DISCUSSION PAPER SERIES

DP17937

STRATEGIC TIER DESIGN IN HEALTH INSURANCE: THE CASE OF MEDICARE PART D

Léa Bignon, Alessandro Iaria and Laura Lasio

INDUSTRIAL ORGANIZATION

CEPR

ISSN 0265-8003

STRATEGIC TIER DESIGN IN HEALTH INSURANCE: THE CASE OF MEDICARE PART D

Léa Bignon, Alessandro Iaria and Laura Lasio

Discussion Paper DP17937
Published 25 February 2023
Submitted 22 February 2023

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

STRATEGIC TIER DESIGN IN HEALTH INSURANCE: THE CASE OF MEDICARE PART D

Abstract

We study the role of tier design in Medicare Part D. In the period 2013-2017, plans expanded the number of tiers in their formularies from three/four to five and systematically shifted generics to higher tiers subject to higher cost sharing. The systematic tier upgrading caused significant increases in the out-of-pocket costs, up to six times for some generics. This resulted in additional average per-enrollee spending on generics of $76 in 2017, totalling $1.5 billion for the Part D population, and increased mortality by 5.4% due to reduced utilization of generics with documented mortality benefits.

JEL Classification: N/A

Keywords: N/A

Léa Bignon - lea.bignon@tse-fr.eu
Toulouse School of Economics

Alessandro Iaria - alessandro.iaria@bristol.ac.uk
University Of Bristol and CEPR

Laura Lasio - laura.lasio@mcgill.ca
Mcgill University

Acknowledgements
We thank Francesco Decarolis, Pierre Dubois, Keith Marzilli Ericson, and Clara Soh for useful comments. We gratefully acknowledge financial support from the McGill SSHD fund.

Strategic Tier Design in Health Insurance: The Case of Medicare Part D

Léa Bignon, Alessandro Iaria, Laura Lasio*

January 2023

Abstract

We study the role of tier design in Medicare Part D. In the period 2013-2017, plans expanded the number of tiers in their formularies from three/four to five and systematically shifted generics to higher tiers subject to higher cost sharing. The systematic tier upgrading caused significant increases in the out-of-pocket costs, up to 6 times for some generics. This resulted in additional average per-enrollee spending on generics of $76 in 2017, totalling $1.5 billion for the Part D population, and increased mortality by 5.4% due to reduced utilization of generics with documented mortality benefits.

Léa Bignon: Toulouse School of Economics (lea.bignon@tse-fr.eu); *Alessandro Iaria:* University of Bristol and CEPR (alessandro.iaria@bristol.ac.uk); *Laura Lasio:* McGill University, CEPR, CIREQ, CIRANO (laura.lasio@mcgill.ca). We thank Francesco Decarolis, Pierre Dubois, Keith Marzilli Ericson, and Clara Soh for useful comments. We gratefully acknowledge financial support from the McGill SSHD fund.

1 Introduction

In industries characterized by complex products or services, consumers may be unable to process every detail, allowing firms to leverage the complexity of their offers to increase profits (Ellison and Ellison 2009; Carlin 2009; Armstrong and Chen 2009). Medicare Part D contracts are notoriously complex: the price is a combination of a premium, a deductible, and non-linear coverage rates that dynamically depend on utilization throughout the year (Dalton, Gowrisankaran, and Town 2019). This makes comparisons difficult: as premiums are clear and certain, while future consumption is not, enrollees tend to base their plan choices mostly on premiums rather than on cost sharing or drug coverage (Handel and Kolstad 2015; Abaluck and Gruber 2011; Abaluck and Gruber 2016; Decarolis, Polyakova, and Ryan 2020). Whereas inertia in enrollees' plan choice led to a steady rise of premiums and triggered stricter regulations around premium setting (Marzilli Ericson 2014; Decarolis 2015; Ho, Hogan, and Scott Morton 2017; Fleitas 2020), the structure of formularies has remained relatively unregulated.

In this paper, we study strategic tier design in Medicare Part D. Plans are required to cover at least two drugs in the most commonly prescribed categories and all drugs that treat certain conditions. However, insurers are free to choose both the type (copayment or coinsurance) and the level of cost sharing, which usually increases in the tier, as long as the plan is actuarially equivalent to a standard plan. Insurers use the tier structure to steer consumption to cheaper types of medical care. First, since cheaper therapeutically equivalent substitutes (mostly generics) are provided at lower cost sharing, the tier structure increases demand elasticity to price and insurers' bargaining power vis-à-vis drug manufacturers, driving list prices down (Duggan and Scott Morton 2010; Olssen and Demirer 2021). Second, plans that bundle pharmaceutical and medical benefits internalize the externality of drug utilization on inpatient hospitalization, thus offering more generous drug coverage (Lavetti and Simon 2018; Starc and Town 2019).

We use publicly available data on formularies, enrolment, and drug utilization for Medicare Part D stand-alone prescription drug plans between 2013 and 2017 to investigate tier design by insurers and their impact on enrollees' out-of-pocket costs, demand, and spending for generics. We document that, over this period, plans made larger use of five-tiered formularies, which include two generic tiers, two brand tiers, and a specialty tier. Over time, plans increasingly placed generics in higher tiers (Avalere 2018; Fix, Brennan, Donthi, and Whorley 2022), even those usually reserved for branded drugs and subject to higher cost sharing—effectively making the cheapest available treatments more expensive for millions of enrollees. This shrunk the size of the first tier (with the lowest cost sharing), traditionally devoted to generics, which in 2017 included three times fewer drugs than in 2013.

To quantify the effect of tier shifting on out-of-pocket costs, we exploit variation across generic drugs that were moved to higher tiers. To address the endogeneity of tier placement, we leverage the rules on actuarial equivalence and build an instrument that links the probability of tier shifting for each drug to the distance between the effective cost-sharing in the plan and 25%, the rule for the standard plan. The systematic tier upgrading of generics caused an increase in the out-of-pocket costs for the average monthly supply of 6 times for high value generics and of 0.4 times for other generics. This is not due to a handful of high-utilization drugs or a few high-enrolment plans, but affected expensive and cheap generics alike and was so widespread that, even if a sophisticated enrollee could perfectly adjust drug choices (for example choosing therapeutic substitutes in lower tiers) or switch plan, they would still face higher out-of-pocket costs in 2017 than in 2013. We exclude that this increase in out-of-pocket costs was due to a generalized increase in drug prices.

To assess some of the consequences of higher out-of-pocket costs due to tier upgrading of generics, we rely on drug utilization data and estimate a demand model linking purchases of generics to their tier placement. To overcome the endogeneity of tier placement in demand estimation, we build Hausman-type instruments (Hausman 1996; Nevo 2001). We instrument

the tier of a specific drug in a region with the average tier of the same drug in other regions. Controlling for drug, region, and year fixed effects, and excluding shared formularies from the computation, the validity of this instrument rests on the absence of residual aggregate demand shocks that could lead to nation-wide tier shifting of a drug across plans.

We estimate low price elasticities in line with those by Einav, Finkelstein, and Polyakova (2018), but still large enough to reduce consumption compared to a counterfactual scenario in which generics had remained in the same tier as in 2013. Our results illustrate that the average enrollee spent $76 more on generic drugs in 2017 due to tier upgrading. Enrollees who instead adhered to therapy in spite of the higher out-of-pocket costs spent $100 more. Collectively, these increases correspond to an additional $1.5 billions in out-of-pocket spending for the Medicare Part D population in 2017.

Notably, the generics in our sample include high value medications with documented mortality benefits: if utilization dropped due to higher out-of-pocket costs, enrollees may have suffered adverse health outcomes. A back-of-the-envelope calculation in the spirit of Chandra, Flack, and Obermeyer (2021) shows that reduced utilization due to tier upgrading for drugs in classes with documented mortality benefits resulted in increases in mortality by 5.4%. We also document an additional welfare-decreasing effect of tier upgrading: contrary to what insurance theory deems optimal (Besley 1988; Feldstein 1973; Einav, Finkelstein, and Polyakova 2018), the generics moved to higher tiers were those with lower demand elasticity to price, hence those less prone to moral hazard. By distorting the optimal cost sharing balancing risk protection and moral hazard, tier upgrading may have thus negatively affected welfare beyond reductions in utilization and increases in spending.

We interpret our results as lower bounds for the effects of tier shifting on expenditures and welfare, as our estimates do not capture the full substitution across drugs, health outcomes, and public spending. First, the combination of higher cost sharing for generics and the increasing role of rebates may favor brand-name medications (Dafny, Ody, and Schmitt

2017; Dubois and Lasio 2018; Dusetzina, Jazowski, Cole, and Nguyen 2019). In turn, lower use of generics may affect long-run entry decisions of generic manufacturers, leading to even fewer alternatives, lower competition, and further risk of shortages in the future (Berndt, Conti, and Murphy 2017). Higher cost sharing may also result in higher public spending. For enrollees with the low-income subsidy, Medicare fully covers the out-of-pocket costs. Also, enrollees may reach the catastrophic coverage threshold at a faster pace ($4,950 in 2017), after which Medicare covers 80% of the expenses. Finally, lower therapy adherence may result in inefficient substitution to other types of medical care (Chandra, Gruber, and McKnight 2010; Starc and Town 2019), with the potential for increased hospitalization and higher costs for society.

The rest of the paper is organized as follows. Section 2 describes the empirical setting and data. Section 3 provides evidence of the systematic tier upgrading of generics. The impact of tier upgrading on out-of-pocket costs is studied in Section 4 and on demand and total spending in Section 5. Section 6 discusses some welfare implications of tier upgrading. Section 7 concludes.

2 Data

We use three sources of data from Medicare Part D, available from the Centers for Medicare and Medicaid Services (CMS). First, we rely on formulary data from 2013-2017 to retrieve information on the characteristics of the formulary for each plan-year: the list of drugs identified by their unique National Drug Code (NDC), the tier they belong to, the cost sharing rules, and plan-level list prices (for 2013 and 2017 only). We use the NDC to identify the Anatomical Therapeutic Chemical (ATC) codes from the WHO for each drug, as well as the drug type (branded/generic). Second, we use the Prescriber Event file to recover quantities (in 30-day supply) and the total cost for each drug. Finally, we refer to

enrolment data to compute plan-level market shares.

Following Einav, Finkelstein, and Polyakova (2018), a drug is defined by its non-proprietary name and whether it is branded or generic. If a drug appears in several tiers, we consider the lowest; if it appears in different dosages or forms in the same tier, we consider the least expensive version. A drug class is defined at the level 4 of the WHO ATC classification (ATC4), our measure of the product market. We follow the literature and exclude from the analysis drug classes with less than 100,000 claims over the period 2013-2017 for the main 34 geographical markets. Quantities are defined in 30-day supply units. We combine plan-level formulary data and enrolment shares to recover the average tier of a drug in a given market for a given year. We deflate list prices and OOP costs using the US CPI with 2013 as the base year.

We focus on stand-alone prescription drug plans (PDPs). We observe 1,471 distinct PDPs between 2013 and 2017. 441 plans are present throughout the period, while 420 enter and 782 exit. Towards the end of the period, plan consolidation due to mergers led the number of plans to decline (-15% between 2016 and 2017), a tendency started around 2015. At the same time, differentiation increased, with several insurers offering at least one basic plan and one enhanced plan per region. Plans differ along several dimensions, mainly premiums and generosity (deductible, cost sharing, and coverage). On average, premiums remained approximately constant or decreased slightly throughout the period.

Formularies covered on average 1,123 drugs in 2013 (around 49% generics) and 1,180 in 2017 (around 53% generics), slightly expanding over time as a consequence of both branded and generic entry. Five-tiered formularies became the norm in later years: they usually include two generic tiers (preferred and non-preferred), two brand tiers (preferred and non-preferred), and a single specialty drug tier. Since 2017, CMS allowed the non-preferred brand tier to be replaced by a less restrictive non-preferred drug tier, which could include also generics. Some plans include a sixth tier for injectable drugs.

3 Tier Upgrading for Generics

Figure 1 documents a systematic shift of generics from lower to higher tiers in the period 2013-2017. Figure 1(a) illustrates how, in 2013, around 90% of all generics across plans belonged to tier 1 or 2, with 220 distinct drugs in tier 1. By 2017, only around half of all generics were in tier 1 or 2. Tier 1 had on average shrunk in size to 73 distinct drugs, losing roughly two thirds of the generics. Higher tiers, associated to higher cost sharing, saw an influx of drugs, both branded and generics. Although some of these were new and expensive, which could justify higher cost sharing, most of the shift is attributable to older generics, predominantly upgraded to tier 2 (non-preferred generics) (Figure 1(b)). The bottom panels of Figures 1(a) and (b) conversely show that tier shifting for branded drugs was limited. The number of branded drugs in tiers 3 and 4 remained stable, while the increase in the size of tier 5 was mostly attributable to the entry of expensive branded drugs. Indeed, in more than 90% of the plans, tier 5 is a specialty tier restricted to drugs with a list price for 30-day supplies above $600. Insurers were allowed to offer a sixth tier for "selected care" drugs associated with a $0 copayment. As illustrated by Figures 1(a) and 1(b), very few plans used this sixth tier. Overall, this suggests that generic rather than branded drugs tended to be upgraded to higher tiers in 2013-2017, and this will be the focus of the paper.

Figure 1(c) shows the transition probability of a drug with a certain tier in 2013 (x-axis) to another tier in 2017 (y-axis). Nearly 40% of the drugs available in both years were moved up by one or two tiers. Conversely, transitions to lower tiers were limited (fewer than 8% of drugs). Interestingly, many generics were also available in tier 3 and 4, mainly devoted to branded drugs, more so in the last years: cheap generics (priced $10-50) increased by 28% their presence in tiers 3 and 4 (non-preferred drugs) (Figure 1(d)). This pattern also holds for the most prescribed generic drugs, the top 10 prescribed classes, and those for which CMS mandates that all drugs should be covered in all formularies. This is consistent with Oster and Fendrick (2014), who show that even guideline-recommended medications were

often moved out of tier 1 to higher tiers.

4 Changes in Out-Of-Pocket Costs

Higher tiers imply higher cost sharing within a plan. In our data, generics moved to higher tiers, on average, experience a doubling in OOP costs: between tier 1 and 2, copayment increased from around $1 to more than $3 in 2017. Generics that are not moved to higher tiers instead display a stable or even decreasing trend in cost sharing since, conditional on tier, plans slightly reduced coinsurance rates. While changes in OOP costs of generics over time are driven by various concurring factors, in this section we attempt to isolate the part due to tier upgrading.

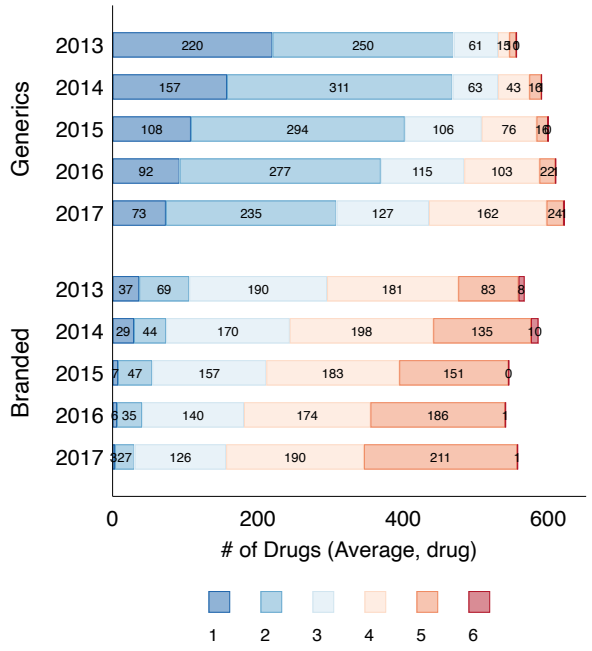
We consider OOP costs for 30-day supply in a preferred pharmacy network in the initial coverage phase of the plan. We denote by ΔOOP_{jpr} and by $\Delta Tier_{jpr}$ the changes, respectively, in out-of-pocket costs and in tier between 2013 and 2017 for drug j in plan p offered in region r, and estimate the following regression:

$$\Delta OOP_{jpr} = \beta_0 + \beta_{1k}\Delta Tier_{jpr} + \delta_j + \delta_p + \varepsilon_{jpr}. \tag{1}$$

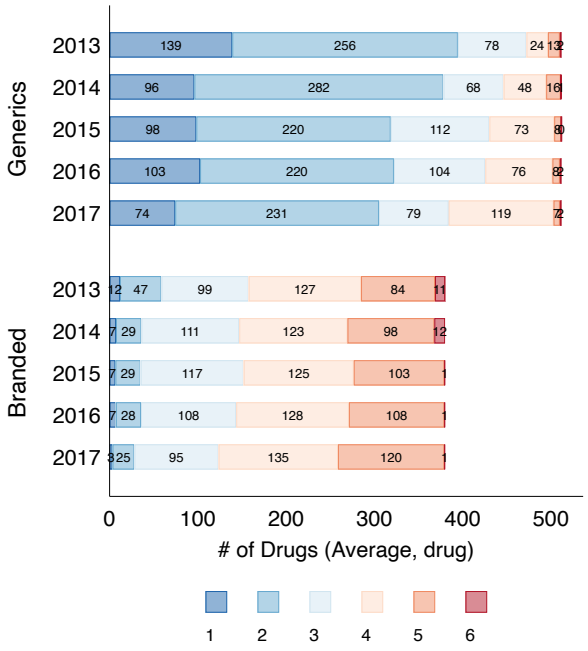
We allow the coefficient on $\Delta Tier_{jpr}$ to differ across two categories of drugs $k \in \{$High Value, Others$\}$. We follow Chandra, Flack, and Obermeyer (2021) and define a drug to be high value if clinical trials demonstrate large mortality benefits.[1] To account for drug-specific changes in OOP costs across plans and regions, we include drug fixed effects δ_j and weigh each observation by the quantity of the corresponding drug-region in 2013. We also include plan fixed effects δ_p, which control for changes in plan design that may have affected *all* drugs in a plan, such as changes in the cost sharing rules for all tiers.

[1] High value drugs include statins, ACE inhibitors, β-blockers, thiazide diuretics, calcium channel blockers, angiotensin receptor blockers, diabetes drugs, and inhalants.

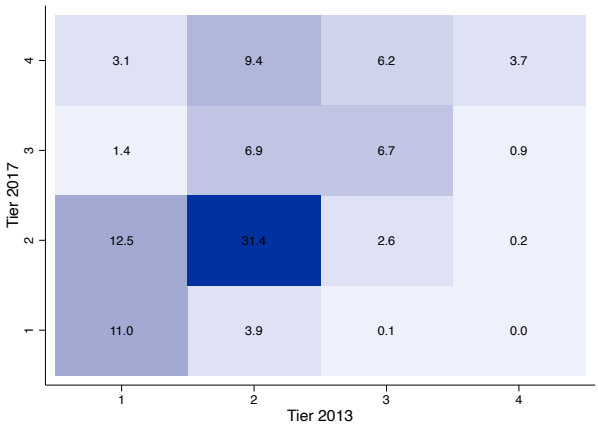
Figure 1: Generics moved to higher tiers



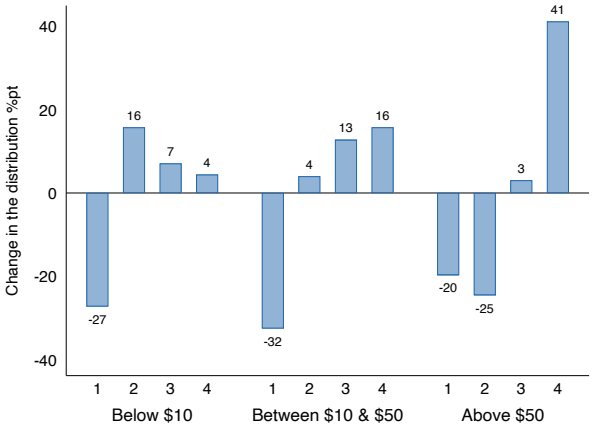
(a) All Part D plans and drugs, 2013-2017



(b) Fixed set of plans and drugs



(c) Tier transition matrix



(d) By price group (based on 2013 list price)

Notes: Figure 1(a) counts the average number of distinct drugs per tier from 2013 to 2017 across plans. Figure 1(b) does the same, fixing the set of plans and drugs as observed in 2013. Average tier size is displayed for generics and branded drugs separately. Figures 1(c) and 1(d) focus on tiers up to the fourth: we exclude drugs with list prices per 30-day supply above $600 ($670 in 2017), since they are eligible for a specialty tier intended for expensive drugs. Figure 1(c) maps generic drugs from their tier in 2013 to their tier in 2017. Figure 1(d) shows the change in the distribution of generics across tiers within a certain price group, where price groups are computed on the basis of 2013 list prices.

Because formulary design is ultimately a choice of the insurer, we consider $\Delta Tier_{jpr}$ as potentially endogenous and estimate regression (1) using an instrumental variable that leverages the relative generosity of plan p for drug j in 2013 compared to the Medicare standard plan. All Medicare Part D plans are required to be at least actuarially equivalent to the government-designed standard plan, which offers a uniform 25% coinsurance rate in the cost-sharing arm above the deductible and below the donut hole. To meet actuarial equivalence, insurers face an incentive to shift to higher tiers those drugs for which the plan is more generous than the standard one, i.e. with a coinsurance *lower* than 25%. For each drug j in plan p, we then compute the difference between the 2013 drug-plan specific coinsurance (as a percentage of the list price) and 25%, and use this as an instrument for $\Delta Tier_{jpr}$.

Table 1, column 1, reports the weighted least squares (WLS) estimates of regression (1), while column 2 reports the corresponding weighted two-stage least squares (W2SLS) estimates. Compared to generics that did not change tier between 2013 and 2017, those that were moved up experienced an increase in OOP costs of \$10.6. The strong first stage results (panel B) and the difference in the estimates between columns 1 and 2 (panel A) suggest that, indeed, formulary design may be endogenous and that insurers did not move generics to higher tiers at random, but rather moved those with OOP costs expected to increase less or even decrease over the period (WLS appears to be downward biased). The relative increase in OOP costs associated to generics that were moved to a higher tier is substantial (column 3): \$12.6 for high value generics and \$9.5 for the others, amounting to a 6 times increase for high value generics and a 0.4 times increase for the other generics.[2] In columns 4 (WLS), 5 and 6 (W2SLS) of Table 1, we estimate a regression analogous to (1) using changes in the list prices of generics between 2013 and 2017 as the dependent variable. These estimates illustrate that the generics moved to higher tiers were *not* those with relatively increasing

[2]From column 3, Table 1, we compute 6 and 0.4 as, respectively, $\frac{12.62-1.8}{1.8}$ and $\frac{9.45-6.8}{6.8}$.

Table 1: Effect of tier shifting on out-of-pocket costs and list prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		ΔOOP		Plan level ΔList price			Aggregate list price
	WLS	W2SLS	W2SLS	WLS	W2SLS	W2SLS	WLS
	A. Effect of tier shifting						
$\Delta Tier$	5.929	10.60		3.112	-6.548		
	(0.0273)	(0.109)		(0.0787)	(0.304)		
$1_{\text{High Value}} \times \Delta Tier$			12.62			-3.170	
			(0.179)			(0.507)	
$(1 - 1_{\text{High Value}}) \times \Delta Tier$			9.446			-8.478	
			(0.107)			(0.305)	
$1_{\text{High Value}} \times Year$							-1.172
							(0.0480)
$(1 - 1_{\text{High Value}}) \times Year$							-1.221
							(0.0386)
	B. First Stage						
Dist 25		0.732			0.732		
		(0.00594)			(0.00594)		
$1_{\text{High Value}} \times$ *Dist* 25			0.552			0.552	
			(0.00752)			(0.00752)	
$(1 - 1_{\text{High Value}}) \times$ *Dist* 25			0.858			0.858	
			(0.00674)			(0.00674)	
Weak IV Fstat		15,205	8,197		15,205	8,197	
Observations	195,534	195,534	195,534	195,534	195,534	195,534	102,296
R-squared	0.476	0.074	0.103	0.431	-0.069	-0.068	0.924
Mean Y	6	6		-2.3	-2.3		122.2
Mean Y High value			1.8			.70	53.4
Mean Y (1-High value)			6.8			-2.9	134.4
Mean Δ tier	.8	.8		.8	.8		
Mean Δ tier High value			.4			.4	
Mean Δ tier Others			.8			.8	
Drug FE	✓	✓	✓	✓	✓	✓	✓
Plan FE	✓	✓	✓	✓	✓	✓	
Market FE							✓

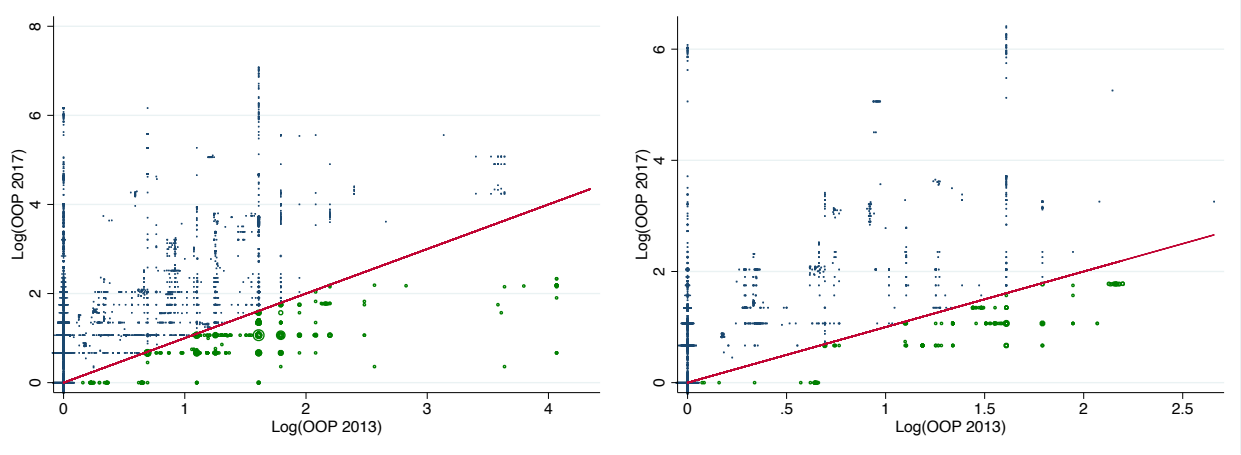
Notes: *** p<0.01, ** p<0.05, * p<0.1. Columns 1 to 3 report WLS (weighted least squares) and W2SLS (weighted two-stage least squares) estimates of regression (1), where the the first stage regressions are reported in panel B. The sample excludes drugs with list prices per 30-day supply above $600 ($670 in 2017), given their eligibility for a specialty tier intended for expensive drugs. All regressions include drug fixed effects and weigh each observation by the quantity of the corresponding drug-region combination in 2013. "High Value" generics are defined following the classification from Chandra, Flack, and Obermeyer (2021) (see footnote 1). As an instrument for $\Delta Tier_{jpr}$, we leverage the distance between the cost sharing in 2013 and the standard benefit cost sharing rule (25%). Columns 4 to 6 perform similar regressions using ΔList price as dependent variable. Column 7 reports estimates of the list price variation across years using market level data for each generics from the Medicare Part D Event file.

list prices. More broadly, column 7 of Table 1 shows that the list prices of generics did not increase over the period 2013-2017. These findings suggest that the generalized tier upgrading observed in the period 2013-2017 was not motivated by higher costs of generics for insurers.

Allowing for drug and plan choice adjustments, OOP still increased. In response to increasing OOP costs for those generics that were moved to higher tiers, enrollees may have re-optimized their drug or plan choices. First, some may have switched to therapeutic substitutes at the ATC4 level that were more generously covered. Yet, while in 2013 40% of drug classes (ATC4) had an alternative in tier 1, only 17% had one in 2017. In addition, some enrollees may have switched to plans with lower cost sharing for the drugs that treat the same condition. Although the existing literature has shown that this behavior is not common and plan choices display significant inertia, we allow for this possibility and compute the lowest OOP cost across the plans available in a given Part D market in 2013 and 2017 for a hypothetical enrollee who purchased a drug with a generic available in 2013.

Figure 2 summarizes these results. Despite high dispersion, Figure 2 clearly shows an upward trend in the OOP costs needed to purchase a 30-day supply of a generic drug. In Figure 2(a), more than 90% of drug-market combinations are on or above the 45 degree line (of which 70% are strictly above). Allowing for broader substitution at the class level, in Figure 2(b) more than 95% of the combinations are on or above the 45 degree line (of which 50% are strictly above). Hence, tier upgrading increased OOP costs even for the most savvy enrollees. In section 5, we enrich this exercise on the basis of the estimated effect of tier upgrading on purchased quantities and OOP spendings.

Figure 2: Minimum out-of-pocket costs increase



(a) Generic name level

(b) ATC4 level

Notes: The figure plots the minimum OOP cost in each Medicare Part D market in 2017 against its corresponding value in 2013. The minimum is computed in panel (a) at the molecule level and in panel (b) at the ATC4 level, allowing for substitution to the cheapest molecule within a drug class. We focus on molecules for which at least one generic was available in 2013.

5 Changes in Quantity and Spending

To shed light on the consequences of tier upgrading of generics on enrollees, we first investigate its effect on the demand for generics.

We define quantity Q_{jrt} as the 30-day supply of a generic drug j, Medicare Part D region r, and year t. We estimate the following regression:

$$\log(Q_{jrt}) = \alpha_0 + \alpha_{1k} Tier_{jrt} + X_{jrt}\alpha_2 + \zeta_j + \zeta_r + \zeta_t + \nu_{jrt}, \tag{2}$$

where $k \in \{\text{High Value, Others}\}$. We compute $Tier_{jrt}$ as the weighted average of the tiers which generic drug j belongs to in each plan, using enrolment weights, and round it to the nearest integer.[3] X_{jrt} includes as controls generic drug coverage in the market (share of plans), entry at the ATC4 level, coverage of the branded alternative (share of plans), and size of the market (in number of enrollees).

[3]Using non-rounded measures of average tier at the market level yields similar estimates.

Similar to the price regression (1), $Tier_{jrt}$ in regression (2) is likely to be endogenous: generic drugs with larger unobserved components of demand may be placed in higher tiers to monetize a positive demand shock. We build a Hausman-type instrument for $Tier_{jrt}$ (Hausman 1996; Nevo 2001) as the average tier of generic j in regions other than r. This is expected to correlate with $Tier_{jrt}$ due to the common components of cost incurred by insurers for offering generic j in their plans independently of the region (e.g., bargaining of insurers with drug manufacturers), but should be uncorrelated with the local demand shock ν_{jrt}. Controlling for drug, region, and year fixed effects, the validity of this instrument rests on the absence of residual aggregate demand shocks correlated both with ν_{jrt} and with $\nu_{jr't}$, $r' \neq r$, and that led to a national-wide tier shifting for generic j across plans.

Given that insurers may use the same formulary in several Part D regions, generic j's tier in region r' could correlate with ν_{jrt} through a common formulary used both in regions r' and r. Hence, we exclude common formularies from the instrument. Moreover, we check the robustness of our results by adding region-specific time trends and drug class (ATC3)-specific time trends meant to capture residual nation-wide demand shocks that may invalidate our instrument.

Table 2: The Effect of Tier on Demand, 2013-2017

	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
	A. Effect of tier on $\log(Q_{jrt})$					
$Tier$	-0.0324	-0.173		-0.204	-0.155	-0.191
	(0.00466)	(0.0249)		(0.0299)	(0.0318)	(0.0384)
$1_{\text{High Value}} \times Tier$			-0.318			
			(0.0732)			
$(1 - 1_{\text{High Value}}) \times Tier$			-0.165			
			(0.0237)			
	B. First Stage					
Average of j's tier in $r' \neq r$		0.230	0.230	0.209	0.179	0.166
		(0.00512)	(0.00512)	(0.00500)	(0.00484)	(0.00484)
Weak IV Fstat		2,012	174.8	1,752	1,370	1,176
Observations	83,232	83,157	83,157	83,157	83,157	83,157
R-squared	0.968	0.799	0.798	0.726	0.806	0.733
Drug FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓			
Region FE $\times$ $Year_t$				✓		✓
ATC3 FE $\times$ $Year_t$					✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table reports OLS and 2SLS estimates of various versions of regression (2), where the the first stage regressions are reported in panel B. Column 1 reports OLS estimates. Columns 2 to 6 instead report 2SLS estimates using the average tier of generic j in regions other than r as an instrument for $Tier_{jrt}$. Column 3 reports separate estimates for high value and other generics, with "high value" generics defined according to the classification from Chandra, Flack, and Obermeyer (2021) (see footnote 1). Columns 4 to 6 further include region-specific and drug class-specific time trends to control for national-wide aggregate demand shocks that would invalidate our instrument.

Column 1 of Table 2 reports the OLS estimates of regression (2), while columns 2-6 the corresponding 2SLS estimates. A comparison of the OLS estimates in column 1 with the 2SLS estimates in column 2 (around 5 times more negative, with a strong first stage in panel B) confirms that $Tier_{jrt}$ may be the outcome of endogenous insurers' decisions and is unlikely to be independent of unobserved demand shocks. Reassuringly, the estimated effect of $Tier_{jrt}$ on $\log(Q_{jrt})$ appears to be robust to the inclusion of region-specific and drug class-specific time trends (columns 4-6). In line with Chandra, Flack, and Obermeyer

(2021), column 3 illustrates that the effect of $Tier_{jrt}$ on $\log(Q_{jrt})$ is estimated to be stronger for high value (-0.318) than for other generics (-0.165).

To put these estimates into perspective, we combine them with those from Table 1 and compute the elasticity of demand with respect to the increase in OOP costs implied by tier upgrading, $\epsilon = \frac{\Delta Q}{Q}\frac{OOP}{\Delta OOP} = (\exp(\alpha_{1k}) - 1)\frac{OOP}{\beta_{1k}}$. The average estimated elasticity among all generics is $\epsilon_{\text{all}} = -0.18$, which is in line with the estimate of -0.14 by Einav, Finkelstein, and Polyakova (2018) for the Medicare Part D population close to the coverage gap. By considering high value and other generics separately, we obtain $\epsilon_{\text{high value}} = -0.12$ and $\epsilon_{\text{others}} = -0.21$, which suggests that the demand for high value generics is *less* elastic than that for the other generics. This is consistent with the lower elasticities reported by Einav, Finkelstein, and Polyakova (2018) for chronic and maintenance drugs, a category that includes high value drugs.

Counterfactuals. The above evidence suggests that enrollees paid more for generics due to tier upgrading and that higher cost sharing caused a decrease in their purchased quantities. In this section, building on the idea of Figure 2 and on our regressions, we evaluate these changes from the perspective of enrollees' total spending.

To approximate the total annual OOP spending (OOPS) per-enrollee for purchases of generic drugs, we use aggregate Medicare Part D prescriber quantities and cost sharing rules at the plan level, weighted by plan enrolment:

$$\begin{aligned} OOPS_{rt} &= \frac{1}{N_{rt}} \sum_{j \in \mathcal{J}_{rt}} \left(Q_{jrt} \times \sum_{p \in \mathcal{P}_{jrt}} m_{jprt} \times OOP_{jprt} \right) \\ &= \frac{1}{N_{rt}} \sum_{j \in \mathcal{J}_{rt}} \left(Q_{jrt} \times OOP_{jrt} \right), \end{aligned} \tag{3}$$

where, for each region r and year t: N_{rt} is the total number of Medicare Part D enrollees; $\mathcal{J}_{rt}$ is the set of generic drugs available; $\mathcal{P}_{jrt}$ is the set of plans that include generic j; m_{jprt} is the

observed market share of plan p (among those covering j); Q_{jrt} is the purchased quantity of generic j; OOP_{jprt} is the OOP cost of generic j in plan p for a 30-day supply in a preferred pharmacy during the initial coverage period; and OOP_{jrt} is the weighted average of OOP_{jprt} across plans covering j.

We ask the following question: how did tier upgrading between 2013 and 2017 affect OOP spending in 2017? Relying on the estimates of regressions (1) and (2) from Tables 1 and 2 (column 3 for both), we simulate OOPS (3) in 2017 given the tier structure observed in 2013. We exclude from the analysis the generics observed to enter or exit in 2017 as well as those for which the tier did not change between 2013 and 2017, as for these drugs we would not be able to compute any counterfactual change. The generics included in our sample represent 74% of all generics and 68% of total purchased quantities of generics in 2017. To simplify the simulations, we assume that the plan market shares in (3) remained constant at their observed levels in 2017 when altering the tier structure to that observed in 2013.[4]

To isolate the contribution of tier shifting to the change in cost sharing between 2013 and 2017, we use the estimates from regression (1) (column 3) and compute counterfactual OOP costs in 2017 as:

$$OOP^c_{jpr17} = \widehat{\Delta OOP}_{jpr} - \widehat{\beta}_{1k}\Delta Tier^c_{jpr} + OOP_{jpr13}, \tag{4}$$

where $\widehat{\Delta OOP}_{jpr}$ is the fitted value of regression (1), $\widehat{\beta}_{1k}$ is the corresponding estimate of β_{1k}, $\Delta Tier^c_{jpr}$ is a counterfactual shift in tier (e.g., 0 in the absence of a change or $-n$ for a decrease of n tiers) and OOP_{jpr13} is the OOP cost observed in 2013. We denote by OOP^c_{jr17} the weighted average of OOP^c_{jpr17} across plans using plan enrolment weights, m_{jpr17}.

To account for the effect of tier shifting on demand for generics, we use the estimates of

[4]In general, this assumption could be relaxed and the variable m_{jprt} in equation (3) endogenized by estimating a plan level choice model along the lines of Decarolis, Polyakova, and Ryan (2020).

regression (2) (column 3) and compute counterfactual purchased quantities in 2017 as:

$$Q^c_{jr17} = \widehat{Q}_{jr17} \exp\left(\widehat{\alpha}_{1k} \times \Delta Tier^c_{jpr}\right), \tag{5}$$

where $\widehat{Q}_{jr17}$ is the fitted value for 2017 of regression (2), $\widehat{\alpha}_{1k}$ is an estimate of α_{1k}, and $\Delta Tier^c_{jpr}$ is a counterfactual shift in tier.

Combining (3), (4), and (5), we compute the total counterfactual change in OOP spending in 2017 as if tier shifting between 2013 and 2017 had not taken place:

$$\Delta OOPS^{\text{c}}_{r17} = \frac{1}{N_{r17}} \sum_{j \in \mathcal{J}_{r13}} \left(\widehat{Q}_{jr17}\widehat{OOP}_{jr17} - Q^c_{jr17}OOP^c_{jr17}\right),$$

where $\mathcal{J}_{r13}$ denotes the set of generics available both in 2013 and 2017 and that changed tier and $\widehat{OOP}_{jr17}$ is computed on the basis of (4) evaluated at $\Delta Tier^c_{jpr} = 0$ as $\widehat{OOP}_{jr17} = \sum_{p \in \mathcal{P}_r} m_{jpr17} \times \left(\widehat{\Delta OOP}_{jpr} + OOP_{jpr13}\right)$. In words, $\Delta OOPS^{\text{c}}_{r17}$ is the difference between $\widehat{Q}_{jr17}\widehat{OOP}_{jr17}$, the predicted OOPS in 2017 given the tier structure in 2017, and $Q^c_{jr17}OOP^c_{jr17}$, the counterfactual OOPS in 2017 given the tier structure in 2013. In evaluating $\Delta OOPS^{\text{c}}_{r17}$, we use the model's prediction of the factual OOPS ($\widehat{Q}_{jr17}\widehat{OOP}_{jr17}$) rather than the corresponding observed value ($Q_{jr17}OOP_{jr17}$) to obtain a cleaner comparison with the counterfactual OOPS ($Q^c_{jr17}OOP^c_{jr17}$), which can only be predicted by the model.

While $\Delta OOPS^{\text{c}}_{r17}$ measures the total counterfactual change in OOPS due to higher OOP costs and implied demand responses, we disentangle the contribution of these channels by decomposing $\Delta OOPS^{\text{c}}_{r17}$ in two parts. We compute the part of the counterfactual change in OOPS due to the higher OOP costs implied by tier upgrading between 2013 and 2017 as:

$$\Delta OOPS^{\text{oop}}_{r17} = \frac{1}{N_{r17}} \sum_{j \in \mathcal{J}_{r13}} Q^c_{jr17} \left(\widehat{OOP}_{jr17} - OOP^c_{jr17}\right).$$

We then compute the part of $\Delta OOPS^{\text{c}}_{r17}$ due to the lower purchased quantities implied by

tier upgrading between 2013 and 2017 as:

$$\Delta OOPS^{\text{q}}_{r17} = \frac{1}{N_{r17}} \sum_{j \in \mathcal{J}_{r13}} \left(\widehat{Q}_{jr17} - Q^{c}_{jr17} \right) \widehat{OOP}_{jr17},$$

such that $\Delta OOPS^{\text{c}}_{r17} = \Delta OOPS^{\text{oop}}_{r17} + \Delta OOPS^{\text{q}}_{r17}$.

Table 3 reports the results of the counterfactual, for all drugs (column 1) and separately for drugs in the high value and in the others category. For each category, we further separate the effects for drugs that were moved to higher tiers (column "Up") from the handful that were moved down (column "Down"). Panel A displays the breakdown of drugs in terms of number of distinct products and sales.

Panel B presents the effect of tier shifting between 2013 and 2017 on OOP spending in 2017. Compared to a scenario in which the tier structure had remained the same as in 2013, OOP spending per-enrollee in 2017 would have increased by \$76, accounting for two thirds of the total increase in spending on generics between 2013 and 2017, \$116. This corresponds to an additional \$1.5 billions in OOP spending for the Medicare Part D population in 2017. As expected by their pervasiveness on formularies and their higher prices and tiers, drugs in the "Others" category that were moved to higher tiers are the largest contributors to these estimated increases, although upgraded high value drugs also account for an important share of the change in OOP spending. The total effect on OOP spending is mitigated by a few drugs that were moved to lower tiers between 2013 and 2017 (the negative change in spending in the columns denoted by "Down").

The increase of \$76 can be decomposed in two parts. First, if demand had not decreased in response to the higher OOP costs, OOP spending per-enrollee would have increased by \$100, a third more. Second, the reduction in demand induced by the higher OOP costs would have led to a decrease in OOP spending per-enrollee by \$24, had tier placement not changed compared to 2013. Thus, despite the low elasticity estimated by our model and

the literature, the large increase in cost sharing induced a reduction in consumption, which translated into lower spending as measured by $\Delta OOPS^{q}_{r17}$. The decomposition of the total counterfactual change highlights a trade-off between adherence to therapy and spending and suggests interesting heterogenous effects across drugs and enrollees. An hypothetical enrollee on anti-diabetics, a class with an estimated perfectly inelastic demand to price (Einav, Finkelstein, and Polyakova 2018), would have spent $100 more in 2017 in order to perfectly adhere to therapy. Conversely, an enrollee on anti-hypertensive or β-blockers, two classes with a more elastic demand despite high mortality benefits, would have cut on drugs to reduce spending, increasing their health hazards.

Table 3: Counterfactual Change in OOP spending per enrollee

	All	High Value		Others	
		Up	Down	Up	Down
	A. Tier shifting between 2013 and 2017				
Drugs (%)	100	8.9	1.5	60.9	2.6
Quantity (%)	100	13.3	7.6	40.2	6.7
	B. Change in OOP Spending in 2017 ($)				
Total change: $\Delta OOPS^{c}_{r17}$	75.7	15.8	-10.1	75.0	-4.4
Part due to ΔOOP costs: $\Delta OOPS^{oop}_{r17}$	99.5	20.4	-10.5	94.8	-4.7
Part due to ΔQuantities: $\Delta OOPS^{q}_{r17}$	-23.9	-4.7	0.5	-19.8	0.3
Enrolment 2017	19,694,854				

Notes: The table reports the counterfactual per-enrollee change in OOP spending on generics in 2017 due to tier shifting between 2013 and 2017. We restrict the analysis to common drug classes (with more than 100,000 claims over the period) and to generics available both in 2013 and 2017 that changed tier between 2013 and 2017. The counterfactual computations are based on the estimates of regressions (1) and (2) from Tables 1 and 2 (column 3 for both), and equations (3), (4), and (5). Panel A shows the distribution of drugs by category (high value and other generics) and tier shifting status between 2013 and 2017. The difference between 100 and the sum of the last four columns refers to drugs that remained in the same tier (not reported in the interest of space). Panel B shows the corresponding counterfactual per-enrollee change in OOP spending on generics in 2017 ($\Delta OOPS^{c}_{r17}$), and its decomposition into the part due to changes in OOP costs ($\Delta OOPS^{oop}_{r17}$) and the part due to changes in quantities ($\Delta OOPS^{q}_{r17}$).

6 Welfare Implications

In this section, we discuss some of the welfare implications of the observed tier upgrading of generics from 2013 to 2017. First, we use the adjusted mortality data from Chandra, Flack, and Obermeyer (2021) to perform a back-of-the-envelope calculation of the consequences of cutting on high value drugs due to tier upgrading on mortality.[5] Our estimates imply that tier shifting caused a 10% reduction in the consumption of these drugs compared to a scenario without tier upgrading, which would translate into mortality effects of 3.7% for ACE inhibitors, thiazide diuretics, and angiotensin-receptor blockers and of 8.2% for β-blockers. To scale these to the relevant populations, we use the shares of eligible enrollees by class from Chandra, Flack, and Obermeyer (2021).[6] Summing up across the four high values classes, accounting for the different levels of utilization in the Part D population across them, we obtain an overall increase in mortality of 5.4%.

In addition to significant increases in spending and possible adverse health consequences due to reduced adherence to therapy, tier upgrading may have also affected welfare by distorting the optimal cost sharing required to balance risk protection and moral hazard. In line with the theory of optimal insurance (Feldstein 1973; Besley 1988), Einav, Finkelstein, and Polyakova (2018) document that, in the period 2007-2011, drugs with higher demand elasticity to price (that is, more subject to moral hazard) had higher cost sharing due to placement in higher tiers. Yet, their results suggest lower than optimal average coverage. In this sense, tier upgrading in the period 2013-2017 may have narrowed the gap and brought

[5] Among the high value drugs, we exclude antidiabetics, calcium channel blockers, and inhalants, as their demand is estimated to be almost perfectly inelastic by Einav, Finkelstein, and Polyakova (2018). We are possibly underestimating the quantity effect on the remaining high value drugs, as our demand model has a single coefficient for all high value drugs. We also exclude statins, since one of the main drugs in this class, atorvastatin, was moved to a lower tier.

[6] We do not use the fraction of beneficiaries by class in 2013 from our data, since it would significantly overestimate the relevant population: our aggregate data only report the number of beneficiaries at the drug level, so we would count more than once those that use more than one drug in the same class in the same year. The shares reported in Chandra, Flack, and Obermeyer (2021) include also branded drugs, so may be overestimated, but are lower than those in our data and provide a reasonable approximation.

further reductions in moral hazard. We investigate this possibility and ask whether drugs with higher demand elasticity were more likely to be moved to higher tiers. By matching our data to the estimated demand elasticities for common drugs by Einav, Finkelstein, and Polyakova (2018), we find that the generics moved to higher tiers between 2013 and 2017 tended to have *lower* rather than higher estimated demand elasticity. This suggests that tier upgrading, by moving the cost sharing structure further away from optimality, may have negatively affected welfare beyond reductions in consumption and increases in spending.

7 Conclusions

In this paper, we document that, in the period 2013-2017, Medicare Part D plans systematically upgraded many generic drugs to higher tiers, with an implied average increase in OOP spending per-enrollee of $76, or $1.5 billion for the entire Medicare Part D population.

The formulary is a key strategic variable for insurers and changes in tier design are consistent with the nature of competition in Medicare Part D. As documented by an extensive literature, premiums are the most salient feature on which consumers compare plans and insurers compete fiercely over them. Moreover, increased regulatory scrutiny has contributed to a remarkable stability of premiums over the past years, despite significant growth in spending for Part D's catastrophic benefits. Formularies, on the other hand, remain relatively unregulated, inducing insurers to exploit this flexibility to increase profits.

While sizeable, our estimates are likely to be a lower bound for the total increase in both private and public spending. A lower effective OOP difference between brand-name and generics may shift some consumption towards the former (Dafny, Ody, and Schmitt 2017; Dubois and Lasio 2018) and increase OOP even further. In turn, higher OOP costs may push some enrollees to the catastrophic threshold at a faster pace, increasing total expenditures for Medicare. Additionally, lower utilization of high value drugs may lead to a surge in

hospitalization (Chandra, Gruber, and McKnight 2010; Chandra, Flack, and Obermeyer 2021), with higher costs for both the enrollees and Medicare.

Our results hinge on a number of assumptions. First, given the aggregate nature of our data, we do not consider substitution across drugs, which may affect health outcomes and spending. Also, our counterfactuals consider plan market shares to be unaffected by tier shifting and thus cannot capture potential heterogeneous effects across enrollees. Finally, we provide back-of-the-envelope welfare computations that rely on estimates from the literature. All these limitations could be addressed by developing a richer model estimated with individual-level data, which we leave for future research.

8 References

Abaluck, J. and J. Gruber (2011, June). Choice inconsistencies among the elderly: Evidence from plan choice in the medicare part d program. *American Economic Review 101*(4), 1180–1210.

Abaluck, J. and J. Gruber (2016, August). Evolving choice inconsistencies in choice of prescription drug insurance. *American Economic Review 106*(8), 2145–84.

Armstrong, M. and Y. Chen (2009, 05). Inattentive Consumers and Product Quality. *Journal of the European Economic Association 7*(2-3), 411–422.

Avalere (2018). Generic drugs in medicare part d. trends in tier structure and placement. Technical report, Avalere.

Berndt, E., R. Conti, and S. Murphy (2017). The landscape of US generic prescription drug markets, 2004-2016. NBER Working paper No. 23640.

Besley, T. J. (1988). Optimal reimbursement health insurance and the theory of ramsey taxation. *Journal of Health Economics 7*(4), 321–336.

Carlin, B. I. (2009). Strategic price complexity in retail financial markets. *Journal of Financial Economics 91*(3), 278–287.

Chandra, A., E. Flack, and Z. Obermeyer (2021). The health costs of cost-sharing. Technical report, National Bureau of Economic Research.

Chandra, A., J. Gruber, and R. McKnight (2010). Patient cost-sharing and hospitalization offsets in the elderly. *American Economic Review 100*(1), 193–213.

Dafny, L., C. Ody, and M. Schmitt (2017, May). When discounts raise costs: The effect of copay coupons on generic utilization. *American Economic Journal: Economic*

Policy 9(2), 91–123.

Dalton, C. M., G. Gowrisankaran, and R. J. Town (2019, 04). Salience, Myopia, and Complex Dynamic Incentives: Evidence from Medicare Part D. *The Review of Economic Studies 87*(2), 822–869.

Decarolis, F. (2015, April). Medicare part d: Are insurers gaming the low income subsidy design? *American Economic Review 105*(4), 1547–80.

Decarolis, F., M. Polyakova, and S. P. Ryan (2020). Subsidy design in privately provided social insurance: Lessons from medicare part d. *Journal of Political Economy 128*(5), 1712–1752.

Dubois, P. and L. Lasio (2018). Identifying industry margins with price constraints: Structural estimation on pharmaceuticals. *American Economic Review 108*, 3685–3724.

Duggan, M. and F. Scott Morton (2010, March). The effect of medicare part d on pharmaceutical prices and utilization. *American Economic Review 100*(1), 590–607.

Dusetzina, S. B., S. Jazowski, A. Cole, and J. Nguyen (2019). Sending the wrong price signal: Why do some brand-name drugs cost medicare beneficiaries less than generics? *Health Affairs 38*(7), 1188–1194. PMID: 31260351.

Einav, L., A. Finkelstein, and M. Polyakova (2018). Private provision of social insurance: Drug-specific price elasticities and cost sharing in medicare part d. *American Economic Journal: Economic Policy 10*, 122–153.

Ellison, G. and S. F. Ellison (2009). Search, obfuscation, and price elasticities on the internet. *Econometrica 77*(2), 427–452.

Feldstein, M. S. (1973). The welfare loss of excess health insurance. *Journal of Political Economy 81*(2, Part 1), 251–280.

Fix, A., J. Brennan, S. Donthi, and M. Whorley (2022). 57% of generic drugs are not on 2022 part d generic tiers. Technical report, Avalere Health.

Fleitas, S. (2020). Who benefits when inertia is reduced? competition, quality and returns to skill in health care markets. Technical report, CEPR discussion paper DP14292.

Handel, B. R. and J. T. Kolstad (2015, August). Health insurance for "humans": Information frictions, plan choice, and consumer welfare. *American Economic Review 105*(8), 2449–2500.

Hausman, J. A. (1996). Valuation of new goods under perfect and imperfect competition. In *The economics of new goods*, pp. 207–248. University of Chicago Press.

Ho, K., J. Hogan, and F. Scott Morton (2017). The impact of consumer inattention on insurer pricing in the medicare part d program. *The RAND Journal of Economics 48*(4), 877–905.

Lavetti, K. and K. Simon (2018, August). Strategic formulary design in medicare part d plans. *American Economic Journal: Economic Policy 10*(3), 154–92.

Marzilli Ericson, K. M. (2014, February). Consumer inertia and firm pricing in the medicare part d prescription drug insurance exchange. *American Economic Journal: Economic Policy 6*(1), 38–64.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica 69*(2), 307–342.

Olssen, A. L. and M. Demirer (2021). Drug rebates and formulary design: Evidence from statins in medicare part d. In *Massachusetts Institute of Technology Working Paper*.

Oster, G. and A. Fendrick (2014, 09). Is all "skin in the game" fair game? the problem with "non-preferred" generics. *The American journal of managed care 20*, 693–5.

Starc, A. and R. J. Town (2019, 09). Externalities and Benefit Design in Health Insurance. *The Review of Economic Studies 87*(6), 2827–2858.