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Amanda Starc
Ashley Swanson

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ABSTRACT

Selective contracting is an increasingly popular tool for reducing health care costs, but these savings must be weighed against consumer surplus losses from restricted access. In both public and private prescription drug insurance plans, issuers utilize preferred pharmacy networks to reduce drug prices. We show that, in the Medicare Part D program, drug plans with more restrictive preferred pharmacy networks, and plans with fewer enrollees who are insensitive to preferred pharmacy discounts on copays, pay lower retail drug prices. We then use estimates of plan and pharmacy demand to estimate the first-order costs and benefits of selective contracting in the presence of enrollees with heterogeneous sensitivity to preferred supplier incentives.

Amanda Starc
Kellogg School of Management
Northwestern University
2001 Sheridan Road
Evanston, IL 60208
and NBER
amanda.starc@kellogg.northwestern.edu

Ashley Swanson
The Wharton School
University of Pennsylvania
3641 Locust Walk
Philadelphia, PA 19104
and NBER
aswans@wharton.upenn.edu

1 Introduction

In this paper, we examine the effects of selective contracting by health insurers on prices and consumer access to providers. Intuitively, restrictive networks could help insurers reduce costs through three key mechanisms. Selective contracting could screen out unprofitable enrollees (Shepard (2016)), steer enrollees to low-cost pharmacies (Gruber & McKnight (2016), Prager (2017)), and/or give insurers additional leverage to negotiate discounts with pharmacies (Ghili (2018), Gowrisankaran et al. (2015), Ho & Lee (2017), Liebman (2018), Sorensen (2003)). Any cost savings may be mitigated by lack of enrollee sensitivity to cost sharing. Furthermore, consumers may prefer access to a broad set of providers, making them more likely to choose plans with less restrictive networks, even if those plans have higher premiums.

We quantify this trade-off in the Medicare Part D program, the federal prescription drug benefit for the elderly in the United States. The private firms offering Part D plans are heavily regulated and subsidized, but in general have both motive and opportunity to manage utilization and seek lower prices. Indeed, researchers examining the early rollout of Part D beginning in 2006 concluded that the program had a negative effect on average prices, due mainly to plans' use of formularies and other utilization management tools to steer enrollees to lower cost drugs and to negotiate lower prices with pharmaceutical manufacturers (Duggan & Scott Morton (2010)). More recently, Part D insurers have begun to use similar tactics in negotiation with pharmacies, by forming restrictive preferred pharmacy networks that exclude many local pharmacies. This paper is, to our knowledge, the first empirical analysis of pharmacy network contracting.

In Section 2, we describe the institutional details of the setting and document variation in prices for prescription medications purchased in the Medicare Part D program from 2011 to 2014. We provide results for both branded and generic drugs, but focus particular attention on the market for generic prescription drugs.[1] Drug prices are important for policy: in April 2015, the Kaiser Family Foundation found that "making sure that high-cost drugs for chronic conditions are affordable to those who need them" and "government action to lower drug prices" were the public's top two health cost priorities for President Barack Obama and Congress (Altman (2015)). Simultaneously, there has been significant consolidation at multiple points of the pharmaceutical supply chain (The Health Strategies Consultancy LLC (2005)), implying that price disper-

[1] We do this because the role of unobserved manufacturer rebates is less important in generic drug markets and therefore our estimates more likely reflect true price variation (Association for Accessible Medicines (2017)); PBMs are able to secure rebates of 5-25 percent for branded drugs (CMS (2016), The Health Strategies Consultancy LLC (2005)). Moreover, economists and policymakers have historically thought of generic drugs as a competition success story. Branded drugs have generally been targeted in policy discussions of drug pricing, and generic utilization is encouraged by both payers and policymakers. Indeed, 80 percent of prescriptions filled in $300b US market are generic today (IMS (2012), Thomas (2013)).

sion and growth will remain policy-relevant issues. Our most striking finding regarding prices is that there is significant price dispersion even within extremely narrowly-defined products and even within generic drugs; in 2011, the average coefficient of variation across pharmacy chains, within plan, was 0.30 for the same exact generic drug. This evidence of substantial generic price variation suggests that the issue of market power in generics be revisited, but generic drug prices receive little research or policy attention (see Berndt et al. (2017) for a recent exception and helpful review).

Section 2 also describes the rise of preferred network contracting and its impact on different enrollees' prices over this period. While only 13 percent of sample plans used preferred pharmacy networks in 2011, this rose to 70 percent in 2014. The copay differentials between preferred and non-preferred pharmacies ranged from \$6-\$8 per 30-day supply for the most popular plan formulary tiers, indicating that the incentive to use preferred pharmacies within preferred-network plans was substantial. However, these copay differentials did not generally apply for low-income subsidy (LIS) enrollees, who comprise about 30 percent of plan enrollment. For example, for LIS enrollees, the maximum copay was \$2.55 per 30-day supply for a generic drug in 2014: both preferred and non-preferred pharmacy copays generally exceed this maximum, effectively removing the copay differential and, in turn, the incentive to visit preferred pharmacies.

In Section 3, we briefly outline a model of bargaining between pharmacies and plans over prices, preferred network status, and in-network status. We use the model to motivate two reduced form empirical predictions. The first prediction is that plans with more restrictive pharmacy networks will be able to negotiate lower prices and will achieve further savings from enrollee steering. The second is that plans with copay-insensitive enrollees will capture limited savings from steering enrollees and will also negotiate higher prices.

To examine the first empirical prediction, Section 4 begins by estimating the impact of selective contracting between plans and pharmacies on prices. We determine the percent of Medicare-contracting pharmacies in each Part D region that appear in each plan's preferred pharmacy network, and analyze the extent to which more restrictive pharmacy networks impact prices.[2] We employ an instrumental variables specification based on heterogeneous diffusion of restrictive networks across issuers over time, and use different levels of fixed effects specifications to separately identify the effects of patient selection, steering, and negotiation. The estimates from the preferred specification indicate that a standard deviation increase in the

[2] This is similar in spirit to Sorensen (2003), in which selective contracting by managed care organizations is used to characterize MCOs' "steering ability": their ability to differentially channel enrollees across providers.

comprehensiveness of a plan's local preferred pharmacy network (27 percentage points) implies a 1.5-3 percent retail drug price increase. The coefficients are smaller but still significant after controlling for pharmacy fixed effects, suggesting that results are driven in part by restrictive plans steering enrollees to lower cost pharmacies and in part by restrictive plans extracting larger discounts from pharmacies.

To examine the second empirical prediction, Section 4 next examines drug prices across plans with high versus low percentages of low-income subsidy enrollees. The limited ability to steer these consumers is predicted to affect total drug costs as well as drug-specific negotiated prices. Using a causal identification strategy based on the institutional rules regarding auto-enrollment of LIS enrollees in the Part D program, we show that a standard deviation increase in the LIS share of enrollees (14 percentage points) leads to about an 8-9 percent increase in drug price. Specifications including pharmacy fixed effects have similar magnitudes, implying that the effect of LIS enrollment on drug prices cannot be attributed entirely to plans' differential ability to steer enrollees to low-cost pharmacies.

Having confirmed that the expected relationships among steering ability, preferred network contracting, and price hold true in the data on aggregate, Section 5 estimates models of demand to more clearly link the reduced form patterns to the mechanisms from the model. We allow for enrollees' preferences over pharmacies to depend flexibly on location, age, LIS status, and spending history. We focus our analysis of preferred network preferences on LIS status and spending history as a proxy for expected costs: as described previously, LIS enrollees are less exposed to pharmacy copay differentials, but we also note that very high-cost enrollees' *marginal* prices do not depend on preferred network status and thus that we might expect their preference for preferred pharmacies to be muted. First, we show that preferred status has a large positive effect on pharmacy demand, which is largest for non-LIS enrollees and relatively low cost enrollees – preferred pharmacies receive 8 percentage points greater market share among non-LIS enrollees (16 percent) due to preferred status alone. In contrast, LIS enrollees and very high-cost enrollees are less responsive to preferred status. Second, we demonstrate that plans face tradeoffs in setting the comprehensiveness of their networks: plans with more comprehensive preferred networks receive greater enrollment, all else equal, and the average enrollee is willing to pay an additional $82 annually for a unit increase in network comprehensiveness (approximately a standard deviation). Third, we simulate counterfactual spending and consumer surplus under networks that treat preferred and non-preferred pharmacies equivalently, in order to understand how policies that limit preferred network contracting would impact pharmacy costs. Due to subsidies and cost-sharing structures that limit enrollees' exposure to preferred pharmacy copay differentials, increased costs from moving to fully comprehensive preferred networks would be relatively small under the observed distribution of enrollees. On balance, the results imply that preferred network contracting saved \$9 per enrollee-year (1 percent annual savings for the average enrollee-year) in 2012-2014. This works out to approximately \$150 million in increased costs for preferred network plans during the same period. Finally, these modest cost increases are smaller than the consumer welfare benefits associated with moving to comprehensive preferred networks (\$16 per enrollee-year), given enrollees' revealed willingness to pay ex ante for network coverage.

This paper draws on and contributes to the literature on drug pricing as well as the literature on market power and bargaining. While the rising cost of branded drugs is the focus of much attention from economists, patient advocates, and policymakers (see, e.g., Howard et al. (2015)), the story of generic drug pricing has generally been a positive one – Scott Morton (1999) demonstrates that patent expiration has historically been followed by generic entry capturing half of molecule volume at prices 30-50 percent lower than the branded price. Researchers have argued that Part D has lowered the price of drugs by increasing insurer market power relative to that of drug manufacturers (Duggan & Scott Morton (2010)); these potential efficiencies, along with a shift toward generic drugs, have led to program costs lower than forecasted when this benefit was passed into law. This is not to say that Part D insurers act as perfect agents of enrollees, but rather that they are well-incentivized to reduce costs; as demonstrated by Ho et al. (2017), drug prices in Part D plans increased only about 2 percent between 2007 and 2010, but plan premiums grew by 62.8 percent. Finally, our paper is closely related to the relatively new literature on bilateral bargaining in health care markets – this literature articulates the important insight that demand intermediaries can exert competitive pressure in markets with price-insensitive end-users.[3]

[3]For example, Grennan (2013) estimates a model of bargaining between hospitals and medical device suppliers; and Capps et al. (2003), Sorensen (2003), Gowrisankaran et al. (2015), and Ho & Lee (2017) examine bargaining between insurers and hospitals. Some papers in this literature explore the nuances of bilateral hospital-insurer contracting when restrictive networks are possible in equilibrium, as they are in our pharmacy network setting: Shepard (2016) shows that restrictive networks can be used to select against high-cost enrollees. Ho & Lee (2018) and Ghili (2018) develop methods for estimating models of endogenous restrictive networks and show that restrictive networks can increase plans' bargaining leverage with respect to in-network enrollees. In closely related work, Gruber & McKnight (2016) show quasi-experimental evidence that state employees in Massachusetts who moved to limited network plans spent 40 percent less on medical care. Finally, Prager (2017) shows that plan networks with multiple hospital tiers can sensitize consumers' demand to cross-hospital cost variation and yield significant savings.

2 Medicare Part D and the Pharmaceutical Supply Chain

2.1 Setting

Medicare is a social insurance program providing health insurance to elderly Americans. Initially passed in 1965, the plan did not cover prescription drugs; a prescription drug benefit was added in 2003. Critically, the law authorizing this additional benefit – known as Medicare Part D – stipulated that prescription drug coverage be provided by private health insurers. As a result, enrollees are able to choose from dozens of plans offered in their local geographic markets. Nearly 41 million of the 57 million people on Medicare (71 percent) enrolled in a Part D plan in 2016 (Hoadley et al. (2016)).[4]

Though offered by private insurers, Part D is a government benefit and is strictly regulated by the federal Centers for Medicare and Medicaid Services (CMS). CMS mandates coverage generosity of plans in terms of actuarial value, types of drugs covered, and pharmacy network breadth. Enrollees are entitled to basic coverage of prescription drugs by a plan with equal or greater actuarial value to a standard Part D plan with a deductible, an initial coverage region with 75 percent coverage, another coverage gap (known as the "donut hole"), and a catastrophic region with 95 percent coverage.[5] The majority of Part D enrollees are not enrolled in standard plans, but rather in actuarially equivalent or "enhanced" plans with non-standard deductibles and tiered copays, so that cost-sharing varies across drugs and pharmacies.[6]

The private insurers participating in the Medicare Part D program are free to negotiate drug prices with drug manufacturers, distributors, and pharmacies.[7] While Medicare Part D plans must meet certain standards of coverage for their overall pharmacy networks, plans increasingly use preferred pharmacy networks in or-

[4]Medicare-eligible individuals can acquire prescription drug coverage through standalone Part D plans or can obtain drug coverage bundled with medical and hospital coverage in the form of "Medicare Advantage" plans. We limit our analysis to standalone Part D plans in this study, covering about 60 percent of enrollees.

[5]Prior to 2011, the donut hole in the standard plan involved no plan coverage of prescription fills. The ACA stipulated that the donut hole be filled in by 2020. The standard plan for the year 2014 had the following features: a deductible of $310; 75 percent coverage in the initial coverage region (up to $2,850 in total spending); 52.5 percent coverage of branded costs in the donut hole; and 95 percent coverage in the catastrophic region (above $6,455 in total spending).

[6]With copays, enrollees pay a flat fee out-of-pocket for each prescription; with coinsurance, enrollees pay a percentage of the total point-of-sale price. Part D issuers' revenues include premiums paid by enrollees, as well as several types of payments from CMS, which are about 90 percent of the plans' revenues in total (Decarolis (2015)): a risk-adjusted direct subsidy for each enrollee; a low-income subsidy to cover enrollees' premiums and cost-sharing; reinsurance covering 80 percent of drug spending above the catastrophic threshold; and "risk corridor" transfers such that the issuers' profits/losses are within certain bounds.

[7]For example, insurers can obtain "rebates" from manufacturers in exchange for preferred placement on insurer formularies. Essentially, pharmaceutical manufacturers give plans a discount in exchange for plans steering consumers to their drugs. In this study, we focus on the negotiation between insurers (or rather the pharmacy benefit managers (PBMs) acting as insurers' imperfect proxies) and pharmacies. While many studies of drug pricing have focused on manufacturers' market power, pharmacy companies are quite concentrated and increasingly so – five companies share 60 percent of prescription revenues, and Walgreens and Rite Aid abandoned plans to merge in 2017. See also Zhu & Hilsenrath (2014).

der to steer consumers to lower cost pharmacies and potentially negotiate lower overall reimbursements.[8] The pharmacy networks designed by plans in the Part D program may exclude independent pharmacies or entire pharmacy chains, so that enrollees will not be able to use plan coverage for prescription fills at those pharmacies. Alternatively, a pharmacy can be designated as preferred or non-preferred in a plan's network, where preferred status implies reduced out-of-pocket costs to enrollees. Critically, network adequacy standards do not apply to the *preferred* network, so *preferred* pharmacy networks can be much more restrictive than plans' overall networks. This distinction prompted CMS to investigate Part D preferred network coverage in 2015; the report found that plans' overall networks met or exceeded the statutory access standard, but one in ten preferred networks offered sufficient preferred pharmacy access to fewer than 40 percent of urban beneficiaries in their plans' service areas (CMS (2015*b*)).

Differential cost sharing can be used to steer consumers and in turn reduce costs, but also exposes enrollees to additional financial risk and reduced access. This may be harmful for low income consumers in particular; accordingly, approximately 30 percent of Part D enrollees (henceforth, "LIS enrollees") qualify for low-income subsidies, which entitles them to substantial reductions in premiums and out-of-pocket costs. LIS enrollees can enroll premium-free in "benchmark plans": plans for which premiums are below a market benchmark are eligible for auto-enrollment of LIS enrollees if they do not make an active plan choice.[9] CMS pays LIS enrollees' benchmark plan premiums, and plan sponsors receive monthly prospective payments from Medicare for LIS enrollees' estimated cost-sharing, which is later reconciled based on actual prescriptions filled. Critically, copays for LIS enrollees are low or zero: in 2014, the maximum copay for LIS enrollees prior to the catastrophic threshold was \$2.55 for generic drugs and \$6.35 for branded drugs. LIS enrollees tend to have high drug spending and are less likely to respond to copay differentials across drugs and pharmacies; nevertheless, they may be generally profitable for issuers.[10] About one-third of government expenditure on Part D is directly for LIS-related subsidies.

[8] CMS evaluates Part D retail pharmacy networks against standards established for the U.S. military's TRICARE programs: e.g., at least 90 percent of beneficiaries must reside within two miles of a network retail pharmacy. The analogous standards for suburban and rural areas are 90 percent within five miles, and 70 percent within fifteen miles, respectively. CMS (2015*a*) Throughout this draft, we distinguish preferred pharmacy networks from "overall pharmacy networks," which include preferred and non-preferred pharmacies in preferred-network plans.

[9] LIS enrollees may actively choose to enroll in non-benchmark plans and pay the differential between the plan premium and the benchmark premium. A plan may also voluntarily waive the portion of its premium that is a *de minimis* amount above the benchmark level and retain some additional auto-enrolled LIS enrollees.

[10] This reflects several countervailing factors. LIS enrollees' costliness is offset by risk-adjustment and the fact that they account for more spending in the catastrophic region, which is reinsured by CMS. Moreover, auto-enrollment implies that it may be "cheap" to acquire LIS enrollees (MedPAC (2016)), and Decarolis (2015) notes that plans were historically able to inflate the benchmark premium by offering multiple plans in each region.

Table 1: Price Summary Statistics

	2011			2014		
	Brand	Generic	All	Brand	Generic	All
Price	188.9	19.89	66.97	271.2	18.41	71.56
	(455.4)	(52.24)	(255.9)	(1002.1)	(56.83)	(473.6)
CV across j, w/in Brand	0.119	0.237	0.210	0.181	0.296	0.277
CV across H, w/in Brand	0.156	0.399	0.364	0.229	0.531	0.504
CV across j, w/in NDC	0.118	0.247	0.215	0.187	0.314	0.291
CV across H, w/in NDC	0.133	0.304	0.260	0.185	0.325	0.301
N	4,308,886	11,987,079	16,295,965	3,976,904	13,725,537	17,702,440

Notes: The number of observations is the number of NDC-plan-chain observations for each year-category. Pharmacy chains identified by the parent and relationship ID variables in the CMS pharmacy files. NDCs grouped into "Brands" using the brand name and generic name fields in the CMS prescription drug event files.

2.2 Data

We utilize data on prescription drug events, plan demand, pharmacy demand, plan characteristics, and pricing from CMS. We observe every prescription fill for the years 2011-2014 for a random 10 percent sample of all Medicare eligibles. We augment these data with additional information on plans' formularies, copays, premiums, and bids. Retail prices are calculated from the prescription drug event data as the total (enrollee plus plan) cost per day's supply.[11]

Table 1 describes the retail price variation in our sample in 2011 and 2014, collapsed to the national drug code (NDC)-plan j-pharmacy chain H-year level.[12] The vast majority of claims in the data are for generic, rather than branded, drugs, and that proportion is increasing over the time horizon we consider.

In the top row of Table 1, we summarize the distributions of price per 30 days supplied. There is substantial heterogeneity in drug prices, and the distribution of prices has a long upper tail within each year. The skewness of the price distribution is primarily driven by the long upper tail of branded drugs. The mean price of branded drugs is 9-15 times as large as that for generic drugs, which accounts for the disproportion-

[11] The total point-of-sale price we observe will be the sum of a fixed fee per prescription fill plus a fee for the specific drug. Each is subject to negotiation by a given pharmacy-plan pair.

[12] The NDC is a unique 10-digit identifier for human drugs in the United States. It uniquely identifies the labeler (roughly, the pharmaceutical manufacturer); the specific strength, dosage form (i.e, capsule, tablet, liquid) and formulation; and the package size and type. A given drug as defined by its brand name or generic name (e.g., atorvastatin calcium for treatment of cholesterolemia, or the original atorvastatin brand Lipitor) may have many associated NDCs.

ate policy attention given to the less-frequently prescribed branded drugs. However, we observe substantial price dispersion even within generic drugs: in 2011, the standard deviation of generic drug prices was \$52, relative to a mean price of \$20.

The Table also shows the weighted average coefficient of variation (standard deviation divided by the mean) of prices across plans j and pharmacy chains H, holding drug "Brand" (e.g., branded Lipitor or generic atorvastatin) or NDC fixed. The second and fourth rows show the coefficient of variation across plans within pharmacy chain and, respectively, Brand and NDC. The standard deviation of price across plans is 12-18 percent of the mean for branded drugs, versus 24-30 percent of the mean for generic drugs. The third and fifth rows show the coefficient of variation across pharmacy chains within plan and, respectively, Brand and NDC. For branded drugs, the coefficients of variation are a bit larger across chains than across plans: 13-16 percent versus 12 percent in 2011, and 19-23 percent versus 18-19 percent in 2014. This is also the case for generic drugs, but it bears noting that the "within Brand" price dispersion is much larger than the "within NDC" price dispersion, reflecting the fact that different pharmacy chains may stock different generic NDCs, potentially from different pharmaceutical manufacturers, within a given drug. Arguably, it is this "formulary power" that pharmacies have for generic drugs that enables them to make much larger margins on generic drugs than branded drugs (Sood et al. (2017)). To put these statistics in context, the coefficient of variation for prices charged by different hospitals is 0.32 for knee replacement and 0.4 for magnetic resonance imaging (Cooper et al. (2015)); and the average coefficient of variation across retail stores for common household goods is 0.18 (Scholten & Smith (2002)). Thus, there is economically meaningful price dispersion across both plans and pharmacy chains within truly homogeneous products, and even within the generic drug markets, where one might expect close to perfect competition.

To more concretely show how price dispersion persists even within narrowly defined product categories, Figure 1 describes two examples of the above phenomenon. First, in the top two panels, we display prices for Crestor, a popular branded statin drug for hyperlipidemia. Among all NDCs, there is evidence of price dispersion (the coefficient of variation is 0.34), and even within the most popular single NDC – 10mg of the drug packaged in a 90 day supply – the interquartile range in price per day supply is \$1.23 (the mean is \$5.15 and the coefficient of variation is 0.15). Among generics, there is even more dispersion in relative terms. In the bottom two panels, we display prices for levothyroxine, a popular drug used to treat hyperthyroidism. Among all NDCs, we see substantial variation, though the bimodal price distribution could reflect variation across products and manufacturers. However, when we restrict attention to the highest volume NDC – 50 microgram tablets, manufactured by Mylan – we still see substantial variation in prices across plans (the coefficient of variation is 0.40).

Table 2 describes the plans in our data. The first row indicates whether a given plan relied on preferred pharmacy networks; the proportion of plans with preferred networks increased from 13 percent in 2011 to 70 percent in 2014.[13] While we focus on selective contracting in Medicare Part D, it should be emphasized that commercial payers have begun to use narrow pharmacy networks in recent years as well; e.g., almost half of all employers had a narrow pharmacy network in 2016 (Fein (2017)). The next row shows a measure of pharmacy network coverage for each plan – this measure equals the percent of Medicare Part D-contracting pharmacies in a given plan's Part D region that are in the plan's preferred network.[14] The coverage rate of local pharmacies drops from 63 percent in 2011 to 35 percent in 2014. The rise of preferred networks and the narrowing of preferred networks implies significant growth in the prevalence of restrictive-network plans with fewer than 50 percent of local pharmacies preferred. The next row shows that the prevalence of restrictive networks grew from 22 percent in 2011 to 76 percent in 2014. A plan can have a restrictive preferred network either if it has a restrictive overall network (whether it relies on preferred network contracting or not) or if it only has a restrictive *preferred* network – 60 percent of preferred networks were restrictive in 2011, versus 99 percent in 2014. [15]

To provide more granular detail on this phenomenon, Table 12 in the Appendix displays transition matrices regarding retail chains' preferred status across all plans in 2012-2013. While chains C and D

[13]We classified each plan and retail pharmacy with non-zero claims as preferred versus non-preferred using both an "empirical" networks file and the CMS public use plan network files. The empirical networks file was created by analyzing the observed enrollee out-of-pocket cost for all claims for the initial coverage phase, for non-LIS enrollees, in fills that were for multiples of a 30-day supply, and that had a formulary tier assignment. We only analyzed observations where network status could potentially be detected (e.g., enrollee out-of-pocket cost < total retail cost). We compared out-of-pocket costs to copays for preferred and non-preferred retail pharmacies in the beneficiary cost files. We generated two "preferred" flags: (1) an indicator for the plan-pharmacy being flagged as preferred more often than not; and (2) a more conservative indicator that (a) there were at least 25 informative claims for the plan-pharmacy, (b) the plan-pharmacy had at least 5 "preferred" claims, and (c) the plan-pharmacy matched as "preferred" for at least 5 more claims than as "non-preferred." To combine the empirical and public use network files, we prioritized the more conservative empirical networks preferred flag, then the less conservative empirical networks preferred flag, then the public use flag. Where we have both empirical and public use network observations, they are consistent 99 percent of the time. Finally, we combine observations across pharmacies in the same retail chains: preferred status is consistent across pharmacy within plan-chain 99 percent of the time.

[14]Preferred network status is inferred by comparing observed copays for non-subsidized enrollees in the prescription drug event data to copays for preferred and non-preferred pharmacies in the beneficiary cost files. For plans without preferred networks, all pharmacies in the retail network are considered preferred.

[15]A natural question that arises is why plans began relying heavily on preferred network contracting only after 2011. A complete answer to this question is outside the scope of this paper, but we note several factors that may have been influential. First, early preferred network arrangements involved plan-pharmacy co-branding (e.g., The Humana Walmart-Preferred Rx Plan, introduced in 2011) (Snook & Filipek (2011), Hoadley et al. (2015)). Second, high-profile disputes between Walgreens and two large PBMs in 2010 and 2012 – CVS Caremark and Express Scripts – resulted in short-term removal of Walgreens from the PBMs' networks, during which the PBMs noted limited disruptive impacts of restrictive networks (Casey (2013)).

Figure 1: Drug Retail Price Variation

All NDCs | Most Common NDC

(Branded) Crestor

(Generic) Levothyroxine

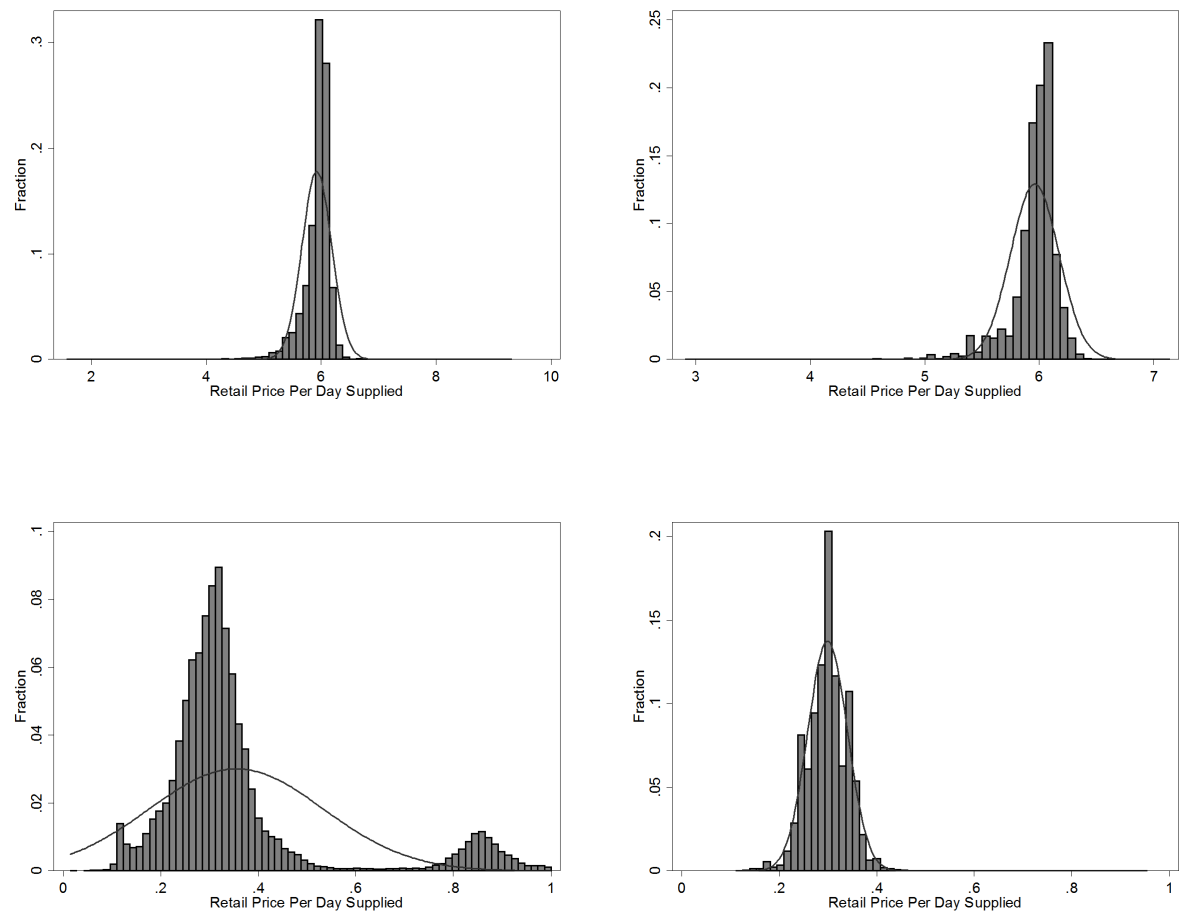


Table 2: Plan Summary Statistics

	2011	2012	2013	2014	Total
1{Preferred Network Plan} [N=4,186]	0.130	0.203	0.412	0.701	0.361
% Preferred [N=4,186]	0.633	0.623	0.505	0.351	0.528
	(0.229)	(0.249)	(0.266)	(0.236)	(0.271)
1{<50% Preferred} [N=4,186]	0.218	0.214	0.453	0.756	0.410
% LIS [N=4,186]	0.195	0.200	0.190	0.173	0.190
	(0.141)	(0.148)	(0.141)	(0.129)	(0.140)
Below Benchmark (Current Year) [N=4,186]	0.376	0.360	0.368	0.329	0.358
Below Benchmark 2009 [N=3,088]	0.234	0.244	0.246	0.261	0.244
Restrictive Plan, Avg. Spend [N=1,717]	3461.6	3234.0	3460.1	3677.2	3534.8
	(2510.3)	(1861.6)	(2578.1)	(1895.3)	(2177.8)
Restrictive Plan, Avg. Days Supply [N=1,717]	1512.6	1566.3	1662.3	1696.9	1645.4
	(540.1)	(469.5)	(411.3)	(423.7)	(449.6)
Non-Restrictive Plan, Avg. Spend [N=2,469]	3491.9	3681.5	3852.7	4610.9	3750.7
	(1129.7)	(1178.9)	(1261.8)	(1526.4)	(1264.0)
Non-Restrictive Plan, Avg. Days Supply [N=2,469]	1561.7	1679.7	1772.7	1738.0	1664.3
	(278.9)	(283.3)	(313.1)	(264.8)	(298.0)
Non-LIS Enrollees Avg. Spend	2486.9	2563.8	2699.1	2868.0	2653.4
	(1174.6)	(1365.0)	(2158.9)	(1849.6)	(1672.8)
Non-LIS Enrollees Avg. Days Supply	1434.3	1521.5	1591.1	1604.9	1536.0
	(402.7)	(398.7)	(441.3)	(490.4)	(440.2)
LIS Enrollees Avg. Spend	5191.8	5353.8	5474.3	5843.2	5463.2
	(2945.5)	(2632.7)	(2714.8)	(4016.5)	(3146.3)
LIS Enrollees Avg. Days Supply	1710.8	1862.4	1952.7	1848.3	1839.2
	(482.0)	(480.1)	(480.5)	(530.9)	(501.5)

Notes: Number of plan-year observations across 2011-2014 indicated for each plan-level variable.The "% Preferred" variable is calculated as the ratio of the count of preferred pharmacies in the plan's PDP region to the count of pharmacies in the same PDP region across all sample plans' preferred and non-preferred networks. LIS enrollees identified as those with any low-income cost-sharing subsidies in the prescription drug event data.

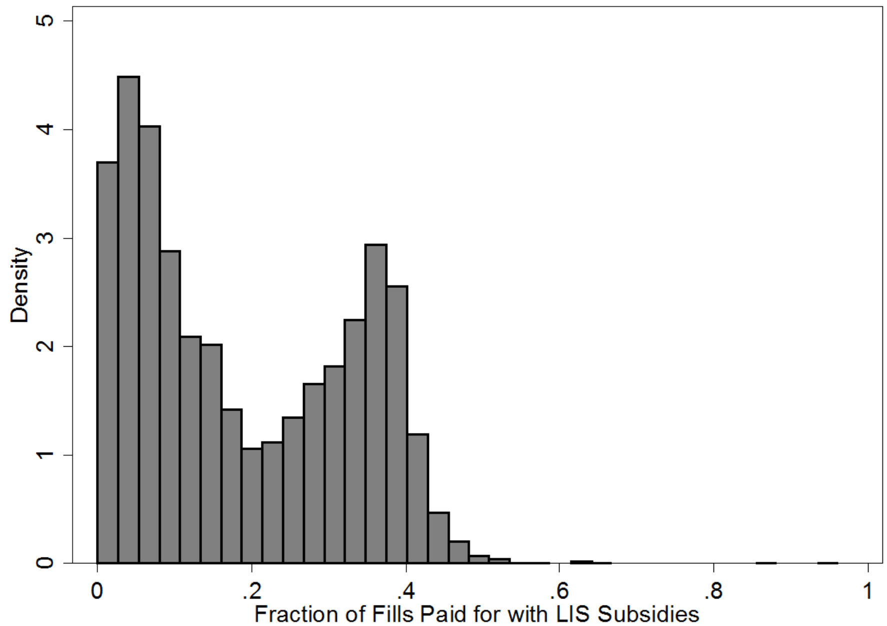
were preferred in over half of preferred-network plans in 2013, chain A was preferred in only 38 percent of plans and chain B in only 5 percent of plans. Preferred network status is fairly stable within plans across years, though there are notable exceptions. For example, chain A was dropped from 7 percent of preferred networks between 2012 and 2013, while chain C was added to 6 percent of preferred networks in the same time frame. We will leverage the variation in network generosity across plans in our reduced form analyses in Section 4.1; we will also rely on variation across plans in which chains are in the preferred networks in Section 5.

The next rows in Table 2 describe plans' coverage of LIS enrollees in our data. We construct the "% LIS subsidy" as the percentage of the plan's total drug bill paid for by the federal government in the form of cost-sharing subsidies for low-income consumers. While the average coverage of LIS enrollees is stable at around 17 to 20 percent of drug spending, this conceals considerable variation. Figure 2 shows that the distribution of this variable is bimodal; there are a set of plans with very few consumers eligible for these subsidies, and plans for which LIS subsidies represent a major component (nearly 40 percent) of reimbursements. Some of this heterogeneity is driven by variation in benchmark status, which we leverage in our identification strategy below. To be eligible for auto-enrollment of LIS beneficiaries, plans must have bids below a benchmark level. Table 2 also shows that approximately one-third of plans are below the benchmark.

Finally, Figure 3 summarizes the differences between preferred and non-preferred pharmacy copays by year and formulary tier. We focus on copays for drugs on tiers one through three of Part D plan formularies, as preferred copays are rarely used for higher drug tiers.[16] As expected, copays were increasing in formulary tier within each year as drugs become less and less preferred – the average tier one (three) preferred pharmacy copay was \$1 (\$43) over this time period. Second, the absolute differences in copays across preferred and non-preferred pharmacies were relatively flat across formulary tier, ranging from \$6 for tier one drugs to \$8 for tier three drugs in the average plan-year. Accordingly, relative copay differentials were often largest for tier one drugs, which were typically preferred generics. At an extreme, copays for tier one fills for preferred pharmacies were \$0 for 36 percent of preferred network plan-years, implying that the non-preferred pharmacy copays for tier one fills were infinitely higher. Finally, given the observed copays,

[16]High drug tiers are generally reserved for branded drugs, implying that variation in prices across pharmacy chains is smaller in relative terms. Moreover, another way for plans to steer enrollees is to charge enrollees a coinsurance rather than a copay. If there are significant price differentials across pharmacies (and enrollees are aware of these differences), then coinsurance may work just as well as copays; accordingly, coinsurance is generally used for enrollee cost-sharing for high-cost specialty drugs on formulary tiers five and six.

Figure 2: Histogram of "% of LIS Subsidy"



it is notable that preferred copay differentials were only relevant for LIS enrollees for tier one generic drug fills: as noted above, LIS enrollees faced maximum copays of $2.55 and $6.35 in 2014 (and in a similar range in earlier years).

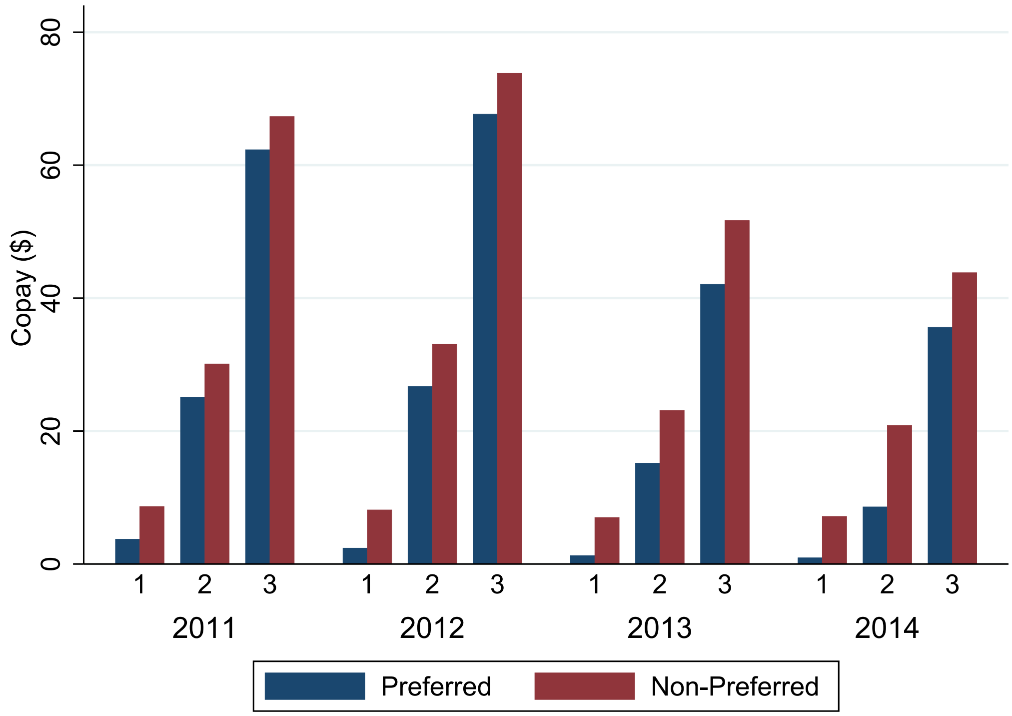
3 Preferred Network Contracting: Mechanisms and Predictions

Gatekeeping by insurers may increase or decrease total welfare; to understand the impact of preferred pharmacy networks, we must understand the incentives for insurers to offer such plans. As noted previously, selective contracting could reduce insurers' costs by selecting favorable enrollees, steering enrollees to low-cost providers, and/or providing leverage to negotiate lower prices. In this Section, we focus on the steering and bargaining mechanisms, and outline a model of pharmacy demand, plan demand, and bargaining.[17] The model largely follows the literature on insurer-hospital bargaining as in Ho & Lee (2017) and Gowrisankaran et al. (2015): negotiated prices are a Nash equilibrium of simultaneous bilateral Nash bargains and maximize the Nash product of the upstream (pharmacy) and downstream (plan) firms' gains from trade.

As described in detail in Appendix B, we generate empirical predictions using a model in which a set of

[17]We explicitly allow for rich consumer heterogeneity and selection in our demand estimates in Section 5.

Figure 3: Copays by Formulary Tier and Preferred Status



pharmacies bargains with a set of plans over network status and point-of-sale drug prices. Consistent with the institutional details of the setting, a given pharmacy-plan pair may be in the preferred network, in the non-preferred network, or out of network. Given pharmacy networks, premiums, copays, and other plan, individual, and market characteristics, each Medicare beneficiary chooses which plan to enroll in, if any. After enrolling in their Part D plans, individuals receive prescriptions from physicians and choose which pharmacy to frequent.

Both plans and pharmacies face important trade-offs in this negotiation. From the pharmacies' perspective, plans may steer additional consumer demand to a specific pharmacy or pharmacy chain in exchange for retail price discounts. From the plans' perspective, restrictive networks allow plans to steer consumers to lower cost pharmacies, and the threat of exclusion could lead to a lower negotiated price at a given pharmacy; however, if consumers have a strong tastes for broad networks, narrower networks will reduce enrollment. These mechanisms rely on consumer demand being responsive to differential copays; this may not be true if a large subset of consumers is insulated from cost sharing.

The Appendix presents a formal description of the Nash bargaining solution. In short, the model illustrates that the price negotiated between a given pharmacy and plan is mediated by several factors, similar to those presented in detail in Ho & Lee (2017). These are: the plan's relative bargaining power; the pharmacy's ability to "recapture" volume from other plans when the pharmacy's network status changes; a "premium effect" capturing plan premium revenue lost if enrollees re-sort when the pharmacy's network status changes; a "price reinforcement" effect resulting from strategic complementarity of competing pharmacies' prices; and finally, a "preferred capture effect" embodying the change in the pharmacy's volume if it loses preferred-network status.[18]

For our purposes, the theory provides two key predictions for how the threat of exclusion will impact drug prices over and above those achieved directly by steering enrollees to cheaper pharmacies. First, plans with more restrictive networks are expected to have larger preferred capture effects (similar to Sorensen (2003)) and smaller price reinforcement effects, each of which implies lower negotiated prices. Second, plans with more "copay-sensitive" enrollees are expected to have larger preferred capture effects and, in turn, lower negotiated prices with preferred network pharmacies.[19] LIS enrollees are unlikely to respond to preferred/non-preferred pharmacy copay differentials, so that LIS enrollment will limit the cost-savings available with preferred networks.

4 Reduced Form Analyses of Price Levels

In this Section, we use Medicare pricing data to test the two key empirical predictions outlined above. First, we estimate the effect of plans' network comprehensiveness on prices. Second, we examine the effect of coverage of low-income subsidy enrollees on negotiated prices.

4.1 Prices and plan network generosity

The model predicts that plans with high usage of selective contracting will be able to obtain lower prices for drugs. In this Section, we examine the relationship between network restrictiveness and the level of retail

[18]The key distinctions between our model and that in Ho & Lee (2017) are that we model both preferred and non-preferred prices, and that the preferred price is a function of the "preferred capture" effect.

[19]The preferred capture effect is an equilibrium artifact – it will be higher if enrollees are more sensitive to copay differentials between preferred and non-preferred pharmacies.

prices. We estimate specifications of the following type:

$$ln\left(p_{djhq}\right) = \alpha + \beta * \%Pref_{jq} + \mathbf{X}'_{djhq}\gamma + \varepsilon_{djhq}.$$

In this equation, our coefficient of interest is β, which represents our estimate of the average impact of having more local pharmacies in a plan's preferred network on negotiated prices. We also allow for specifications in which the percentage preferred enters nonlinearly. We model drug prices at the plan-quarter-pharmacy-NDC level, and all specifications include quarter fixed effects. We also show specifications that include fixed effects for NDC, pharmacy and, in some cases, issuer.[20]

Table 3 shows several different versions of the effect of selective contracting. In this Table, each number shown is the result of a separate regression of log price on a particular sample (Panel A: All Drugs; versus Panel B: Generic Drugs only), with a particular set of fixed effects (different columns), and with a different right-hand-side variable proxying for comprehensiveness (different rows within each panel).

First, we focus on the top row in each panel, in which network size is measured as "% Preferred." Column (1) shows that negotiated prices are increasing in the percent of local pharmacies in a plan's preferred network; the standard deviation of this measure in our sample is 27 percentage points, so the estimated coefficient of 0.324 (0.205 for generic drugs only) implies that a standard deviation increase in pharmacy coverage increases price by 9 percent (6 percent for generics only). However, column (1) controls only for quarter fixed effects; it does not account for the potential that plans with more restrictive pharmacy networks attract healthier enrollees taking cheaper drugs. In Table 2, we see that plans with less than 50 percent of pharmacies preferred enroll beneficiaries with lower utilization (an average 1,645 days supply or $3,535 in total drug spending per year, which is slightly lower than the 1,664 days supply ($3,751) observed for non-restrictive plans).

To address this, column (2) includes NDC fixed effects, so that we now examine the association between pharmacy network breadth and pricing for a narrowly-defined product. This reduces the coefficient substantially – within NDC, a standard deviation increase in preferred network size is associated with a price increase of about 3 percent. Column (3) adds pharmacy fixed effects; the coefficient on network coverage is cut roughly in half, implying that a standard deviation in preferred network size is associated with a price

[20] In the foregoing, we will generally use the terms "contract" and "issuer" interchangeably – e.g., Humana or United.

Table 3: Correlation between Network Generosity and Retail Prices

Dependent Variable: log(Retail Price / Days Supply)						
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: All Drugs			
% Preferred	0.324***	0.0928***	0.0500***	0.184***	0.0733***	0.0468***
	(0.0402)	(0.0144)	(0.0110)	(0.0278)	(0.0111)	(0.0103)
1{<50% Preferred}	-0.215***	-0.0561***	-0.0267***	-0.123***	-0.0393***	-0.0249***
	(0.0262)	(0.00965)	(0.00754)	(0.0160)	(0.00736)	(0.00702)
1{Top Quartile	0.162***	0.0417***	0.0170***	0.0926***	0.0347***	0.0186***
% Preferred}	(0.0227)	(0.00863)	(0.00644)	(0.0118)	(0.00475)	(0.00461)
N	126,833,815	126,831,388	126,830,879	126,833,815	126,831,388	126,830,879
			Panel B: Generic Drugs			
% Preferred	0.205***	0.106***	0.0532***	0.136***	0.0827***	0.0518***
	(0.0278)	(0.0169)	(0.0130)	(0.0185)	(0.0128)	(0.0120)
1{<50% Preferred}	-0.142***	-0.0630***	-0.0266***	-0.0869***	-0.0440***	-0.0270***
	(0.0176)	(0.0113)	(0.00880)	(0.0111)	(0.00848)	(0.00812)
1{Top Quartile	0.0944***	0.0476***	0.0177**	0.0634***	0.0392***	0.0207***
% Preferred}	(0.0157)	(0.0104)	(0.00773)	(0.00752)	(0.00559)	(0.00544)
N	100,115,691	100,114,477	100,113,944	100,115,691	100,114,477	100,113,944
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
NDC FE	No	Yes	Yes	No	Yes	Yes
Pharmacy FE	No	No	Yes	No	No	Yes
Contract FE	No	No	No	Yes	Yes	Yes

Notes: Each coefficient is estimated $\hat{\beta}$ from a separate regression of $ln(p_{djhq})$ on a proxy for network comprehensiveness (% Preferred, 1{<50% Preferred}, or 1{Top Quartile % Preferred}), for a given sample (All Drugs or Generic Drugs Only) and fixed effects specification (Quarter, NDC, Pharmacy, and Contract fixed effects are included in the richest specification). Standard errors clustered by plan reported in parentheses.

increase of about 1.4 percent. Thus, about half of the association between restrictive networks and prices exists within pharmacy.

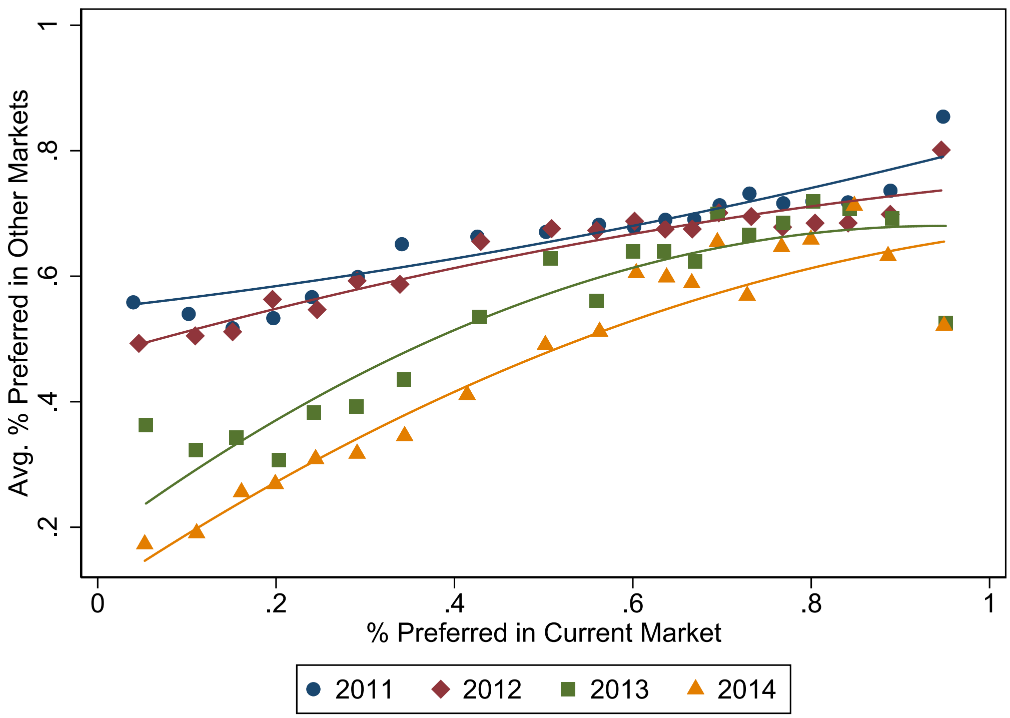
Columns (4)-(6) estimate the same specifications as in columns (1)-(3), but with the addition of contract fixed effects. These specifications control for unobserved, time-invariant differences across issuers in their ability to negotiate prices and/or steer enrollees. Column (4) estimates a significantly smaller effect than column (1) – i.e., some of the raw correlation between network size and prices is due to unobserved differences across issuers. However, columns (5) and (6) are similar to (2) and (3), indicating that within-issuer variation in preferred network size is significantly associated with retail prices.

The second and third rows in each panel show nonlinear versions of this result in both absolute and relative terms (recall that we saw previously that average network restrictiveness is increasing over 2011-2014). In the second row, we estimate that plans with "restrictive networks," defined as those covering less than 50 percent of local pharmacies, have 4-6 percent lower prices, conditional on NDC fixed effects (columns (2) and (5)); to put this in perspective, recall that 41 percent of plans covered less than 50 percent of local pharmacies in 2011-2014 overall, versus 76 percent in 2014. Columns (3) and (6) show that about half of this association remains when we add pharmacy fixed effects. The third row shows that plans in the top 25 percent of plans in terms of network coverage *within a given year* (82 percent of local pharmacies covered on average in 2011-2014, and 71 percent in 2014 alone) negotiate 3-5 percent higher prices than plans in the bottom 75 percent. This decreases to about 2 percent when we include pharmacy fixed effects.

One potential concern with these OLS specifications is that selective contracting may be endogenous; for example, plans that are for unobservable reasons better able to negotiate favorable discounts with local pharmacies may also be better able to construct high-quality limited pharmacy networks. In alternative specifications, we use general trends in selective contracting over time, which are borne out differentially across geographic regions, to provide plausibly exogenous variation in selective contracting across plan-years. We argue that network comprehensiveness is a strategic decision taken at the issuer-year level (based, perhaps, on issuer-time-varying factors that impact average prices), but that price negotiations for a given contracting organization and year vary across markets due to plausibly exogenous factors such as the pre-existing geographic footprint of pharmacy chains. Motivated by this reasoning, we present analyses in which we instrument for network coverage in a given issuer-year-region using that same issuer-year's average network coverage (weighted by enrollment) across *other regions*.

The first stage of this identification approach can be seen visually in Figure 4, which shows a binned

Figure 4: Correlation in Generosity across Markets within Contract-Year



scatterplot of the instrumental variable (weighted average percent of networks that are preferred in all other markets, within the same issuer-year) versus the potentially endogenous variable of interest (percent of networks that are preferred by the issuer in the current market). This is shown separately for each year. First, we observe a general trend toward more selective contracting (fewer pharmacies preferred) over time. Second, Figure 4 shows that this trend is correlated within issuer-year: within each year 2011-2014, there is a significant positive correlation between current-market preferred network size and preferred network size in other markets, within the same issuer.

This relationship can be seen more formally in the first row in each panel of Table 4, which shows the linear first stage relationship between our variable of interest (percent of local pharmacies preferred) and our instrument (weighted average percent of pharmacies preferred in other markets for the same issuer-year). Different columns show the results for different fixed effects specifications as in Table 3 above. In all cases, the first stage relationship is highly significant and close to one-for-one.

The second and third rows in each panel show the reduced form and two-stage least squares results, respectively. The results, including those that include contract fixed effects to control for potential differences

Table 4: Impact of Network Generosity on Retail Prices

Dependent Variable: log(Retail Price / Days Supply) Endogenous Variable: % Preferred Excluded Instrument: % Preferred (Same Contract-Year, Other PDP Regions)						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Drugs						
First Stage	1.099***	1.090***	1.075***	0.959***	0.959***	0.956***
	(0.0474)	(0.0464)	(0.0417)	(0.0268)	(0.0264)	(0.0255)
Reduced Form	0.375***	0.109***	0.0649***	0.0784***	0.0484***	0.0318*
	(0.0500)	(0.0238)	(0.0205)	(0.0198)	(0.0166)	(0.0165)
2SLS	0.342***	0.100***	0.0604***	0.0818***	0.0505***	0.0332*
	(0.0445)	(0.0204)	(0.0183)	(0.0198)	(0.0170)	(0.0170)
N	117,540,139	117,537,756	117,537,237	117,540,139	117,537,756	117,537,237
Panel B: Generic Drugs						
First Stage	1.111***	1.103***	1.086***	0.958***	0.958***	0.956***
	(0.0473)	(0.0463)	(0.0415)	(0.0263)	(0.0259)	(0.0250)
Reduced Form	0.247***	0.128***	0.0726***	0.0699***	0.0533***	0.0352*
	(0.0379)	(0.0282)	(0.0241)	(0.0191)	(0.0188)	(0.0187)
2SLS	0.223***	0.116***	0.0668***	0.0730***	0.0556***	0.0368*
	(0.0324)	(0.0240)	(0.0213)	(0.0194)	(0.0192)	(0.0193)
N	92,897,092	92,895,922	92,895,377	92,897,092	92,895,922	92,895,377
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
NDC FE	No	Yes	Yes	No	Yes	Yes
Pharmacy FE	No	No	Yes	No	No	Yes
Contract FE	No	No	No	Yes	Yes	Yes

Notes: Table reports estimated first stage, reduced form, and two-stage least squares coefficients for the dependent variable $ln(p_{djhq})$, endogenous variable "% Preferred", and instrument "% Preferred (Same Contract-Year, Other PDP Regions)", for each sample (All Drugs or Generic Drugs Only) and fixed effects specification (Quarter, NDC, Pharmacy, and Contract fixed effects are included in the richest specification). Standard errors clustered by plan reported in parentheses.

across contracting organizations in their ability to negotiate with pharmacies, are similar to our OLS results above. The results with NDC fixed effects (columns (2) and (5)) indicate that a standard deviation increase in network size implies a causal increase in price of 1.5-3 percent. The results with NDC and pharmacy fixed effects (columns (3) and (6)) shrink this effect to 1-1.8 percent. Results are similar for all drugs and for generic drugs only. Point estimates are generally smaller when we include contract fixed effects, suggesting the importance of controlling for time-invariant differences across issuers even in this instrumental variables specification; however, the difference between specifications with and without contract fixed effects tend not to be statistically significant.

The above analyses indicate that plans with larger preferred networks pay significantly higher prices, and that this relationship is causal. Also, we found that about one-half to two-thirds of the estimated effects of network size on price persist within pharmacy and thus can be explained by the impact of threat of exclusion on negotiated prices. The remainder can be explained by the effects of steering, though standard errors are large and limit our ability to precisely isolate steering and "threat of exclusion" effects.

4.2 Prices and steering

Given the model described in the previous Section, we hypothesize that patient cost-sharing subsidies will reduce the price sensitivity of the ultimate consumers of drugs. Therefore, the "supply side" of the market (which includes manufacturers, wholesalers, and pharmacies) will be able to command higher prices for drugs. We now turn to documenting this fact and providing causal evidence linking subsidies to higher drug prices. Specifically, we estimate the effect of the presence of LIS subsidies on retail prices, using specifications of the following type:

$$ln\left(p_{djhq}\right) = \alpha + \beta * \% LIS_{jq} + \mathbf{X}'_{djhq}\gamma + \varepsilon_{djhq}.$$

In this equation, our coefficient of interest is β, which represents our estimate of the average impact of the presence of inelastic LIS consumers on negotiated prices. We also estimate a specification in which the fraction of LIS enrollees enters nonlinearly. As before, we model drug prices at the plan-quarter-pharmacy-NDC level. All specifications include quarter fixed effects.

Table 5 describes the correlation between LIS coverage and price in several ways; in this Table, each number shown is the result of a separate regression of log price on a particular sample (Panel A: All Drugs;

versus Panel B: Generic Drugs only), with a particular set of fixed effects (different columns), and with a different right-hand-side variable proxying for LIS enrollment (different rows within each panel). In the first row of each panel, we show the association between price and our measure, by plan, of the percent of drug spending that is covered by LIS cost sharing subsidies. This measure ranges from 0 percent (no LIS beneficiaries) to 96 percent, depending on the plan; the mean across plan-years in our data is 19 percent. Column (1) shows that the higher this measure of exposure to LIS enrollees is, the higher the average negotiated drug price. The coefficient of 0.917 (0.533 for generics) implies that a standard deviation increase in this measure (14 percentage points) would increase the price of the average drug by 13 percent (7 percent for the average generic drug). However, LIS enrollees tend to be sicker – in Table 2, we see that LIS enrollees have $5,500 in annual drug spending, versus $2,700 for non-LIS enrollees. Some of this may of course be accounted for by the mechanism of interest – the inability to steer LIS enrollees – but LIS enrollees also consume more prescriptions per year, averaging 1,800 days supply (versus 1,500 for non-LIS enrollees).[21]

To account for both selection and manufacturer market power, column (2) includes NDC fixed effects, so that we now examine the association between LIS coverage and pricing for a narrowly-defined product, and holding the pharmaceutical manufacturer fixed. Inclusion of NDC fixed effects reduces the magnitude of the coefficient substantially, to 0.15-0.16, now implying that a standard deviation increase in LIS coverage is associated with a small, but statistically significant, 2 percent increase in price. We next control for pharmacy fixed effects – by comparing columns (2) and (3), we can distinguish between LIS enrollees' use of high-cost pharmacies (column (2)) and a tendency of plans covering many LIS enrollees to pay higher prices within pharmacy (column (3)). In column (3), the association between "% LIS" and price becomes negative and insignificant, indicating that the positive correlation between LIS coverage and price does not hold within pharmacy. Column (4) further controls for contract fixed effects and thus isolates variation in the number of LIS beneficiaries across plan-years within a given issuer – the results are similar to the third column, though with more precise standard errors.

There is, of course, no reason to believe that the relationship between LIS exposure and retail prices

[21] Moreover, LIS enrollees are insulated from copay differentials across pharmacies and across drugs (with the exception of the brand-generic distinction in the maximum LIS copay) – insurers' inability to steer LIS enrollees to inexpensive drugs may increase prices set by pharmaceutical manufacturers. The larger relative magnitude of this coefficient for all drugs versus generics may be consistent with the latter mechanism.

Table 5: Impact of LIS Enrollees on Retail Prices, OLS

Dependent Variable: log(Retail Price / Days Supply)				
	(1)	(2)	(3)	(4)
Panel A: All Drugs				
% LIS Subsidy	0.917***	0.152***	-0.0391	-0.0494***
	(0.0891)	(0.0427)	(0.0334)	(0.0186)
1{Top Quartile % LIS}	0.185***	0.0334***	-0.00217	0.00276
	(0.0233)	(0.0120)	(0.00910)	(0.00618)
N	126,833,835	126,831,408	126,830,899	126,830,899
Panel B: Generic Drugs				
% LIS Subsidy	0.533***	0.164***	-0.0631	-0.0640***
	(0.0639)	(0.0516)	(0.0401)	(0.0208)
1{Top Quartile % LIS}	0.120***	0.0391***	-0.00342	0.00486
	(0.0182)	(0.0149)	(0.0113)	(0.00740)
N	100,115,711	100,114,497	100,113,964	100,113,964
Quarter FE	Yes	Yes	Yes	Yes
NDC FE	No	Yes	Yes	Yes
Pharmacy FE	No	No	Yes	Yes
Contract FE	No	No	No	Yes

Notes: Each coefficient is estimated $\hat{\beta}$ from a separate regression of $ln(p_{djhq})$ on a proxy for LIS coverage (% Preferred or 1{Top Quartile % LIS}), for a given sample (All Drugs or Generic Drugs Only) and fixed effects specification (Quarter, NDC, Pharmacy, and Contract fixed effects are included in the richest specification). Standard errors clustered by plan reported in parentheses.

would be linear. To capture potential non-linearities, the second row in each panel of Table 5 instead analyzes the association between drug price and a dummy for the top quartile of LIS exposure; we report the effect of being in the top quartile of plans in terms of LIS coverage as compared to the first through third quartiles. The patterns here largely mimic those in the first row of each panel. Plans in the top quartile of LIS coverage pay 12-18 percent higher prices, but this figure drops to 3-4 percent within NDC. As before, the results shrink to zero and (in some cases) become negative with the inclusion of pharmacy fixed effects.

One potential concern is that factors associated with high LIS enrollment in particular plans are not captured adequately by our controls. This concern is mitigated by focusing on price variation within a well- and narrowly-defined product (the NDC). However, plans that choose to "specialize" in LIS enrollees may be more or less able to extract discounts from pharmacies for a variety of reasons.[22] To account for this potential issue, we next use the structure of the LIS program to generate variation in the level of subsidies across plans.

To illustrate this identification strategy, we compare plans with bids above (not eligible for LIS auto-assignment) and below (eligible for LIS auto-assignment) the benchmark amount. Because of LIS auto-assignment, bidding below a benchmark amount will lead to a large influx of price insensitive consumers. Figure 5 shows that the fraction of drug spend covered by LIS subsidies changes discontinuously as one moves across the discontinuity at the benchmark.[23] We hypothesize that this will also increase the retail prices paid by plans.

To explore this hypothesis, we next plot a binscatter of the prices for the cholesterol-lowering statin Crestor (one of the most popular drugs within the Part D program) as a function of bids relative to the benchmark. Figure 6 shows a discontinuous drop in retail prices for Crestor as one crosses the benchmark, which, as shown above, corresponds to a decrease in the number of LIS beneficiaries (and associated sales) within a plan.

Of course, it is not necessarily suprising that branded manufacturers have the ability to price discriminate based on plan demographics.[24] However, Figure 6 also shows a similar discontinuous price drop for generic

[22]For example, given the potential profitability of LIS enrollees noted by Decarolis (2015), savvy issuers that are particularly successful at attracting LIS enrollees might also be particularly successful at negotiating lower drug prices.

[23]The relationship would be even more pronounced absent the *de minimis* policy, which "allows full premium subsidy eligible beneficiaries to remain enrolled in these plans and essentially pay a zero Part D premium." (See https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/MemoDeMinimisClarification_102706.pdf for more information.) This policy implies that the bin just to the right of the "discontinuity" includes some plans allowed to continue auto-enrollment. As a result, some of our instrumental variables estimates discussed below are from a fuzzy regression discontinuity design.

[24] Appendix Figure 9 shows a similar pattern for another statin, atorvastatin (Lipitor); unlike Crestor (rosuvastatin calcium),

Figure 5: Effect of Benchmark on LIS Enrollment

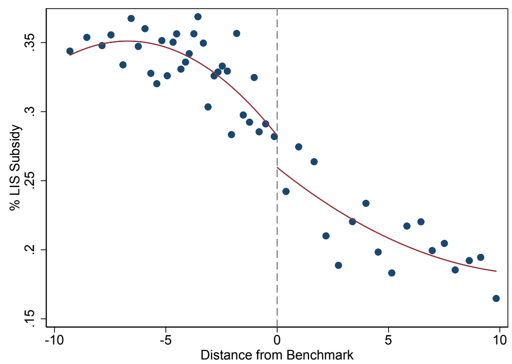
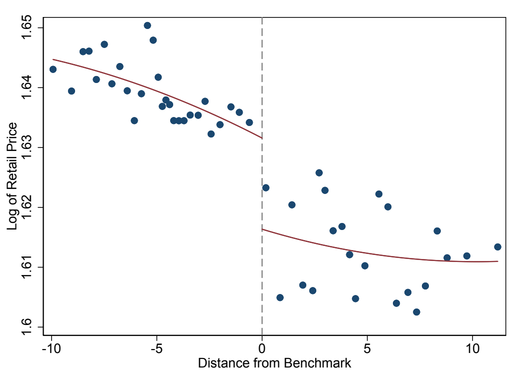
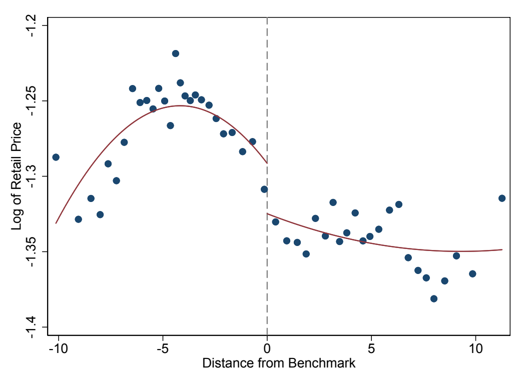


Figure 6: Effect of Benchmark on Crestor and Levothyroxine Prices

(a) Crestor



(b) Levothyroxine



levothyroxine, a hypothyroidism drug and was the second most prescribed drug within the Medicare Part D program.[25]

To operationalize this identification strategy, we instrument for "% LIS" in our specifications above using benchmark bidding. Contemporaneous benchmark bidding may not satisfy the exclusion restriction: to the extent that the benchmark is (even imperfectly) known in advance, firms could strategically choose to be above or below the benchmark, and this choice could be correlated with other factors influencing negotiated prices. To address this issue, we examine the impact of being just below the *2009* benchmark.[26] Given the substantial level of inertia exhibited by consumers in this market (Ho et al. (2017)), this variable will predict the level of LIS subsidies within a plan two to five years later. In all specifications, we also include quadratic controls for the difference between the bid and the benchmark. Finally, in some specifications, we narrow in on the key variation of interest (the discontinuity introduced by the benchmark) and identify the effect of LIS enrollment using variation from plans with bids within \$4 of the benchmark, where \$4 is the optimal bandwidth from Ericson (2014).

Table 6 presents the first stage, reduced form, and two-stage least squares estimates for this instrumental variables strategy. As before, Panel A shows results for all drugs, Panel B for generics only. Given that our instrument based on 2009 benchmark status is cross-sectional, we omit contract fixed effects from these specifications, but again include specifications with quarter fixed effects only (columns (1)-(2)), quarter and NDC fixed effects (columns (3)-(4)), and quarter, NDC, and pharmacy fixed effects (columns (5)-(6)). The first row in each panel shows that 2009 benchmark status leads to roughly a 7-10 percentage point increase in LIS enrollment in 2011-2014; results are larger when we focus on a narrow bandwidth around the benchmark discontinuity. The second row in each panel shows the reduced form effect of prior benchmark status on contemporaneous prices. The results show that being just below the 2009 benchmark leads to 12-23 percent higher retail prices, with the lower range pertaining for generics. However, as with the OLS results, we are concerned about this being driven by LIS enrollees' higher latent drug needs or steering of LIS enrollees

atorvastatin had generic substitutes available for much of our sample period.

[25]The most popular drug by claim count, lisinopril, a blood pressure drug, experienced a number of voluntary recalls during our sample period.

[26] In 2009, the formula used to calculate benchmarks was modified and the transition to enrollment-based benchmarks was completed (Decarolis (2015)), making it more difficult for firms to "game" the benchmark.

Table 6: Impact of LIS Enrollees on Retail Prices, OLS

Dependent Variable: log(Retail Price / Days Supply)
Endogenous Variable: % LIS Subsidy
Excluded Instrument: 1{Below 2009 Benchmark}

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Drugs						
First Stage	0.0763***	0.109**	0.0723***	0.105**	0.0625***	0.0706***
	(0.0187)	(0.0520)	(0.0184)	(0.0493)	(0.0126)	(0.0269)
Reduced Form	0.195***	0.226***	0.0401**	0.0669*	0.0259*	0.0524**
	(0.0398)	(0.0865)	(0.0186)	(0.0392)	(0.0148)	(0.0257)
2SLS	2.560***	2.077***	0.555**	0.639**	0.414*	0.743*
	(0.568)	(0.625)	(0.252)	(0.313)	(0.250)	(0.395)
N	107,553,009	46,771,244	107,550,667	46,768,922	107,550,156	46,768,185
Panel B: Generic Drugs						
First Stage	0.0766***	0.113**	0.0726***	0.109**	0.0627***	0.0725***
	(0.0193)	(0.0535)	(0.0190)	(0.0507)	(0.0128)	(0.0275)
Reduced Form	0.125***	0.142**	0.0497**	0.0799*	0.0298	0.0610*
	(0.0288)	(0.0645)	(0.0228)	(0.0471)	(0.0182)	(0.0311)
2SLS	1.625***	1.261***	0.685**	0.735**	0.475	0.841*
	(0.398)	(0.439)	(0.310)	(0.368)	(0.306)	(0.464)
N	84,275,580	36,741,753	84,274,404	36,740,635	84,273,855	36,739,814
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
NDC FE	No	No	Yes	Yes	Yes	Yes
Pharmacy FE	No	No	No	No	Yes	Yes
Sample	Full	w/in $4	Full	w/in $4	Full	w/in $4

Notes: Table reports estimated first stage, reduced form, and two-stage least squares coefficients for the dependent variable $ln(p_{djhq})$, endogenous variable "% LIS Subsidy", and instrument "1{Below 2009 Benchmark}," for each sample (All Drugs or Generic Drugs Only) and fixed effects specification (Quarter, NDC, and Pharmacy fixed effects are included in the richest specification). Results shown separately for full sample and $4 window around benchmark. Standard errors clustered by plan reported in parentheses.

across drugs.[27] Indeed, when we include NDC fixed effects, these magnitudes decrease to 4-8 percent. Finally, we continue to see a positive and usually significant reduced form effect of benchmark status on prices when we include pharmacy fixed effects.

The last row in each panel of Table 6 presents the results of the two-stage least squares specifications. Our results are much larger in the first set of specifications (excluding NDC fixed effects), as we saw in the reduced form. Once we include NDC fixed effects, the results are consistent across the remainder of the specifications shown, and do not differ significantly between "All Drugs" and "Generics Only." Focusing

[27] These would still be causal effects, but would not be driven by the mechanism of interest – steering of enrollees across pharmacies.

on all drugs, the results imply that a standard deviation in LIS share leads to a 8-9 percent increase in retail prices for a given drug. The 2SLS estimates are larger in magnitude than the OLS results, indicating downward bias in the OLS results.[28] Notably, in the 2SLS specification, the results with pharmacy fixed effects are similar to the results without, implying a 6-10 percent increase in price associated with a standard deviation increase in LIS share.

These results provide evidence of suppliers in this market extracting higher retail prices from plans with larger numbers of price-insensitive enrollees. Notably, the results of the two-stage least squares specifications remain positive and generally significant when we include controls for pharmacy fixed effects. That is, the positive causal effect of LIS enrollment on drug prices cannot be attributed entirely to enrollees using more expensive pharmacies, though the size of confidence intervals limits our ability to decompose price differences into a steering effect and a threat of exclusion effect. Together with the network results, these results are strongly consistent with the mechanism of interest – that high LIS enrollment limits plans' ability to extract discounts from particular pharmacies using preferred pharmacy networks. However, it is still possible that the LIS results are driven by, for example, an effect of LIS enrollment on plans' negotiations with manufacturers for particular drugs. In the next Section, we tie these results together explicitly by demonstrating the effect of preferred networks on LIS and non-LIS enrollees' demand for pharmacies. We also use plan demand analysis to analyze the welfare impacts of restrictive networks.

5 Demand Models and Counterfactuals

Our approach uses plausibly exogenous variation across plans and geographic areas to explore the impact of steering by insurers on drug prices. Gruber & McKnight (2016) find that limited network plans generate large savings on medical care, while Prager (2017) finds savings from tiered hospital plans of 8-12 percent, depending on the policy experiment. We build on these findings in the context of prescription drug insurance, and focus explicitly on a key prediction from theory: limited or preferred networks are only likely to generate savings only to the extent that a plan can steer consumers.

The reduced form results show that a standard deviation increase in plan restrictiveness (27 percentage points) leads to a 1.5-3 percent decrease in average prices paid. By contrast, a standard deviation increase in LIS share (14 percentage points) increases average prices paid by 8-9 percent.[29] In this Section, we

[28]This bias could be due to a number of factors, including confounds that are negatively correlated with LIS enrollment and prices, measurement error, and functional form.

[29]The former result suggests that the causal effect of LIS enrollment is unlikely to be driven entirely by the effect of LIS subsidies

explore the interaction between network comprehensiveness and enrollees' sensitivity to networks directly, and go further to quantify the welfare tradeoffs between cost and access. We measure consumer preferences for physical pharmacy locations given their exposure to cost sharing; using very rich claims-level data, we explore how heterogeneity in demand relates directly to steering ability by insurers. Specifically, we ask two key questions. First, how much would costs increase if preferred networks were eliminated, and how would this effect vary by enrollee type? Second, how much would the cost of the Part D program fall if preferred network plans could be used to steer LIS consumers to cheaper pharmacies? In both cases, we will show modest but meaningful savings and quantify the welfare benefits and costs of restricting pharmacy access.

5.1 Pharmacy Demand Model

Our model of pharmacy demand builds on the approaches of Ho & Lee (2017) and Raval et al. (2017), among others. Given exogenous drug consumption needs, consumers choose a pharmacy to fill their prescriptions. Preferences are allowed to vary flexibly across consumer type, and the estimates are used to calculate the expected utility from each insurer network, which will then be included as a plan characteristic in a model of enrollees choosing Part D plans. We group consumers into types based on quintile of previous drug spending, geography (three-digit zip code), age (above or below age 75), and LIS status. This allows for different substitution patterns based on subsidies, geography, and heterogeneous drug needs in a flexible way. Individuals can visit any in-network preferred or non-preferred pharmacy, but the copay may vary by pharmacy, as described above. We parameterize the utility of consumer of type i in plan j in quarter q filling their prescriptions at pharmacy h as:

$$u_{ijhq} = \delta_{ijy} + \delta_{ihy} + \delta_{iq} + \pi^{ICR}_{jhy} \beta^{c}_{l(i)} + \varepsilon_{ijhq}.$$

This exercise focuses on steering between preferred and non-preferred pharmacies that are part of retail pharmacy chains – 92 percent of preferred pharmacy claims in our sample are in chain pharmacies, and the vast majority of independent pharmacies are non-preferred within plans that utilize preferred networks. The outside option in our model is independent pharmacies, which are normalized to have a utility of zero. Thus, δ_{ijy} captures consumer preferences for chains among type-i enrollees in plan j, year y; δ_{ihy} is the average type-i enrollee's utility at chain pharmacy h in year y, δ_{iq} captures general trends in chain pharmacy

on steering of enrollees across pharmacies. We focus on pharmacy contracting in this paper, but consider the broader impacts of LIS enrollment on pricing to be an important avenue for future research.

utilization for type-i enrollees, π^{ICR}_{jhy} is a dummy for pharmacy h being in plan j's preferred network in year y, and ε_{ijhq} is an idiosyncratic error term assumed to be i.i.d. Type 1 extreme value. Allowing enrollees in different geographic markets to have flexibly different preferences over pharmacy chains is analogous to estimating a distance coefficient. The coefficient of interest is $\beta^{c}_{l(i)}$ – a separate "preferred" pharmacy preference coefficient for each enrollee type $l(i)$ capturing type-i enrollees' quintile of lagged drug costs interacted with LIS status. In some specifications, we instead let π^{ICR}_{ijhy} be average out-of-pocket cost for enrollee type i in combination jhy in the initial coverage phase – this captures a similar mechanism as the preferred dummy, but in principle allows us to examine whether price-sensitivity depends on preferred status *per se* versus intensive margin variation in copay differentials.

The model predicts pharmacy shares, which we aggregate to the enrollee type-plan-quarter (market) level. In reality, enrollees may visit multiple pharmacies in a given quarter; aggregation across consumers within each market allows for this feature. Similar to Berry (1994), we estimate the following equation:

$$log\left(s_{ijhq}\right) - log\left(s_{ij0q}\right) = \delta_{ijy} + \delta_{ihy} + \delta_{iq} + \pi^{ICR}_{jhy}\beta^{c}_{l(i)}.$$

Identification of preferences relies on variation in choice sets and preferred network coverage across markets. The preferred dummy and copay coefficients are identified using variation in networks/copays for the same pharmacies across plans, and are allowed to vary with enrollees' ex ante drug needs and LIS subsidy status. We assume no selection across plans in enrollees' unobservable preferences for specific pharmacies. Finally, we estimate this regression for 2012-2014 only, given that we do not observe lagged enrollee costs for 2011 enrollees.[30]

The pharmacy demand sample is summarized in Table 7. The average enrollee-year chose from 60 pharmacies in 8 retail chains. 63 percent of non-LIS enrollees were in preferred-network plans, versus only 32 percent of LIS enrollees; within preferred-network plans, 61 percent of non-LIS claims in retail chains went to preferred pharmacies, versus only 38 percent for LIS claims. Out-of-pocket cost per day supply in the initial coverage phase was 43 cents for non-LIS enrollees, versus 8 cents for LIS enrollees.[31]

[30]We also estimated specifications in which we instrumented for contemporaneous preferred network status using changes in network status within plan over time. This strategy addresses potential endogeneity due to selection – enrollees may choose a plan based on preferred network status of their favored local pharmacies, but not based on anticipated *changes* in preferred status of those pharmacies. Those specifications yield qualitatively similar results; see Table 14 in the Appendix for details.

[31]This variable is calculated as the weighted average enrollee out-of-pocket price per day supply for each enrollee type-plan-pharmacy chain-year. Only 30-day supplies of prescriptions filled in the initial coverage range – the coverage phase for which plan cost-sharing is most relevant – are included in this calculation. Prices for different drugs are weighted using aggregate consumption weights for the enrollee type (LIS-age-lagged cost quintile)-year.

Table 7: Pharmacy Demand Sample

	Non-LIS Enrollees		LIS Enrollees		All Enrollees	
	Mean	SD	Mean	SD	Mean	SD
N pharmacies in choice set	57.97	49.81	61.69	54.80	59.79	52.34
N chains in choice set	8.41	2.96	8.10	3.06	8.26	3.01
% Preferred networks	0.625	0.484	0.320	0.466	0.476	0.499
% Preferred	0.755	0.295	0.800	0.340	0.777	0.318
% Preferred | Pref. Network	0.608	0.285	0.376	0.309	0.531	0.313
OOPC/Day	0.426	0.297	0.083	0.055	0.259	0.276
N enrollee-years	1,741,045		1,660,804		3,401,849	
N plans	1256		1187		1354	

We use the model of pharmacy demand to predict counterfactual demand patterns and to construct a measure of consumer utility from a given plan-year's pharmacy network and copay structure $\mathscr{G}_{\text{jy}}$. Following the existing literature (e.g., Town & Vistnes (2001), Capps et al. (2003), Ho et al. (2017), among others), we measure enrollee type i's willingness-to-pay (WTP) for a given network; we then aggregate across types to our groups $l(i)$ defined by lagged cost quintile and LIS status using observed enrollment weights p_{iy}:

$$WTP_{l(i)jq}\left(\mathscr{G}_{\text{jy}}\right) = \sum_i p_{iy} * log\left(1 + \sum_{h \in G_{\text{jy}}} exp\left(\hat{\delta}_{ijy} + \hat{\delta}_{ihy} + \hat{\delta}_{iq} + \pi^{ICR}_{jhy}\hat{\beta}^{c}_{l(i)}\right)\right).$$

Note that we estimate pharmacy demand conditional on the enrollee filling a prescription at a retail pharmacy, and we implicitly assume that the probability of any retail pharmacy claim is exogenous and constant across networks. Appendix A describes how we incorporate the pharmacy demand estimates into a model of enrollees choosing among Part D plans, and briefly summarizes the results.

5.2 Pharmacy Demand Estimates

Demand estimates are presented in Table 8 below. We focus on variation in coefficients with enrollees' LIS status and lagged pharmacy cost quintile. Table 13 in the Appendix presents alternative fixed effect specifications and samples; the results are similar in magnitude and direction.[32]

Several interesting patterns emerge. First, preferred network status (the first row in each panel) has a

[32] Our baseline specification includes fixed effects for each type-i interacted with plan-year, pharmacy-year, and quarter-year fixed effects. Table 13 in the Appendix shows the results of a specification with fixed effects for each type-i interacted with plan, pharmacy, and quarter-year fixed effects, for the full sample and for enrollees in preferred-network plans only. The qualitative patterns are similar across all specifications – non-LIS enrollees are more sensitive to the preferred dummy and out-of-pocket cost per day supply than LIS enrollees, and high-cost enrollees tend to be more sensitive than low-cost enrollees. However, the alternative specification estimated within preferred-network plans only is more similar to our baseline results in magnitudes, suggesting that enrollees' preferences over pharmacies vary over time and particularly with plans' preferred network status.

strong positive effect on demand for all non-LIS enrollees. Second, LIS enrollees – who are not exposed to preferred network copay differentials, other than for tier 1 generic drugs – are only about a quarter as responsive.[33] Third, very high-cost enrollees – whose *marginal* prices are less likely to vary by preferred network status due to the catastrophic coverage phase covering 95 percent of drug costs – are significantly less responsive than low-cost enrollees within both LIS and non-LIS groups. To put these numbers in perspective, note that preferred chain pharmacies have a market share of 49 percent among non-LIS enrollees (versus 22 percent among LIS enrollees). Making all pharmacies non-preferred would decrease preferred pharmacies' market share in preferred network plans by 8.0 percentage points (or 16 percent) among non-LIS enrollees, versus 1.4 percentage points (or 6 percent) among LIS enrollees.[34] Thus, about 30 percent of the gap between LIS and non-LIS enrollees' reliance on preferred chain pharmacies can be attributed to preferred status rather than other baseline differences in preferences, such as location or brand preference. Finally, the coefficient on $OOPC/Day$ exhibits the same comparative static across non-LIS and LIS enrollees – non-LIS enrollees have a large negative and significant coefficient on out-of-pocket cost per day, while LIS enrollees' coefficient is in fact small and positive – but the comparative static across quintile of lagged cost is non-monotonic. For both non-LIS and LIS enrollees, the coefficient on $OOPC/Day$ is least negative for very high-cost enrollees, but is highest for quintile 3. This reflects a key difference between the dummy variable $1\{Preferred\}$ and $OOPC/Day$: the latter varies across enrollees based on the composition of the drugs they tend to take. These results suggest that very low-cost enrollees tend to exhibit the strongest preference for frequenting preferred pharmacies within preferred network plans, but that moderate-cost enrollees are more sensitive than very low-cost enrollees to larger effective copay differentials between preferred and non-preferred pharmacies.

5.3 Counterfactuals

To further understand what the results above mean for the costs and benefits of plans' use of preferred network contracting, we use the pharmacy demand estimates to simulate the spending impact of counterfactually making all pharmacies non-preferred. This counterfactual allows enrollees to re-sort across both chain and independent retail pharmacies (the latter representing the outside option), then applies the observed retail and out-of-pocket prices for each pharmacy-plan pair to estimate spending impacts. This counterfactual

[33] 59 percent of fills are for tier 1 generic drugs for LIS enrollees in cost quintile 1, versus only 39 percent of LIS enrollees in cost quintile 5.

[34] These patterns are discussed in more detail in the counterfactual analysis in Section 5.3 below.

Table 8: Pharmacy Demand Coefficients

	Lagged Cost Quintile					
	1	2	3	4	5	All
			Non-LIS Enrollees			
1{Preferred}	0.502***	0.401***	0.396***	0.382***	0.334***	0.407***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.009)	(0.003)
N enrollee-years	333,725	383,429	400,206	402,163	201,136	1,720,659
OOPC/Day	-0.41***	-0.507***	-0.559***	-0.298***	-0.035***	-0.356***
	(0.012)	(0.014)	(0.014)	(0.01)	(0.012)	(0.005)
N enrollee-years	330,494	382,617	399,762	401,790	200,542	1,715,205
			LIS Enrollees			
1{Preferred}	0.189***	0.144***	0.109***	0.059***	0.107***	0.106***
	(0.015)	(0.012)	(0.01)	(0.009)	(0.006)	(0.004)
N enrollee-years	181,052	205,828	255,547	314,921	683,090	1,640,438
OOPC/Day	-0.517***	-0.516***	-0.64***	0.068	0.053**	0.043***
	(0.164)	(0.176)	(0.129)	(0.072)	(0.022)	(0.016)
N enrollee-years	178,605	205,171	255,172	314,594	682,160	1,635,702

Notes: Table reports coefficient estimates from pharmacy demand analysis described in text. Each coefficient from a separate regression of demand dependent variable on $Preferred$ dummy or $OOPC/Day$, plus plan-year-ZIP-demographic group, pharmacy-year-ZIP-demographic group, and quarter-year-ZIP-demographic group fixed effects, within relevant sample defined by LIS status and lagged cost quintile.

is partial equilibrium, in that it does not account for any follow-on effect of comprehensive networks on negotiated prices; we leave this analysis for future research.

The top panel of Table 9 shows baseline point-of-sale (POS) and out-of-pocket (OOP) costs, prices, and utilization for non-LIS, LIS, and all enrollees in preferred network plans. POS and OOP prices are pooled across all observed coverage phases, so that price differentials across preferred and non-preferred pharmacies are muted due to the small or zero differentials present outside the initial coverage phase of the Part D benefit.[35] At baseline, non-LIS enrollees are much more likely than LIS enrollees to use preferred retail pharmacies, perhaps due to the steering mechanism of interest or to other preferences, such as location; recall that we allow preferences over pharmacies to vary flexibly with enrollee type and location. The point-of-sale price per 30 day supply is about 10 percent lower in preferred network pharmacies for both non-LIS and LIS enrollees.

[35] We estimated retail and point-of-sale prices for preferred and non-preferred pharmacies for each LIS-lagged cost quintile-plan-year using regression analysis. Within each LIS-lagged cost quintile group, we regressed $ln(price)$ on dummies for plan-year interacted with pharmacy preferred status, as well as NDC fixed effects in order to purge any potential composition effects from the price differences observed across pharmacies within plan. We then predicted POS and OOP price for each plan-year-LIS-lagged cost quintile for the (weighted) mean NDC for the LIS-lagged cost quintile group.

Table 9: Counterfactual Results

	Non-LIS	LIS	All
Observed Quantities, Prices, and Spending			
Share Preferred	0.488	0.224	0.395
Share Non-Preferred	0.323	0.396	0.349
POS Price/30 Day, Preferred	59.49	85.50	68.63
POS Price/30 Day, Non-Pref	66.35	94.34	76.27
POS Price/30 Day, Average	63.08	92.95	73.59
POS Spend/Year	1592.1	5438.2	2944.7
OOP Price/30 Day, Preferred	26.02	2.525	17.76
OOP Price/30 Day, Non-Pref	30.57	2.461	20.61
OOP Price/30 Day, Average	28.09	2.373	19.05
OOP Spend/Year	528.8	85.14	372.8
Counterfactual Analysis Given Observed Substitution Patterns			
ΔShare Preferred	-0.0801	-0.0143	-0.0570
ΔPOS Price/30 Day	0.709	0.0942	0.493
%ΔPOS Price/30 Day	0.0173	0.00156	0.0118
ΔPOS Spend/Year	12.26	2.890	8.966
ΔCS (ex ante)	-23.80	-1.475	-15.95
Counterfactual Analysis Given "Best Case" Substitution Patterns			
ΔShare Preferred	-0.0975	-0.0617	-0.0849
ΔPOS Price/30 Day	0.835	0.349	0.664
%ΔPOS Price/30 Day	0.0196	0.00524	0.0145
ΔPOS Spend/Year	16.28	12.21	14.85

Notes: Top panel reports baseline share of demand at preferred and non-preferred pharmacies, baseline (observed) point-of-sale prices and spending, and baseline (observed) out-of-pocket prices and spending, within preferred-network plans only. Excluded category is non-chain retail pharmacies. Middle panel reports counterfactual shares, spending, and consumer surplus if all pharmacies are counterfactually made preferred. Last panel reports counterfactual shares, spending, and consumer surplus if all pharmacies are counterfactually made preferred and all enrollees have $Preferred$ dummy coefficient of non-LIS enrollees in lowest cost quintile.

We see strikingly different patterns when we turn to OOP costs. First, OOP cost per 30 day supply is an order of magnitude smaller for LIS than non-LIS enrollees, as expected given the substantial cost-sharing subsidies available to LIS enrollees. Second, non-LIS enrollees pay \$4.30 lower copays on average (a 14 percent discount) at preferred pharmacies. In contrast, for the average drug we observe no preferred copay discount for LIS enrollees (though this average conceals heterogeneity across drugs in different formulary tiers).

The next panel of Table 9 shows the results of the first counterfactual, in which we simulate the effects of making all preferred pharmacies non-preferred. This decreases the (previously) preferred pharmacy share among non-LIS enrollees by 8.0 percentage points, versus just 1.4 percentage points for LIS enrollees. Given the observed point-of-sale price differentials between preferred and non-preferred pharmacies, this in turn translates into a 1.7 percent increase in average POS price for non-LIS enrollees, versus 0.2 percent for LIS. Applying this simulated percentage change in point-of-sale price to baseline spending, the implied spending impact of the counterfactual is small: \$12 per non-LIS enrollee-year and \$3 per LIS enrollee-year. However, scaling these estimates by the 1.08 million non-LIS and 519,000 LIS enrollee-years in our 2012-2014 sample of preferred network enrollees using chain retail pharmacies, and by a factor of 10 to account for this being a 10 percent sample, the cost implications of this counterfactual are \$147 million over three years.[36]

Our pharmacy demand analysis showed that preferred network sensitivity is stronger for non-LIS enrollees, and varies meaningfully across enrollees with different spending histories. We next estimate the spending impact of an alternative counterfactual in which all enrollees are given the preferred network coefficient of non-LIS, low-cost enrollees; this is shown in the last panel of Table 9. This increases the cost implications of the counterfactual to \$15 per enrollee-year, or \$239 million over three years.[37]

Framed differently, these counterfactuals illustrate the cost savings predicted by the model that are driven by steering of enrollees across pharmacies, taking network status, point-of-sale prices, and out-of-pocket prices as given. The counterfactual suggest that savings are modest relative to overall spending, but large when aggregated across a large number of enrollees. Of course, we must consider both the costs and benefits

[36]Note that the calculated dollar savings per enrollee-year is not equivalent to what we see if we multiply the average estimated price change by average total spending at baseline, because the POS price effect of the counterfactual was calculated and applied to enrollee spending for each plan-LIS-lagged cost quintile before calculating the weighted average dollar spending effect shown.

[37]While this analysis is quite out-of-sample and thus only suggestive, it implies that small tweaks to plan design would increase savings significantly. For example, copay differentials between preferred and non-preferred pharmacies could be flat across benefit phases and drug tiers, within LIS status – this would have limited effect on actuarial value or the value of LIS subsidies, but would increase plans' ability to steer enrollees.

of restrictive contracting. Accordingly, the last row in each panel of Table 9 shows the estimated effect of the counterfactual on estimated ex ante consumer surplus, given the plan demand results described in the Appendix and specifically enrollees' willingness to pay higher premiums for more comprehensive preferred networks. These results indicate that, when preferred pharmacies are made non-preferred within preferred-network plans, all else equal, consumer surplus decreases by $23.8 per year for non-LIS enrollees, versus only $1.5 for LIS enrollees, for an average consumer surplus impact of $16 per enrollee-year. That is, the consumer surplus benefit of comprehensive networks is nearly double the cost savings achieve by enrollee steering.

These results raise the question of why insurers offer limited network plans if the cost savings is significantly less than the value of expanded access? We believe three features of this market can explain the discrepancy. First, similar to Shepard (2016), we found that limited network plans attract healthier enrollees; plans could use network breadth as a screening tool. Second, limited pharmacy network plans are a relatively recent phenomenon (Snook & Filipek (2011)). Thus, insurers may be experimenting, and the market may not be in equilibrium during our sample period. Finally, the threat of exclusion may allow insurers to negotiate larger discounts within pharmacy, as discussed in our reduced form results.[38]

6 Conclusion

The rise of narrow pharmacy networks in commercial and public prescription drug insurance markets raises important questions about health care costs and consumer welfare. This paper provides the first evidence on the cost and welfare implications of selective pharmacy contracting.

We use both reduced-form, quasi-experimental evidence and structural demand analysis to illustrate three key insights. First, most unsubsidized enrollees are highly sensitive to copay differentials between preferred and non-preferred pharmacies; as a result, preferred network contracting yields small, but significant drug cost savings. Second, subsidized LIS enrollees and very high-spending enrollees are much less responsive to preferred pharmacy status, which is a limiting factor on the savings due to selective pharmacy contracting.[39] Third, enrollees are sensitive to network generosity when choosing their prescription drug

[38] The third feature above suggests the value of estimating the supply side in this setting; the second feature urges caution in doing so.

[39] The positive effects of subsidized low-income enrollees on the prices paid in the Part D program are not novel or unexpected (see, e.g., Duggan & Scott Morton (2006) regarding similar spillover effects from the Medicaid program). However, the results do suggest that simple tweaks to subsidy design would yield further savings; e.g., the small copay differentials borne by LIS enrollees

insurance plans, and revealed preference plan demand estimates suggest that the consumer surplus losses from restrictive preferred pharmacy networks exceed the cost savings.

The setting considered in this paper presents perhaps a best-case scenario for analyzing the welfare trade-offs inherent in selective contracting: prescription drug needs are more predictable than, say, the need for inpatient hospital care; and frequent, repeated interaction with retail pharmacies implies that enrollees are likely aware at the plan choice stage of the relative convenience and cost of nearby pharmacies. However, we note several fruitful areas to extend this research. First, our reduced form evidence suggested that renegotiation is a significant source of savings due to restrictive preferred networks, but the high degree of network exclusion and presence of multiple network tiers we document introduce complications for structural analysis. Second, an important feature of this environment is that retail pharmacies sell many consumer products other than prescription drugs, and exclusion from a plan's preferred network or overall network likely has a large impact on consumer product sales as well. This may be an important consideration for insurer-pharmacy bargaining..

for tier one drugs could be applied evenly to all drug tiers, improving steering without significantly undermining the generosity of LIS subsidies.

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A Plan Demand

We flexibly estimate Medicare Part D plan demand using a logit model that allows preference parameters to vary with LIS status and lagged drug spending quintile. A consumer's choice set is defined at the PDP region level and a product is a plan-region-specific insurance contract (contract-plan ID combination). For each enrollee type $l(i)$ defined by LIS status and lagged spending quintile, consumer utility for plan j in market m and year y is given by:

$$u_{l(i)jmy} = \overline{\xi_{l(i)j}} + \alpha^{p}_{l(i)} p^{D}_{jmy} + \alpha^{x}_{l(i)} WTP_{l(i)jy} + \xi_{l(i)jmt} + \varepsilon_{ijmt}, \tag{1}$$

where $\overline{\xi_{l(i)j}}$ are time-invariant, vertical plan characteristics (i.e., insurer fixed effects) that vary across consumer types, p^{D}_{jmy} is the plan premium (in hundreds of dollars per year), $WTP_{l(i)jy}$ provides a measure of (potentially type-$l(i)$-specific) pharmacy network breadth, and $\xi_{l(i)jmt}$ represents time varying shocks to unobservable vertical plan characteristics.

The outside option is Medicare Advantage plans. This model is consistent with consumers choosing a plan before they realize the exogenously given need to fill a prescription. Our measures of network generosity include details on preferred network comprehensiveness across plans and enrollee types; combined with insurer fixed effects, these capture plan generosity. The predicted probability that a consumer chooses plan j in year y is given by:

$$\sigma_{l(i)jmy} = \frac{exp\left(\widetilde{u}_{l(i)jmy}\right)}{\sum_{k \in \mathscr{J}_{my}} exp\left(\widetilde{u}_{l(i)kmy}\right)},$$

where $\mathscr{J}_{my}$ is the set of all available plans in market m, which we define by enrollee ZIP code, in year y. The plan demand sample is reported in Table 10. The average sample enrollee-year involved a choice from among 27 plans. The average non-LIS enrollee chose a plan with annual premium of \$506, versus \$28 for LIS enrollees. The Table highlights how the two measures of network generosity capture different variation. Specifically, $\%Preferred$ is an aggregate measure defined for each plan-Part D region-year, regardless of enrollee type. It also treats preferred and non-preferred network plans quite differently – for non-preferred network plans, all pharmacies are preferred, so $\%Preferred$ captures overall network size; whereas for preferred network plans, $\%Preferred$ does not increase with the overall size of the network, conditional on the preferred network size. In contrast, WTP combines enrollee type-specific preferences over *local* in-network pharmacies with enrollee-type-specific preferences for preferred pharmacies. Thus, while $\%Preferred$ and

Table 10: Plan Demand Sample

	Non-LIS Enrollees		LIS Enrollees		All Enrollees	
	Mean	SD	Mean	SD	Mean	SD
N plans in choice set	27.385	2.829	26.773	4.114	27.084	3.532
Premium	5.059	2.302	0.278	0.797	2.713	2.954
% Preferred [N = 3,466,665]	0.480	0.324	0.672	0.339	0.574	0.345
WTP [N = 3,447,358]	1.673	0.985	0.512	0.850	1.102	1.089

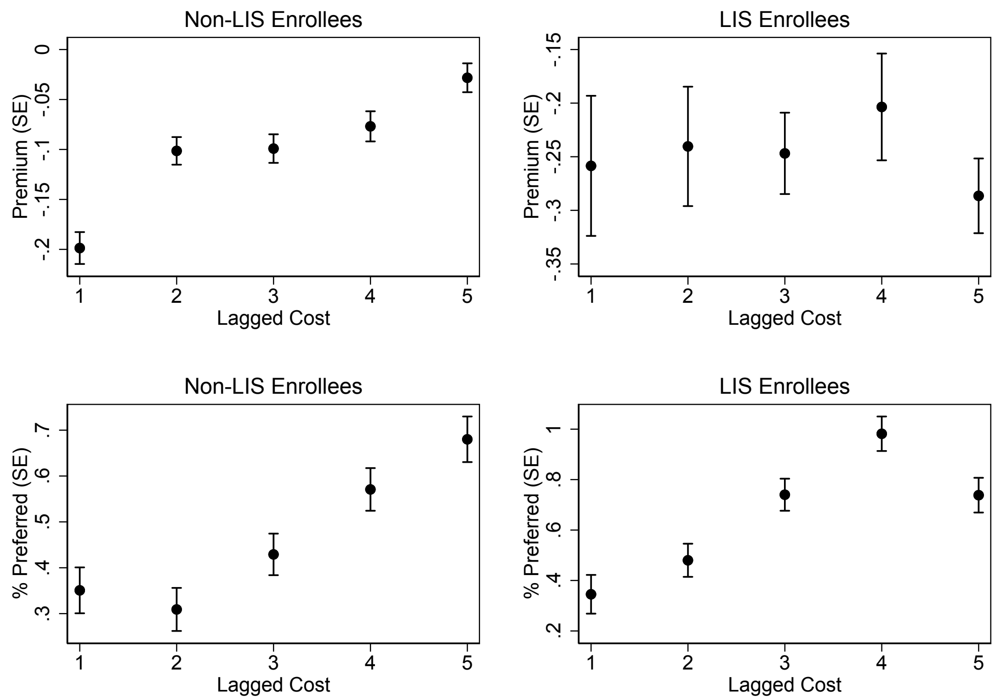
WTP are positively correlated, we do not expect them to necessarily impact enrollment in the same way. Non-LIS enrollees were more likely to enroll in preferred-network plans, so that the average chosen plan's $\%Preferred$ was 48 percent, versus 67 percent for LIS enrollees. However, non-LIS enrollees chose plans with greater overall network comprehensiveness on average: the average WTP measure of plan network generosity was 1.7 for non-LIS enrollees, versus 0.51 for LIS enrollees.

The coefficients are identified from variation in choice sets, within-issuer variation in premiums across markets, and consumer type and geographic variation in the measure of WTP, respectively. We assume that the insurer fixed effects capture a great deal of unobserved product variation that may be correlated with either premiums or WTP.

Our estimates will be biased if $\xi_{l(i)jmy}$ is correlated with premiums or product characteristics. We address this issue via a two-pronged approach. First, we insurer fixed effects, $\overline{\xi_{l(i)j}}$, that are allowed to vary with consumer type: the unobserved product characteristic is the deviation from the plan mean for the LIS-cost quintile group in question. Second, we instrument for premiums. As is common in this setting, we use Hausman-style instruments: we instrument for the premium for a given insurer-market-consumer type-year using the average premium for the same insurer-consumer type-year in all other PDP regions.

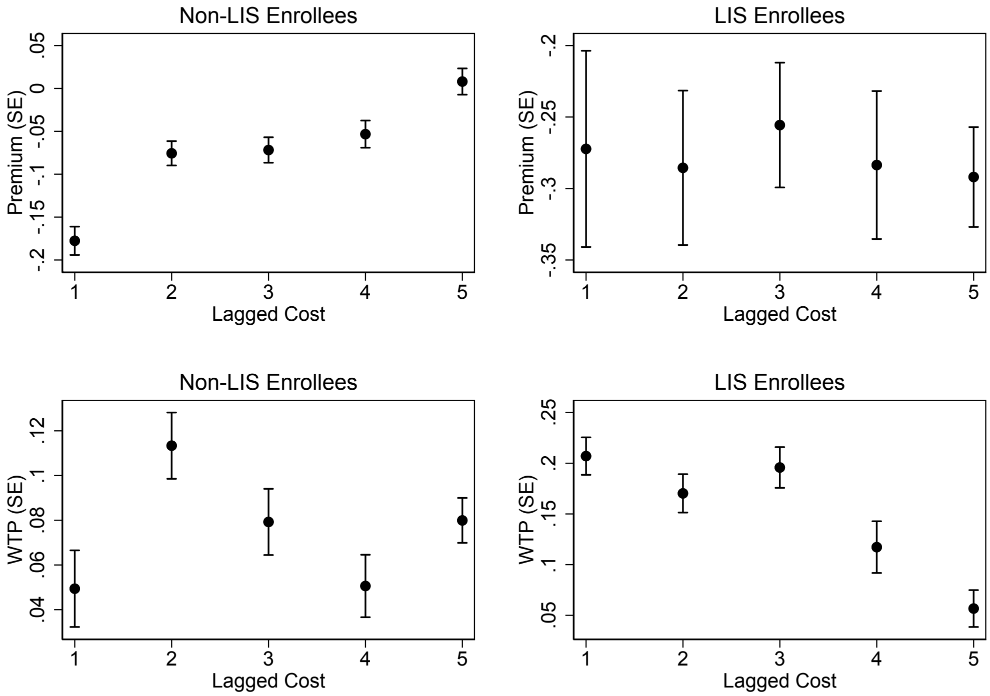
In some specifications, we show results where network comprehensiveness is characterized as in our reduced form results: as the percent of local pharmacies preferred in the Part D region. However, in the specifications we use for our counterfactual analysis in the main text, we rely on results where network comprehensiveness is characterized by the WTP measure resulting from our pharmacy demand regressions. The former are shown for each LIS-cost group in Figure 7; the latter are shown in Figure 8. The premium coefficient estimates (top two panels in each figure) are quite similar across specifications. We observe that LIS enrollees are more sensitive to variation in their effective (post-subsidy) premiums than are non-LIS enrollees; this is not unexpected given the tendency of low-income individuals to be highly price-sensitive, but we note that LIS enrollees' premium coefficients are noisier than non-LIS enrollees' given the limited variation in LIS enrollee premiums. Within non-LIS enrollees, higher-cost enrollees are also less sensitive to premium than lower-cost enrollees; this is likely due to the greater total insured benefit for higher-cost enrollees.

Figure 7: Plan Demand Estimates, *%Preferred* Measure of Network Generosity



Notes: Plots parameters of plan demand, as described above. The outside share is constructed as all Medicare eligibles not enrolled in a stand-alone Medicare Part D plan. In all specifications, we include LIS*cost quintile fixed effects interacted with insurer, year, and ZIP fixed effects. Excluded instruments are premiums in other PDP regions for the same insurer-year-enrollee type. Plan network generosity defined as the percent of pharmacies in the PDP region that are preferred; all pharmacies in non-preferred-network plans are considered “preferred.”

Figure 8: Plan Demand Estimates, WTP Measure of Network Generosity



Notes: Plots parameters of plan demand, as described above. The outside share is constructed as all Medicare eligibles not enrolled in a stand-alone Medicare Part D plan. In all specifications, we include LIS*cost quintile fixed effects interacted with insurer, year, and ZIP fixed effects. Excluded instruments are premiums in other PDP regions for the same insurer-year-enrollee type. Plan network generosity defined as $WTP_{l(i)jy}$ from the pharmacy demand model.

The estimates regarding enrollees' value for network comprehensiveness (bottom two panels in each figure) are somewhat different. First, the results in Figures 7 and 8 each indicate that enrollees are willing to pay more for plans with greater network coverage. Second, the coefficients are much larger for $\%Preferred$ than for WTP. Third, the comparative statics across enrollee type are somewhat different. LIS enrollees appear to have a stronger positive preference for network generosity than non-LIS enrollees within each measure. At first glance it may seem surprising that LIS enrollees value comprehensive networks, given that they are not subject to most preferred-pharmacy copay differentials. However, LIS enrollees may have a strong preference for overall network size, which is also embodied in these measures. Finally, the clear positive gradient of the preference for $\%Preferred$ in cost quintile is not present in the WTP results. This likely reflects the net effects of high- versus low-cost enrollees' different ex post demand for pharmacies conditional on filling a prescription, and high- versus low-cost enrollees' different ex ante value for comprehensive networks.

We estimate pooled coefficients within non-LIS and LIS enrollees for the specifications we take to the counterfactual analysis in the main text. These results are summarized in Table 11. For each group as defined by LIS status, we show results for several different specifications of controls: columns (1), (4), and (7) include contract-LIS-lagged cost quintile fixed effects; columns (2), (5), and (8) add in year-LIS-lagged cost quintile fixed effects; and columns (3), (6), and (9) add in ZIP-LIS-lagged cost quintile fixed effects. The top panel shows results with $\%Preferred$ as the network generosity variable; the bottom panel shows results with WTP as the network variable. The premium coefficients are generally quite stable with respect to the fixed effects specification employed, as are the coefficients on $\%Preferred$. However, the coefficients on WTP are more sensitive: the controls for ZIP are necessary to ensure a positive coefficient, likely reflecting the fact that network generosity for a given insurer can vary dramatically across local geographic regions.

In order to quantify the trade-offs between limited pharmacy access and cost control, we must quantify enrollee preferences over network breadth in dollar terms. For any enrollee type i, this object V_i can be calculated as

$$V_i = \frac{\alpha_i^x}{\alpha_i^p} * 100. \tag{2}$$

This measure calculates the ex ante tradeoff between one unit of network generosity and one dollar in annual premiums. Our preferred specification uses the results in columns (3) and (6) in Table 11, which imply that non-LIS enrollees are willing to pay \$102 in additional annual premiums for a unit increase in network generosity (approximately a standard deviation), whereas LIS enrollees are willing to pay only \$39 for a unit increase in network generosity.

B Bargaining Solution

Denote the relative Nash bargaining parameter of plan j with respect to pharmacy h as γ_{jh}. We solve by backward induction.

The negotiated non-preferred price maximizes the Nash product:

$$\begin{aligned} p_{hj}^{np*} &= argmax_{p_{hj}^{np}} \quad [\pi_j^{\mathscr{P}}(\mathscr{G}, \mathscr{G}^{pref} \setminus hj, \mathbf{R}, \mathbf{p}) - \pi_j^{\mathscr{P}}(\mathscr{G} \setminus hj, \mathscr{G}^{pref} \setminus hj, \mathbf{R}, \mathbf{p_{-hj}})]^{\gamma_{jh}} \\ &\quad \times [\pi_h^{\mathscr{H}}(\mathscr{G}, \mathscr{G}^{pref} \setminus hj, \mathbf{R}, \mathbf{p}) - \pi_h^{\mathscr{H}}(\mathscr{G} \setminus hj, \mathscr{G}^{pref} \setminus hj, \mathbf{R}, \mathbf{p_{-hj}})]^{1-\gamma_{jh}}. \end{aligned}$$

Table 11: Plan Demand

	Non-LIS Enrollees			LIS Enrollees			All Enrollees		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Premium	-0.113***	-0.118***	-0.104***	-0.286***	-0.303***	-0.269***	-0.151***	-0.156***	-0.137***
	(0.00583)	(0.00587)	(0.00346)	(0.0141)	(0.0142)	(0.00996)	(0.00538)	(0.00543)	(0.00351)
% Preferred	0.424***	0.524***	0.453***	0.723***	0.804***	0.731***	0.605***	0.698***	0.616***
	(0.0158)	(0.0185)	(0.0111)	(0.0229)	(0.0245)	(0.0166)	(0.0123)	(0.0142)	(0.00925)
N (enrollee-years)	1,765,430	1,765,430	1,765,001	1,701,235	1,701,235	1,701,099	3,466,665	3,466,665	3,466,100
Premium	-0.102***	-0.0995***	-0.0770***	-0.339***	-0.322***	-0.290***	-0.138***	-0.130***	-0.111***
	(0.00606)	(0.00605)	(0.00357)	(0.0135)	(0.0143)	(0.0101)	(0.00563)	(0.00567)	(0.00367)
Ex Ante WTP for Network	-0.0100*	-0.00973	0.0787***	0.194***	0.197***	0.114***	0.0813***	0.0828***	0.0906***
	(0.00506)	(0.00506)	(0.00327)	(0.00606)	(0.00613)	(0.00460)	(0.00393)	(0.00393)	(0.00282)
N (enrollee-years)	1,751,424	1,751,424	1,751,208	1,696,441	1,696,441	1,695,863	3,447,865	3,447,865	3,447,071
Contract-LIS-Lagcost FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-LIS-Lagcost FEs	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
ZIP-LIS-Lagcost FEs	No	No	Yes	No	No	Yes	No	No	Yes

The disagreement payoff from the non-preferred network stage is based on out-of-network status, so the negotiated price maximizes the Nash product of pharmacy h's and plan j's gains from in-network status. Next, the negotiated price p_{hj}^{pref} maximizes the Nash product:[40]

$$\begin{aligned} p_{hj}^{pref*} &= argmax_{p_{hj}^{pref}} \quad [\pi_j^{\mathscr{P}}(\mathscr{G},\mathscr{G}^{pref},\mathbf{R},\mathbf{p}) - \pi_j^{\mathscr{P}}(\mathscr{G},\mathscr{G}^{pref}\setminus hj,\mathbf{R},p_{hj}^{np},\mathbf{p_{-hj}})]^{\gamma_{jh}} \\ &\qquad \times[\pi_h^{\mathscr{H}}(\mathscr{G},\mathscr{G}^{pref},\mathbf{R},\mathbf{p}) - \pi_h^{\mathscr{H}}(\mathscr{G},\mathscr{G}^{pref}\setminus hj,\mathbf{R},p_{hj}^{np},\mathbf{p_{-hj}})]^{1-\gamma_{jh}}. \end{aligned}$$

Here, the negotiated price maximizes the Nash product of pharmacy h's and plan j's gains from moving from non-preferred to preferred status.

The entire price negotiation occurs simultaneously for each pair hj, so that in the event of bargaining breakdown in either stage, all other preferred-network pairs $\mathscr{G}^{pref}\setminus hj$, non-preferred network pairs $\mathscr{G}\setminus(\mathscr{G}^{pref}\cap hj)$, and prices $\mathbf{p_{-hj}}\equiv\mathbf{p}\setminus p_{hj}$ are assumed to be held fixed in pair hj's disagreement payoffs at each stage.

For the sake of brevity, all arguments are dropped from the notation in the following. For any general outcome Y_{nk} regarding pharmacy n and plan k, let $Y_{nk}\equiv Y(\mathscr{G},\mathscr{G}^{pref},\mathbf{R},p_{hj}^{pref},\mathbf{p_{-hj}})$ denote the value of the outcome if hj is preferred, $Y'_{nk}\equiv Y(\mathscr{G},\mathscr{G}^{pref}\setminus hj,\mathbf{R},p_{hj}^{np},\mathbf{p_{-hj}})$ denote the value of the outcome in the event hj is non-preferred, and $Y''_{nk}\equiv Y(\mathscr{G}\setminus hj,\mathscr{G}^{pref}\setminus hj,\mathbf{R},\mathbf{p_{-hj}})$ denote the value of the outcome in the event hj is out-of-network. Also, let the difference between preferred and non-preferred Y be $[\Delta_{hj}Y_{nk}]\equiv Y_{nk}-Y'_{nk}$; and let the difference between non-preferred and out-of-network Y be $[\Delta'_{hj}Y'_{nk}]\equiv Y'_{nk}-Y''_{nk}$.[41] Finally, let enrolled beneficiary pharmacy demand be $D_{nk}\equiv s_kQ_{nk}$.

The solution defines total payments $D'_{hj}p_{hj}^{np*}$, if pair hj is non-preferred, and payments $D_{hj}p_{hj}^{pref*}$, if pair hj is preferred, by:

$$\begin{aligned} D'_{hj}p_{hj}^{np*} &= \gamma(D'_{hj}w - \sum_{k\in\mathscr{G}_h\setminus j}[\Delta'_{hj}D'_{hk}](p_{hk}-w)) \\ &\quad +(1-\gamma)(D'_{hj}c_j^{np} + R_j[\Delta'_{hj}s'_j] - \sum_{n\in\mathscr{G}_j\setminus h}[\Delta'_{hj}D'_{nj}](p_{nj}-c_{nj})) \end{aligned}$$

[40] For the sake of exposition, we assume here that if $(hj\in\mathscr{G}^{pref})$ dominates $(hj\in\mathscr{G}, hj\notin\mathscr{G}^{pref})$ in terms of total possible surplus to pair hj, then $(hj\in\mathscr{G}^{pref})$ dominates $(hj\notin\mathscr{G})$ in that sense as well. This assumption can easily be relaxed.

[41] For example, the preferred network gains from trade are $[\Delta_{hj}\pi_h^{\mathscr{H}}]\equiv\pi_h^{\mathscr{H}}-\pi_h^{'\mathscr{H}}$ and $[\Delta_{hj}\pi_j^{\mathscr{P}}]\equiv\pi_j^{\mathscr{P}}-\pi_j^{'\mathscr{P}}$; the non-preferred network gains from trade are $[\Delta'_{hj}\pi_h^{'\mathscr{H}}]\equiv\pi_h^{'\mathscr{H}}-\pi_h^{''\mathscr{H}}$ and $[\Delta'_{hj}\pi_j^{'\mathscr{P}}]\equiv\pi_j^{'\mathscr{P}}-\pi_j^{''\mathscr{P}}$.

$$
\begin{aligned}
D_{hj}p_{hj}^{pref*} - D'_{hj}p_{hj}^{np*} &= \gamma([\Delta_{hj}D_{hj}]w - \sum_{k\in\mathscr{G}_h\setminus j}[\Delta_{hj}D_{hk}](p_{hk}-w)) \\
&\quad +(1-\gamma)(D_{hj}c_j^{pref} - D'_{hj}c_j^{np} + R_j[\Delta_{hj}s_j] \\
&\quad - \sum_{n\in\mathscr{G}_j\setminus h}[\Delta_{hj}D_{nj}](p_{nj}-c_{nj})).
\end{aligned}
$$

Each of these terms is intuitive, mirroring the results regarding hospital-insurer networks in Ho & Lee (2017). Consider first the payments to a non-preferred pair, $D'_{hj}p_{hj}^{np*}$. A plan's ability to extract higher rents (i.e., lower retail prices) in negotiating with a given pharmacy is increasing in its relative bargaining power γ and decreasing in: the pharmacy's ability to "recapture" profits from enrollment in other plans $\sum_{k\in\mathscr{G}_h\setminus j}[\Delta'_{hj}D'_{hk}](p_{hk}-w)$ if hj is out of network; in the extent to which the plan loses premium revenue by dropping that pharmacy from its network entirely $R_j[\Delta'_{hj}s'_j]$ (the "premium" effect); and in a "price reinforcement effect" $\sum_{n\in\mathscr{G}_j\setminus h}[\Delta'_{hj}D'_{nj}](p_{nj}-c_{nj})$ that reflects the strategic complementarity of other pharmacies' prices in the current negotiation. We arrive at a similar expression for the preferred network solution, in which the difference in total payments between preferred and non-preferred network status $D_{hj}p_{hj}^{pref*} - D'_{hj}p_{hj}^{np*}$ is a function of all the same terms, but each effect is defined for a switch from preferred to non-preferred status, rather than from non-preferred status to out-of-network status. We can further split the term $D_{hj}p_{hj}^{pref*} - D'_{hj}p_{hj}^{np*}$ into a price effect and a quantity effect: $D_{hj}p_{hj}^{pref*} - D'_{hj}p_{hj}^{np*} = D_{hj}(p_{hj}^{pref*} - p_{hj}^{np*}) + (D_{hj} - D'_{hj})p_{hj}^{np*}$. This allows us to express the solution in terms of the preferred network price discount:

$$
\begin{aligned}
D_{hj}(p_{hj}^{pref*} - p_{hj}^{np*}) &= \gamma([\Delta_{hj}D_{hj}]w - \sum_{k\in\mathscr{G}_h\setminus j}[\Delta_{hj}D_{hk}](p_{hk}-w)) \\
&\quad +(1-\gamma)(D_{hj}c_j^{pref} - D'_{hj}c_j^{np} + R_j[\Delta_{hj}s_j] \\
&\quad - \sum_{n\in\mathscr{G}_j\setminus h}[\Delta_{hj}D_{nj}](p_{nj}-c_{nj})) - (D_{hj}-D'_{hj})p_{hj}^{np*}.
\end{aligned}
$$

This includes the wholesale cost, recapture, premium and enrollment, and reinforcement effects above, plus a "preferred capture" effect $(D_{hj}-D'_{hj})p_{hj}^{np*}$.[42]

[42] The Nash-in-Nash framework considered in this model is simple and tractable, but has difficulty accommodating the key feature of the setting – that preferred networks are observed to be highly restrictive. In future work, we draw on recent work that endogenizes network formation to estimate a model of bargaining between plans and pharmacies allowing for equilibrium exclusion (see, e.g., Ho & Lee (2018), Ghili (2018), Liebman (2018)).

Table 12: Top Chains Preferred Status Transition Matrix, 2012-3

Chain A

Preferred Status t	Preferred Status $t+1$: Exit$_{t+1}$	Non-Pref	Pref	Total
Entry$_{t+1}$	0.0%	35.4%	20.7%	56.0%
Non-Pref	4.7%	14.9%	0.2%	19.8%
Pref	0.0%	7.0%	17.2%	24.1%
Total	4.7%	57.3%	38.0%	100.0%

Chain B

Preferred Status t	Preferred Status $t+1$: Exit$_{t+1}$	Non-Pref	Pref	Total
Entry$_{t+1}$	0.0%	55.4%	0.6%	56.0%
Non-Pref	1.0%	29.4%	0.2%	30.7%
Pref	3.7%	5.3%	4.3%	13.3%
Total	4.7%	90.2%	5.1%	100.0%

Chain C

Preferred Status t	Preferred Status $t+1$: Exit$_{t+1}$	Non-Pref	Pref	Total
Entry$_{t+1}$	0.0%	34.2%	21.9%	56.0%
Non-Pref	4.7%	6.1%	6.1%	17.0%
Pref	0.0%	0.0%	27.0%	27.0%
Total	4.7%	40.3%	55.0%	100.0%

Chain D

Preferred Status t	Preferred Status $t+1$: Exit$_{t+1}$	Non-Pref	Pref	Total
Entry$_{t+1}$	0.0%	21.7%	34.4%	56.0%
Non-Pref	4.7%	20.0%	0.2%	24.9%
Pref	0.0%	0.0%	19.0%	19.0%
Total	4.7%	41.7%	53.6%	100.0%

Notes: Transition matrices regarding top retail chains' preferred network status for $N = 489$ plans with preferred networks in 2012-3. Top retail chains identified as those with the highest aggregate spending across all years 2011-4. Rows identify chain's preferred status in each plan in 2012 (except for plans entering in 2013, identified by $Entry_{t+1}$). Columns identify chain's preferred status in each plan in 2013 (except for plans exiting in 2013, identified by $Exit_{t+1}$).

C Other Tables and Figures

Table 13: Pharmacy Demand Results – Alternative Specifications

(a) Plan, Quarter, Pharmacy Fixed Effects

		Cost Quintile					
		1	2	3	4	5	All
Non-LIS Enrollees							
1{Preferred}	Pooled Coef.	0.265***	0.248***	0.251***	0.233***	0.179***	0.241***
	(SE)	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.002)
N		338667	387366	403890	406111	205011	1741045
OOPC/Day	Pooled Coef.	-0.261***	-0.401***	-0.412***	-0.199***	-0.041***	-0.231***
	(SE)	(0.009)	(0.013)	(0.012)	(0.008)	(0.007)	(0.004)
N		335588	386499	403393	405675	204285	1735440
LIS Enrollees							
1{Preferred}	Pooled Coef.	-0.014	-0.027***	-0.059***	-0.089***	-0.051***	-0.054***
	(SE)	(0.011)	(0.009)	(0.008)	(0.007)	(0.005)	(0.003)
N		185220	209051	259153	319051	688329	1660804
OOPC/Day	Pooled Coef.	0.502***	10.321***	0.822***	0.303***	0.189***	0.217***
	(SE)	(0.098)	(0.111)	(0.084)	(0.054)	(0.019)	(0.014)
N		182678	208319	258742	318670	687273	1655682

(b) Baseline Controls, Estimated on Preferred Network Plans Only

		Cost Quintile					
		1	2	3	4	5	All
Non-LIS Enrollees							
1{Preferred}	Pooled Coef.	0.339***	0.316***	0.298***	0.282***	0.238***	0.3***
	(SE)	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)	(0.003)
N		233765	251098	244348	239231	114319	1082761
OOPC/Day	Pooled Coef.	-0.275***	-0.566***	-0.567***	-0.278***	-0.035***	-0.307***
	(SE)	(0.011)	(0.016)	(0.017)	(0.012)	(0.011)	(0.006)
N		232708	250783	244142	239058	114002	1080693
LIS Enrollees							
1{Preferred}	Pooled Coef.	0.123***	0.079***	0.062***	0.035***	0.06***	0.06***
	(SE)	(0.018)	(0.013)	(0.012)	(0.01)	(0.006)	(0.004)
N		53390	64793	82461	101745	218350	520739
OOPC/Day	Pooled Coef.	0.306	-0.03	-0.031	0.115	0.096***	0.096***
	(SE)	(0.3)	(0.256)	(0.164)	(0.092)	(0.023)	(0.018)
N		52431	64507	82281	101590	217963	518772

Notes: Table reports coefficient estimates from pharmacy demand analysis described in text. Top panel: each coefficient from a separate regression of demand dependent variable on $Preferred$ dummy or $OOPC/Day$, plus plan-ZIP-demographic group, pharmacy-ZIP-demographic group, and quarter-year-ZIP-demographic group fixed effects, within relevant sample defined by LIS status and lagged cost quintile. Bottom panel: same specification as top panel, preferred network plans only.

Figure 9: Effect of Benchmark on Atorvastatin Prices

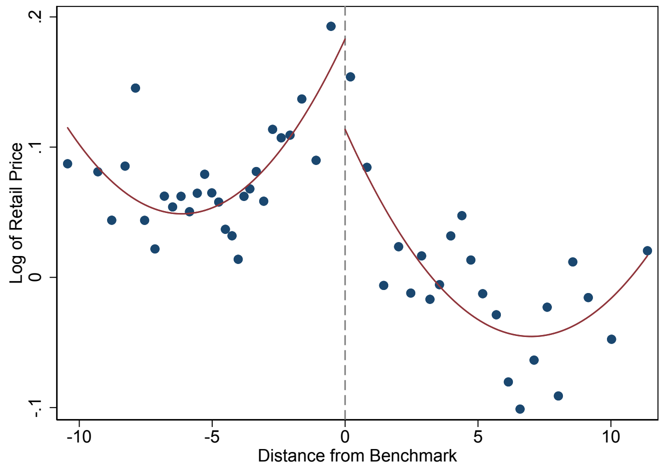


Table 14: Pharmacy Demand Results – Baseline versus Control Function

	Non-LIS Enrollees			LIS Enrollees		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS Specification					
1{Preferred}	0.407***	0.241***	0.3***	0.106***	-0.054***	0.06***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)
N	1,720,659	1,741,045	1,082,761	1,640,438	1,660,804	520,739
	Control Function Specification					
1{Preferred}	0.225***	0.145***	0.165***	0.079***	0.064***	0.083***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
N	1,104,223	1,108,691	891,674	1,067,352	1,073,598	436,029
Group-Quarter-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Group-Plan FEs	Yes	Yes	Yes	Yes	Yes	Yes
Group-Plan-Year FEs	Yes	No	No	Yes	No	No
Group-Pharmacy FEs	Yes	Yes	Yes	Yes	Yes	Yes
Group-Pharmacy-Year FEs	Yes	No	No	Yes	No	No
Preferred Network Plans Only?	No	No	Yes	No	No	Yes

Notes: Table reports coefficient estimates from pharmacy demand analysis described in text. Top panel: OLS demand regression as in main text. Bottom panel: control function pharmacy demand specification based on first stage regression of $Preferred$ status in year y on $Preferred$ status in year $y-1$. Each coefficient from a separate regression of demand dependent variable on $Preferred$ dummy, control function residual, and fixed effects specified, within relevant sample defined by LIS status.