penalty: PBM does not have extra aversion to exclusions $\chi = 0$. 33% Coinsurance: patients face coinsurance rate of 33% with no PBM involvement. List price: market outcomes if firms stick with observed list prices and face 33% coinsurance. Exclude ≤ 1: PBMs can only pick formularies that exclude at most one branded, on-patent drug. Single Tier: PBMs can only choose inclusion or exclusion for branded drugs, with included drugs having copay equal to the preferred copay level. Commit one preferred: PBM commits to only picking formularies that have one branded drug in the preferred copay tier. Commit one exclusive: PBM commits to formularies that include at most one branded drug. No insurance: patients face full price, assuming same $\alpha$ coefficient. Average prices are computed in a weighted manner across the 18 years from 1996-2013, are scaled to daily prices, and only include branded prescriptions. Total payments is computed by multiplying equilibrium negotiated prices by market share and by market size (assuming people who choose a drug take it 90% of the days in a year), and summing over all years.
### Table 3 Additional Welfare-Related Outcomes

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Demand Stats</th>
<th>Welfare Statistics ($bill)</th>
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<tr>
<td></td>
<td>Switch Rate</td>
<td>Taking Any</td>
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<td>Baseline</td>
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<td>0.477</td>
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<td><strong>Pricing Structure Changes:</strong></td>
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<td><strong>Varying Model Parameters:</strong></td>
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<tr>
<td>No Merck-Medco</td>
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<td>0.476</td>
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<td>No inertia</td>
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<td>0.458</td>
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<tr>
<td>No exclusion penalty</td>
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<td>0.475</td>
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</tbody>
</table>

**Notes:** Additional statistics related to welfare for each of the counterfactual scenarios reported in Table 2. “Switch Rate” refers to the fraction of people who switch from one drug to another year-on-year, not including the outside option. “Taking Any” refers to the fraction of diagnosed patients taking any medication. $W(f)$ is the component representing the welfare from the formulary choice facing patients in Equation (3). “Cost sharing” is the total cost sharing payments made by consumers over the period. “Total Spending” refers to the sum of payments to drug companies and PBMs (from Table 2). “Consumer Surplus” is equal to $W(f)$ minus “Total Spending” plus “Cost Sharing,” as discussed in Section 5.2.
Figure 1 Anti-Cholesterol Market Summary - Demand

Notes: Graphs summarizing demand in the medium-intensity treatment level anti-cholesterol market. Top: number of patients who are taking cholesterol medication and who are diagnosed with high cholesterol but not taking medication, based on MEPS data. The sum represents the market size, which grows at a slowing rate over time. Bottom: given the market size, a plot of the fraction of the market on each branded medication. The red sums together people taking the three main branded drugs plus people taking generics and other minor drugs. Generic entry significantly reduced market shares of branded Zocor (June 2006 generic entry) and branded Lipitor (December 2011 generic entry).
Figure 2 Anti-Cholesterol Market Summary - Prices

Notes: A comparison of average pharmacy and negotiated prices in each year for the three major drugs over the analysis period, showing very different patterns when accounting for rebates. Prices are weighted across medium-intensity treatment level dosages for each drug, with the pharmacy prices coming from median prices in the MarketScan claims data. Smoothed negotiated prices incorporate estimated discounts described in Appendix B and are smoothed out to account for unevenness in wholesale purchasing across years. All prices are adjusted to Year 2000 US dollars.
Drug 1

Drug 2

Drug 3

PBM

Patient/Doctor

\[ P_{1t} \]

\[ P_{2t} \]

\[ P_{3t} \]

• PBMs pick formulary \( f \) to maximize dynamic profits
• \( f \): set of copays (including exclusion)

\begin{itemize}
  \item Maximize dynamic profits
  \item Control: price bid \( (P_t) \)
  \item State: previous market share diluted by new patients
\end{itemize}

Figure 3 Overview of Model

Notes: Each “Drug” box represents a drug company. Other notation follows from the description in the text: \( P \) for price bids, \( f \) for formulary choice.
Figure 4 Model Fit - Predicted vs. Actual Prices

Notes: A comparison of model predictions and data on negotiated prices. The model captures the general dynamics in the negotiated price data, including the key features laid out in Section 2.1. The model rationalizes the gap between Zocor and Lipitor prices in early years, the decrease in negotiated prices after generic Zocor enters the market, and the general increase in price in anticipation of generic Zocor and Lipitor entry. Aspects not matched are due to inflexible features of the model discussed in greater detail in Section 4.3. This includes the size of Zocor’s drop in negotiated prices, Lipitor’s pricing in 2006 relative to 2005, and pricing in 1996 and 1997.

Figure 5 No PBM - Coinsurance

Notes: Counterfactual prices under a scenario where patients face a coinsurance rate of 33% of the prices set by drug companies.
Figure 6 Impact of PBMs on Drug Company Profits by Year

*Notes:* A plot of the percentage loss in drug company profits as a result of PBM activity. This is a breakdown of the comparison presented in Figure 5.
The outline of the Appendix is as follows. Appendix A summarizes the approach uses in a concurrent paper that motivates my demand estimation approach. Appendix B describes the construction of negotiated price data. Appendix C describes the estimation of PBM payments and profits.

A Quasi-Experimental Methodology and Demand Estimates in Feng (2018)

Here, I summarize the quasi-experimental approach taken in Feng (2018) to show history-dependence in prescription drug demand. The approach motivates my cohort-based instrument to estimate demand, which is described in Section 3.2.

The approach is to use temporal discontinuities around drug launches to vary the initial choice sets of patients and then trace out differences in subsequent decisions. My data comes from the MarketScan dataset, which is a long panel of prescription drug claims. Using the data, I identify the date on which a patient starts on anti-cholesterol medication. Then, I identify users that start close to an entry event (e.g. Crestor entry in August 2003), and split them into treatment and control groups, depending on whether they start before or after the entry. Assuming that patients do not wait for the entry to start on drugs, then the treatment group is more likely to start on the entering drug. I then trace out the differences in drug choices over time for these two groups.

Comparing the two groups around the discontinuity, I find that patients in the treatment group are consistently more likely to choose the new drug, even five years after entry. The anti-cholesterol market and other markets I look at in the paper treat chronic conditions, and therefore patients keep making prescription choices over time. I find that the patients in the treatment group have a significantly higher new drug market share, even five or more years after entry. This equates to a very high switching cost. I also find that these patients are less likely to adopt generic versions of other drugs, and are more likely to subsequently take incremental versions of the entering drug.

I then run tests to show that my identification assumption holds. The key assumption here is that patients do not choose their start time, because medical needs arrive exogenously. However, it is possible in some markets that patients wait for the new drug, because the existing drugs are not good fits. This is unlikely in the anti-cholesterol market, where the drugs are generally similar. I test this by re-running the analysis on patients who start around a hospital visit, by looking at the flow of patients over time, and by looking at balance on observables between the two groups.

Finally, I use the variation to estimate a switching cost model of demand. The simple version of the model is the same as the one described by Equation (1). The key challenge is to isolate the exogenous component of the indicator variables, which may be capturing serial correlation in taste shocks. My approach in the paper is to use the idea from the quasi-experimental by leveraging cohort variation. Specifically, I compute a leave-one-out measure of the indicator variables, which is exogenous to personal taste shocks. I
then estimate the model using either the two-stage predictor substitution advocated by Newey (1987) or the two-stage residual inclusion advocated in a recent paper by Terza, Basu and Rathouz (2008). This then gives me estimates of $\gamma$ and $\nu$ that are purged of the effects of unobserved heterogeneity.

B Constructing Negotiated Price Data

In this section, I provide a more detailed description of the challenges in constructing negotiated prices (or net price), the raw data I collect, and my methodology for dealing with problematic aspects of the data.

The high-level approach here is to collect data on net revenues by drug and year in the US market, and divide it by quantity to arrive at average negotiated prices. Here, I discuss the detailed methodology and data sources, and also discuss adjustments to account for different prices across dosages.

B.1 Data Sources – SSR Health, SEC Filings, IMS Top-Line, MEPS

To construct my estimates, I collect revenue data from SEC filings and IMS Top-Line data, US aggregate demand estimates from the Medical Expenditure Panel Survey (MEPS), and additional net price estimates from SSR Health. I then construct negotiated prices based on the data available in each year.

The financial filing data comes from annual company SEC filings (10-K) and conference call transcripts, between 1996-2013. At the start of the period, companies generally report global sales by disease area, but progressively offer more granular data, with the current standard being a breakdown by drug and geographic area (US, Europe, global). Roughly, the financial data coverage is as follows:

1. 1996-2000: Merck reports global aggregate sales for its cholesterol drugs (Mevacor and Zocor) in its 10-K filings; Pfizer reports global Lipitor sales in its 10-K filings.
4. 2003-present: Merck (at the time Schering-Plough) reports global sales of Zetia and Vytorin.

In addition, I collect additional net revenue data from IMS Top-Line Market Data and from media reports on the cholesterol market. The IMS Top-Line data is currently available from 2007.

For demand, I use estimates from MEPS. I break this down by different dosage levels and seller (pharmacy vs. mail order) for each of the cholesterol drugs. MEPS covers the entire period from 1996-2013.

Next, I collect data on gross prices. To do this, I collect average wholesale price (AWP) and median price paid (labeled as “pay” in the MarketScan data) for each drug by dosage by seller from the MarketScan data. Each entry in the data contains these two quantities. The AWP is constant at the national level at a given point in time, while the “pay” variable partially reflects pharmacy markups.

Finally, I obtained estimates of net sales and quantity sold from SSR Health, a pharmaceutical industry consulting company. They estimate negotiated prices for a large number of drugs since 2007 at the quarterly level, and shared with me their estimates for the cholesterol market. Their estimates account for stockpiling and other accounting issues, which leads to smoother estimates. Therefore, I use their numbers for the post-2007 period, but my estimates using raw financial filing data lines up with their estimates as well.

B.2 Calculating Gross and Net Revenue

After collecting all the data and aggregating it to an annual level, I use the following numbers for net revenue:

- In years with reported net US revenue, I just use the number available.
- In years where only net global revenue are reported, I arrive at a net US revenue number by making the assumption that all of the global rebates are from rebates paid in the US. I find that this assumption roughly holds in years with both net global and net US sales numbers.

\[
\text{Net US Revenue} = \text{Net Global Revenue} - (\text{Gross Global Revenue, IMS} - \text{Gross US Revenue, IMS})
\]

I also make the following corrections to account for years in which generics enter in the middle of the year:

- Zocor generics enter in June 2006. Using aggregate revenue for the whole year creates a misleadingly low price for pre-generic net price. This is because after generics enter, branded drugs typically price at a duopoly level to compete with the exclusive generic.\(^{96}\) Instead, I use quarterly revenue from the first two quarters and project out to the whole year.

To arrive at a gross revenue number, I use the data on payments at pharmacies:

\(^{96}\)The first generic entrant typically has an 180-day exclusivity period based on provisions in the Hatch-Waxman Act.
Avg. Gross Price = \[ \frac{\sum_{ij} P_{ij} X_{ij}}{\sum_{ij} X_{ij}} \]

where \( i \) is the drug and \( j \) is the seller (pharmacy or mail order), \( X \) is the sales estimate from MEPS and \( P \) is either the “pay” variable from MarketScan. I also try calculations using AWP, but it is generally considered to be an inaccurate measure of what is actually paid.

**B.3 Accounting for Difference Prices Across Dosages Within a Drug**

A major challenge here is that net sales estimates are at the drug level, but different dosages of the same drug are sometimes priced differently. For example, a 40MG Lipitor tablet has a gross price that is $1 more expensive than the more commonly used 10MG tablet.\(^{97}\) Without additional knowledge, we cannot pin down the negotiated price for medium intensity dosages of each drug, which is the focus of my analysis.

To solve this problem, I assume that discounts per pill are equal across dosages for the same drug. I take the difference in overall gross and net revenue for each drug, and divide it by quantity sold, which gives me a discount per pill under the assumption. I then subtract this discount from the list price of the medium intensity dosage. In the end, I arrive at average negotiated price in the US market for each of the three drugs in each year.

**B.4 Refinements to Aggregate Price Derivations**

The net price derived above depends on two assumptions: i) there is a constant discount per pill across dosages ii) average prices over the whole market are roughly equal to the prices negotiated by PBMs. I then calculate refinements to the estimates above to arrive at potentially more accurate measures of the price obtained by PBMs for the insured part of the market.

First, I derive net prices assuming constant percentage discounts across dosages. In the core derivation, I assume that the dollar discount per pill is the same across dosages. An alternative assumption is that percentage discounts are the same across dosages. As shown in Figure 14, there is very little difference between the two approaches. The biggest deviations are about 5 cents, and Crestor is barely affected, as it starts of pricing all dosages at the same price. The differences that are present depend on how the prices of low-intensity and high-intensity dosages relate to those of the medium-intensity dosages. When high-intensity dosages are priced higher, they absorb more of the discount under the percentage model, which results in higher prices.

A more substantive adjustment is to isolate the negotiated prices in markets covered by PBMs, which generally results in lower derived prices. As noted in Section 1.2, PBMs serve Part D plans and private insurance, which does not include Medicaid, Veterans Administration (VA), and uninsured patients. Uninsured patients pay an amount close

\(^{97}\)Crestor actually sets the same price for all dosage levels.
to list price, and make up about 15-30% of the individuals taking medication. Medicaid and VA patients pay less than or equal to the private market, and account for 10-15% of people. My approach is to first purge the net revenue data of uninsured patients paying list price, which pushes down the effective net price in private markets. Then, to create as high a potential negotiated price as possible, I assume that the VA pays $0 and that Medicaid receives a 30% discount off the net price in the private market. I then obtain the net price by solving out the following accounting identity for $p_{PBM}$:

$$p_{PBM}(s_{Medicare} + s_{Private} + 0.7s_{Medicaid}) + s_{uninsured}p_{list} = p_{net}$$

where $s$ represents the share of individuals taking medication covered under each type of insurance, $p_{net}$ is the overall net price derived earlier, and $p_{list}$ is the list price.

### B.5 Notes on Accounting Data

There are a couple of potentially important accounting issues that I ignore in my main analysis. First, copay assistance programs, which started around 2005, are usually included as variable costs in the net revenue numbers. As studied in Lee (2013), copay assistance programs help cover part of a patient’s cost sharing, in order to push back against unfavorable formularies. One source cited in the paper put the prevalence at around 13% of prescriptions. This action goes the same way as discounts offered to PBMs in terms of spending to create more favorable demand, but is distinct in that many programs such as Medicare do not permit them and may have quantitatively different impacts.

Second, other forms of patient assistance are typically included in the SG&A (overhead) amount. As noted above, uninsured patients typically pay an amount that depends on the list price. However, many companies help fund patient assistance programs by donating to charity organizations. Therefore, the net revenue across the whole market might be misleadingly high, as the numbers do not take into account other forms of spending to acquire patients.

### C More on PBMs: Estimating Fees and Profits, Incentives, and Antitrust Issues

In this section, I document how I estimate payments to PBMs, discuss additional issues surrounding PBM incentives, and also lay out antitrust issues and evidence from my model.

#### C.1 Estimating Payments to PBMs

Here, I detail my approach for estimating how much payers spend on PBM services, which matter for calculating total spending, as well as PBM profits, which matter for understanding potential savings from government-led negotiation. My estimates for the
anti-cholesterol market, which I use in my analysis, are that payers pay PBM $13-18 billion during the period, with PBM earning about $7.5 billion in profits.

PBM financial filings are complex, as numbers are not broken down by market and standard revenues and variable costs incorporate both pass-through items and actual payment for services. One challenge here is that my analysis is of the anti-cholesterol market, and PBM do not break down their revenues by market. A second challenge is that PBM margins are hard to assess, as they incorporate payments for drugs that come from payers and are passed on to drug companies. Therefore, the variable cost numbers mostly include the revenues earned by drug companies, with potentially a small processing cost per prescription included as well. The revenues number would include both payments passed onto drug companies and fees paid by PBM clients.

My approach for estimating payments to PBM uses the revenues and variable costs from their financial filings. The assumptions I make here are that the bulk of variable costs are pass-through payments for drug purchases and that the revenue-to-cost ratio in the anti-cholesterol market is similar to the overall ratio. Then, my formula for payments to PBM is:

$$\text{PBM Paym.} = \frac{\text{PBM Revenues} - \text{PBM Variable Cost}}{\text{PBM Variable Cost}} \times \text{Drug Company Revenues}$$

Essentially, I am netting out the pass-through part of the PBM revenue, and then scaling the net PBM revenue to the size of the anti-cholesterol market. The net revenue to variable cost ratio is approximately 8%, and is pretty consistent over time for the large PBM. One additional factor that might be relevant is processing fees. If they are non-negligible, then payments to PBM would be slightly higher. For example, if processing fees are 5% of total variable costs from the accounting data, then my estimate would roughly be 13% (the PBM looks inefficient under this assumption). Scaling this by drug company revenues in the anti-cholesterol market ($169.8 billion), I arrive at a number between $13-18 billion over the time period, depending on the size of processing fees.

I take a similar approach to estimate PBM profits, which give us a lower bound on the savings government-led negotiation would generate. PBM do report net profits, which equals net revenues minus overhead minus taxes. To estimate PBM profits from just the anti-cholesterol market, I take the net profit to variable cost ratio, and then scale it again by drug company revenues. This ratio fluctuates at times in financial filings, particularly around mergers such as Medco and Express Scripts in 2012. However, this generally stays at around 4-5% of variable costs, equating to about $7 billion in PBM profits from the anti-cholesterol market over the period. If the government decided to set up a negotiation department, it would be able to save this, plus taxes and other fixed costs such as advertising.

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99 Express Scripts filings from 2010-2016 and Caremark filings before merging with CVS in 2007.
C.2 Additional Discussion on PBM Incentives

Here, I discuss two other aspects of PBM incentives that are relevant for my model: the role played by consumer inertia and PBM dynamic incentives.

Based on anecdotal evidence, PBMs are hampered by consumer inertia both in its ability to move drugs to a higher copay tier and to exclude them, a force that I account for in my model. In a market with several substitutable competitors, PBMs would theoretically be able to extract large savings by making drug companies bid for one preferred tier slot. However, multiple decisionmakers in the industry suggested that consumer inertia curbs their ability to extract discounts. First, moving a drug to a higher copay tier can backfire in the form of higher spending if there is significant inertia, as the same patients will still pick the drug, but the drug company may end up not paying any rebates. Second, excluding a drug entirely may lead to complaints from PBM customers, as patients on the excluded drug are forced to switch to a different drug.

Another aspect of PBM behavior relevant to my analysis is that they may be somewhat forward-looking, based on the length of their contracts and their behavior around Zocor generic entry. Based on publicly available information, PBMs sign contracts of varying lengths with customers. In particular, they sign long-term contracts with large insurers, sometimes up to 10 years. PBM behavior around generic Zocor entry provides more direct evidence of dynamic incentives. As detailed in Aitken, Berndt and Cutler (2009) and media coverage, Express Scripts anticipated the launch of generic Zocor by favoring branded Zocor over Lipitor in its formulary placement, even though Zocor was significantly more expensive. Their motivation was to facilitate generic adoption, which would lead to long-run cost savings.

C.3 PBMs and Vertical Integration - Costs and Benefits

Here, I discuss the issues surrounding PBM mergers and antitrust, and show relevant results from my model that speak to the potential issues. The main concern raised by my analysis is that PBM insurance design choices can be influenced by vertical integration, which may be relevant for the current wave of pharmacy-PBM mergers.

C.3.1 Additional Background on PBM Mergers and Antitrust

Throughout the last two decades, PBMs have drawn significant scrutiny from policymakers for their role in increasing drug prices, in part due to the opacity of their contracts. PBM contracts with both drug companies and their customers are proprietary, making

\footnote{This actually played out in the market for Hepatitis C cures.}

\footnote{A recent Bloomberg report highlights the 10-year contracts between Express Scripts and Anthem, as well as Catamaran and Cigna. “Express Scripts’ Anthem Loss Goes Deeper Than Numbers” available at: https://www.bloomberg.com/gadfly/articles/2017-04-25/express-scripts-anthem-loss-cuts-deep}

\footnote{See Chicago Tribune article “Generic Zocor won’t be a market healer” available at http://articles.chicagotribune.com/2005-12-29/business/0512290220_1_generic-zocor-lipitor-generic-version}
it difficult to discern the net price paid to drug companies and the share of the discounts kept by PBMs.\textsuperscript{103} This has led some policymakers and drug companies to blame PBMs for increasing drug costs, including the recent controversy surrounding the price of EpiPens. For example, they claim that PBMs extract a lower price from drug companies, but then pocket all of the discounts, which then means that insurance companies pay close to the full gross price, leading to higher premiums for patients.

In addition, regulators have repeatedly investigated PBMs for violating anti-kickback and anti-fraud statutes, with at least one lawsuit asserting foul play specifically in the anti-cholesterol market. Standard volume-based discounts are legal, but any misleading advertising by PBMs to promote drugs on which they receive the largest discounts would violate the law.\textsuperscript{104} In addition, as mentioned earlier, drug companies once owned large PBMs, leading to accusations of favoritism towards their own drugs in formulary design. A prominent legal case involved the Justice Department’s 2003 lawsuit against Medco for favoring drugs owned by Merck, its parent company.\textsuperscript{105} The complaint, later settled, included the specific accusation that Medco favored Merck’s Zocor over Pfizer’s Lipitor, with the former costing more than the latter.

In recent years, PBMs have moved away from integrating with drug companies, but have moved towards integrating with pharmacies and insurance companies. In this paper, I abstract away from the distribution side of the market, but several large pharmacies have significant market power in the US. In the last decade or so, there have been actual and proposed vertical mergers between PBMs (Caremark, Express Scripts, EnvisionRx) and several large insurers and pharmacy chains. These include Caremark and CVS (2006), CVS/Caremark and Aetna (2017, proposed), Rite Aid/EnvisionRx and Albertsons (2017, proposed), and Cigna and Express Scripts (2017, proposed). Although I do not directly address the effects of PBMs on the pharmacy industry, my evidence on PBMs favoring their parent company in insurance design suggests that PBMs may also strongly favor specific pharmacy chains when integrated, lowering competition in the pharmacy market.

\textbf{C.3.2 The Impact of Vertical Integration - Evidence from Model}

Here, I briefly discuss the effects of vertical integration between PBMs and drug companies. As discussed in Appendix C, Merck purchased Medco in 1993, and started winding down the relationship in 2003, mostly due to regulatory pressure. Neither Pfizer nor AstraZeneca were vertically integrated during the period.

\textsuperscript{103}Express Scripts claimed in a 2017 conference call that its clients receive 89% of rebates on average. Others argue that these statistics can be misleading, as PBMs often shroud discounts in other fees, which creates an inflated pass-through number.

\textsuperscript{104}See \url{http://www.pbmwatch.com/pbm-litigation-overview.html} for a list of major lawsuits involving PBMs and kickbacks.

\textsuperscript{105}See articles “U.S. Is Joining Lawsuit That Says Medco Put Profits Before Patients” in the Wall Street Journal and “Medco to Pay $29.3 Million to Settle Complaints of Drug Switching” in the New York Times for more details. Other large PBMs such as AdvancePCS faced similar accusations at around the same time.
To assess the impact of vertical integration, I run counterfactuals shutting off the Merck-Medco relationship. In Figure 11, I show the counterfactual prices in a setting with no relationship between Merck and Medco ($b_1 = 0$). The qualitative result that Zocor is still priced higher relative to Lipitor is maintained in the counterfactual, highlighting the impact of first-mover advantage. However, prices are significantly lower, and Table 2 shows that total drug company profits would have been $9 billion lower absent the relationship, a different order of magnitude compared to the $30 million dollar settlement paid by Medco in 2003 (see footnote 105) and much closer to the $6 billion Merck acquired Medco.

Three main caveats apply to my interpretation of $b_1$. First, my counterfactuals depend on my estimate of $b_1$, which is only identified from temporal variation in the data. It is possible that other changes in the early 2000s caused the large drop in prices, but the circumstantial evidence suggests that this is unlikely. Second, I do not measure potential benefits of vertical integration, several of which were raised in 1993 and similar ones raised in recent vertical mergers involving PBMs. These include more efficient provision of drugs and reduction in transaction costs. Finally, as noted earlier, 20mg Zocor and 10mg Lipitor may not be the exact comparison for all patients. 10mg Zocor is priced higher but closer to 10mg Lipitor, and therefore $b_1$ may be overstated due to the inexactness of the comparison.

The main takeaway from the analysis is that PBM insurance design decisions may be influenced by vertical integration, an issue that is relevant for PBM-pharmacy mergers but less so for PBM-insurer mergers. As noted earlier, recent PBM mergers have involved either pharmacies or insurers. For pharmacy mergers, the worry is that PBMs will design drug insurance to encourage patients to fill their prescriptions at the pharmacy that they are integrated with, raising the market power of pharmacy chains like CVS and Walgreens. For PBM-insurer mergers, influencing consumer choice is less of a concern, unless the combined entity uses formulary design fees to drive business away from smaller insurers or to force self-insuring firms to use more of their services.

D Additional Model Discussion and Results

D.1 Other Simplifications – Firm Controls, Formulary Restrictions

My model also simplifies away from other important institutional details, including other firm strategies such as advertising and copay vouchers, weaker forms of formulary exclusion, and the distinction between rebates and discounts.

The demand system in my model rules out interactions between pricing and other firm controls such as advertising and copay cards. There is a long literature on the impacts of advertising, both direct-to-consumer and doctor detailing, on drug demand. In addition, there has also been growing attention paid to copay cards, which help cover high copays faced by consumers.\footnote{See aforementioned paper by Lee (2013).} Both actions represent actions available to firms, and may interact with pricing strategy. In addition, as I discuss in Appendix B.5, copay
cards also factor into net revenue accounting. For simplicity, I rule out interactions, and have any effects from other actions absorbed into period specific drug fixed effects.

Another simplification in my model is that the PBM can put a drug in one of two tiers or exclude it, but this structure can qualitatively capture other formulary options. In recent years, insurance plans have typically had two copay tiers for branded drugs with the possibility of exclusion, which forms the basis of formulary choice in my model. However, in addition to excluding a drug outright, a PBM can also put softer restrictions on a drug. For example, many plans restrict drugs by requiring prior authorization, where a doctor has to write a detailed explanation for why a patient needs that drug, or step therapy, where the patient has to start on a different drug before switching to the restricted drug. Adding these options would greatly complicate the formulary options, without adding much from a qualitative perspective. My model allows for a probabilistic distribution across potential formularies, which means a predicted exclusion rate of 20% can partly capture step therapy or prior authorization restrictions.

D.2 Issues with Model Fit

There are minor discrepancies in the model fit discussed in Section 4.4, which result from issues in market size computation and model specification. I detail them in chronological order here.

The first issue with the model is the price predictions in the 1996-1998 period. The model outputs lower quality estimates, as shown in Figure 9 of the Appendix, as the outside option is more popular in early years. This problem may be due to an imprecise calculation of market size, as it’s possible that many diagnosed patients did not even consider statin treatment.\footnote{Medical guidelines generally become more encouraging of statin use over this period.}

A second issue surrounds the pricing level of Zocor. The data suggests a more gradual decline in Zocor net price relative to the model. The source of the discrepancy is that I assume that the Merck-Medco relationship ends entirely after 2003, when in fact it maintained some volume guarantee contracts as part of the spinoff.\footnote{See NY Times article “With Ties Lingering, Medco Leaves Merck” available at http://www.nytimes.com/2003/08/20/business/with-ties-lingering-medco-leaves-merck.html. The article details the penalties Medco would face if Zocor market share dropped below a national target.} This is solvable by adding another flexible parameter to capture the post-2003 relationship, but for my core analysis, I wanted to limit the parameter space.

The third issue surrounds pricing in 2006, the year during which generic Zocor enters. In the data, all three drugs exhibit increased negotiated prices, but my model predicts that Lipitor will set a much lower price, and raise prices in the following year. This is the result of the weaker dynamic incentives of PBMs estimated in the model, as Lipitor has more of an incentive to acquire market share than the PBM has of moving market share to Zocor. As I mentioned earlier, in reality, PBMs may only pursue dynamic strategies at specific times.
D.3 The Role of Inertia – Implications for New Types of Markets

My framework can also help us understand pricing dynamics in markets with different demand features, particular new areas where cures are available such as Hepatitis C. To do this, I compute counterfactuals under alternative values of switching cost parameters.

I evaluate the equilibrium price dynamics under a scenario with no drug-specific switching costs, and find price deflation. To implement this, I run the game under parameters \((\gamma', \nu')\), setting \(\gamma' = 0\) and transferring its effect over to \(\nu' = \nu + \gamma\). This helps preserve the intensive margin versus extensive margin, but removes a drug-specific demand advantage. I also recompute implied drug qualities in each period as an additional way to maintain market shares. Figure 12 presents a comparison of prices under the counterfactual versus those from the baseline model and the “No Inertia” row in Table 2 summarizes outcomes. Prices are generally much lower in level, and the prices shown in Figure 12 exhibit deflation in the period before 2006. This is due to the increasing levels of competition, as each drug can no longer rely on an existing patient base. The prices in later years are only slightly reduced, as lower inertia also hurts the competitiveness of generic Zocor, which no longer benefits from the market share of its branded counterpart. All of these effects would be accentuated if I also set \(\chi = 0\), as PBMs would then exclude popular drugs. Overall, the results suggest that inertia plays a significant role in preventing deflation in drug prices when competitors or generics enter, a finding that is relevant for non-chronic drug markets such as Hepatitis C, where we would expect and have observed deflation.
## Additional Tables and Figures

Table 4 Drug by Dosage Treatment Intensity Classifications

<table>
<thead>
<tr>
<th>Drug</th>
<th>Strength</th>
<th>Treatment Intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lipitor</td>
<td>10 MG</td>
<td>Moderate</td>
</tr>
<tr>
<td>Lipitor</td>
<td>20 MG</td>
<td>Moderate</td>
</tr>
<tr>
<td>Lipitor</td>
<td>40 MG</td>
<td>High</td>
</tr>
<tr>
<td>Lipitor</td>
<td>80 MG</td>
<td>High</td>
</tr>
<tr>
<td>Zetia</td>
<td>10 MG</td>
<td>Low</td>
</tr>
<tr>
<td>Vytorin</td>
<td>10 MG- 10 MG</td>
<td>Moderate</td>
</tr>
<tr>
<td>Vytorin</td>
<td>10 MG- 20 MG</td>
<td>High</td>
</tr>
<tr>
<td>Vytorin</td>
<td>10 MG- 40 MG</td>
<td>High</td>
</tr>
<tr>
<td>Vytorin</td>
<td>10 MG- 80 MG</td>
<td>High</td>
</tr>
<tr>
<td>Crestor</td>
<td>5 MG</td>
<td>Moderate</td>
</tr>
<tr>
<td>Crestor</td>
<td>10 MG</td>
<td>Moderate</td>
</tr>
<tr>
<td>Crestor</td>
<td>20 MG</td>
<td>High</td>
</tr>
<tr>
<td>Crestor</td>
<td>40 MG</td>
<td>High</td>
</tr>
<tr>
<td>Zocor</td>
<td>5 MG</td>
<td>Low</td>
</tr>
<tr>
<td>Zocor</td>
<td>10 MG</td>
<td>Low</td>
</tr>
<tr>
<td>Zocor</td>
<td>20 MG</td>
<td>Moderate</td>
</tr>
<tr>
<td>Zocor</td>
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<td>Moderate</td>
</tr>
<tr>
<td>Zocor</td>
<td>80 MG</td>
<td>High</td>
</tr>
</tbody>
</table>

*Notes*: Categorization of different strengths of each drug into treatment classes. The focus of the analysis is on Zocor 20mg, Lipitor 10mg, and Crestor 10mg, by far the most popular dosages for starting patients. Vytorin strengths report Zetia first, Zocor second. 10 MG- 10MG Vytorin has negligible market share. Sources: Prescriber’s Letters (2011)
Table 5 Formulary Surplus – Incorporating Unobserved Heterogeneity

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Basic</th>
<th>$0.5$</th>
<th>$1$</th>
<th>$2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>145.2</td>
<td>159.4</td>
<td>195.6</td>
<td>330.0</td>
</tr>
<tr>
<td>33% Coinsurance</td>
<td>114.2</td>
<td>126.3</td>
<td>158.6</td>
<td>286.9</td>
</tr>
<tr>
<td>Exclude $\leq 1$</td>
<td>142.6</td>
<td>156.8</td>
<td>192.8</td>
<td>327.1</td>
</tr>
<tr>
<td>Commit one exclusive</td>
<td>127.5</td>
<td>140.3</td>
<td>170.9</td>
<td>279.1</td>
</tr>
</tbody>
</table>

Notes: Formulary surplus $W(f)$ computations under different degrees of unobserved heterogeneity, holding fixed market outcomes.
Figure 7 Net Price Trends Around Competitor LOE (All Drugs)

Notes: A plot of the average net unit price trends of competitors around the first LOE event in the class. Source: SSR Health net price data from 2007-2018.

Figure 8 Evidence of Formulary Exclusions for Anti-Cholesterol Drugs (Part D)

Notes: Exclusion rate for Lipitor and Crestor in Medicare Part D plans, weighted by enrollment. Data is only available starting in 2008.
**Figure 9 Implied Quality Estimates**

*Notes:* A plot of the $\delta_{jk}$ coefficients from Equation (1), with generic Zocor and generic Lipitor qualities replacing their branded counterparts in the series once they enter. The data shows that Zocor has lower implied quality than Lipitor until its generic version enters. Both Lipitor and Crestor experience declines in implied quality once generic Zocor enters. This is because the fraction of diagnosed patients taking a drug stays steady, but generic Zocor begins to take market share from its competitors. Other quality fluctuations are driven by advertising campaigns and changes in medical evidence.
Figure 10 Additional Model Predictions - Formulary Design

Notes: Graphs capturing the equilibrium formulary distribution predicted by the model. The first plots the share of formularies in which each drug is in the non-preferred tier and the second plots the rate of exclusion for each drug. The predictions generally reflect trends found in the MarketScan data and industry reports: i) no exclusion in the early periods ii) Zocor is in the non-preferred tier at higher rates relative to Lipitor iii) after generic Zocor enters, higher copays and formulary restrictions are put on the remaining drugs.
Figure 11 Counterfactual prices without the boost to Zocor \((b_1 = 0)\).

Figure 12 Counterfactual prices in a market with no drug-specific inertia.
Figure 13 Insurance Coverage Type for Cholesterol Patients

Notes: A plot of the percentage of patients taking anti-cholesterol medication who are covered by each type of insurance (a small percentage are covered by multiple). Calculations based on MEPS data.

Figure 14 Difference in Derived Prices: Percentage vs. Constant Discount

Notes: A plot of the difference in derived prices under different assumptions about the discounts by dosage. The outcome variable is prices derived based on the assumption of constant percentage discount across dosages within a drug minus the prices derived based on a constant dollar discount.
Figure 15 Spending Under Different Demand Parameters ($bill)

Notes: A visualization of counterfactual spending (in $billions) under different demand parameters and a 33% coinsurance pricing structure.